DATA ANALYTICS AND BIG DATA A hard enough explanation for non-technical roles



INSIDE THE Organization

OR HOW TO LEAD A DATA-DRIVEN REVOLUTION IN YOUR COMPANY BALANCING BETWEEN TECH, BUSINESS AND DESIGN

By TECHBIZDESIGN.COM

Inside the organization we talk...

About Data-driven The maturity levels, how data-driven are you...

About decisions

Decision making process, bias in decisions...

About Analytical principles

About Analytical value

Value propositions, value pyramid...

About Data governance

Definition, maturity and CDO Role in a Data oriented company

The Data-driven path

A Data-Driven organization is a kind of company who uses **Data Science as a core strategy** for its business

In these types of companies, data is part of the company culture, encouraging their employees curiosity and invite them to look for new ways to exploit the information available to the company.

Data Driven is committed to the **latest data analysis technology**. They're able to optimize their resources, detect market trends and make decisions much faster than a traditional company. These companies **don't just follow the trends**, **they create them**



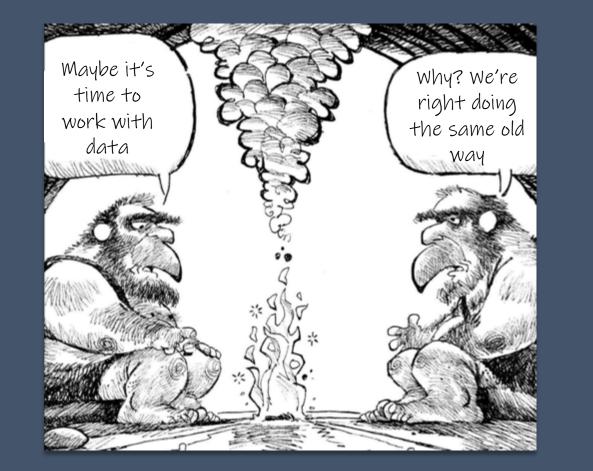
A Data RESISTANT company – The first level

Vision and organizational model

No specific leadership No organizational model defined

Investment and value generation

Their projects and initiatives are still in discussion



Culture and talent

No analytical profiles in company The culture is based on **intuition and experience**

Infrastructure

On-premise models Few **data internal** sources (transactional and CRM)

A Data AWARE company – Time to think on DATA

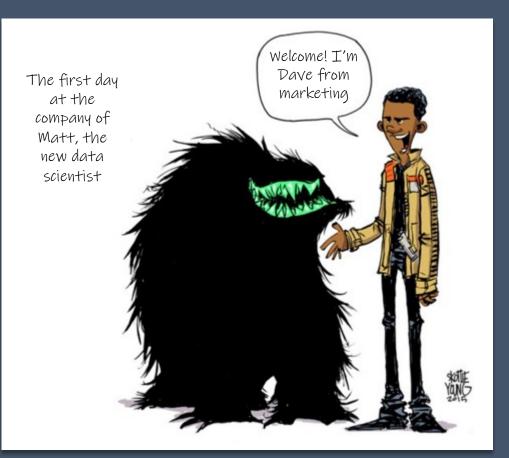
Vision and organizational model

Leadership is **low consolidated** and absolutely focus on reporting. **Model not consolidated** at all. It's decentralized or controlled by a specific unit

Investment and value generation

First Proof of Concept on going

The scope is focused on a specific Business Unit



Culture and talent

Maybe a **data scientist** in the organization. He's a **rara avis**

Basic analysis and visualization is what Data Analytics represent for the organization

Infrastructure

Mainly on-premise architectures

They deal with different internal data sources

The technological stack is concentrated on statistical and data processing software

A Data GUIDED company – Time to analyze the DATA

Vision and organizational model

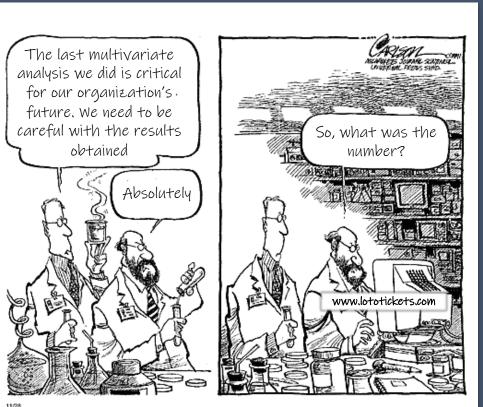
Leadership on consolidation process focus **based on data modelling**

But the model is still low consolidated. Not any defined structure

Investment and value generation

Cross organization projects on going but in a **few Business** Units

They've got first **preliminary** results



Culture and talent

Small Database administration team with data managers They've reached basic analysis, reporting and any multivariate model

Infrastructure

Mainly **hybrid architecture** with a major weight on-premise First external data sources

Statistical and data processing software combined with **Big Data integrated packages**

A Data SAVVY company – Looking desperately for INSIGHTS

Vision and organizational model

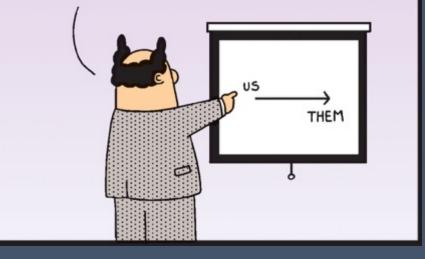
They've got a **consolidated leadership** and a strong promotion of improvement and innovation initiatives

They've created **new Business lines** and the model is far consolidated

Investment and value generation

Consolidated projects with tangible results

If we work hard on our Data Strategy, we'll able soon to predict when we're going to be in front of our competition. Thanks God we use Data Science!



Culture and talent

The analytical teams are involved in support to Business and decision-taking processes

They've implemented **advanced multivariate models** and dome **predictive models**

Infrastructure

Mainly **hybrid architecture** with a major weight cloud Common use of **external data sources**

Data exploitation with script and programming languages

A Data DRIVEN company – When STRATEGY depends on Data

Vision and organizational model

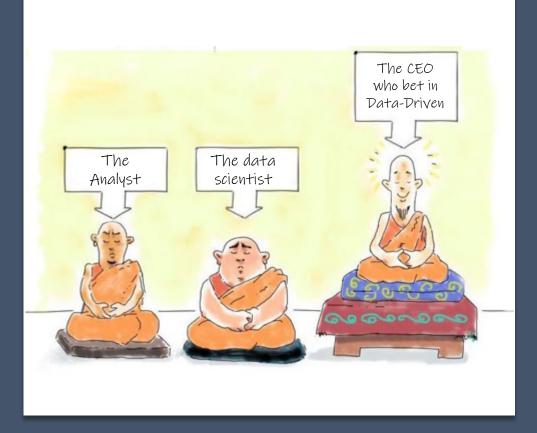
They've got a consolidated leadership, decisive in organization digital strategy and transformation

Model fully consolidated

Investment and value generation

Multiple consolidated projects

and systems in real-time and automatize in production environment



Culture and talent

The analytical teams are fully involved in the organization They've reached **different business analytical stages**

Infrastructure

Hybrid architectures **mostly cloud**

The multiple external data sources are fully integrated

The organization has a **complete usage of technology** depends on analytical domain

So, what Data-driven level are you?

	Data RESISTANT	Data AWARE	Data GUIDED	Data SAVVY	Data DRIVEN
Vision and organizational model	No leadership No organizational model defined	Low consolidated Model not consolidated	Based on data modelling Model low consolidated	Consolidated leadership New Business lines	Decisive in organization digital strategy and transformation Model consolidated
Investment and value generation	Projects in discussion	Proofs of Concept	Few Business Units pushing Preliminary results	Tangible results	Multiple consolidated projects in production
Culture and talent	Intuition and experience	One data scientist as a rara avis	DBA team with data managers Multivariate model	Advanced multivariate models Predictive models	Multiple Business analytical stages reached
Infrastructure	On-premise Internal data	Mainly on-premise Statistical and data processing software	Hybrid architectures Big Data integrated packages	Hybrid architecture (cloud) External data sources	Mostly cloud Complete usage of technology

Are there many data-driven companies? Why do they want to be one of them?

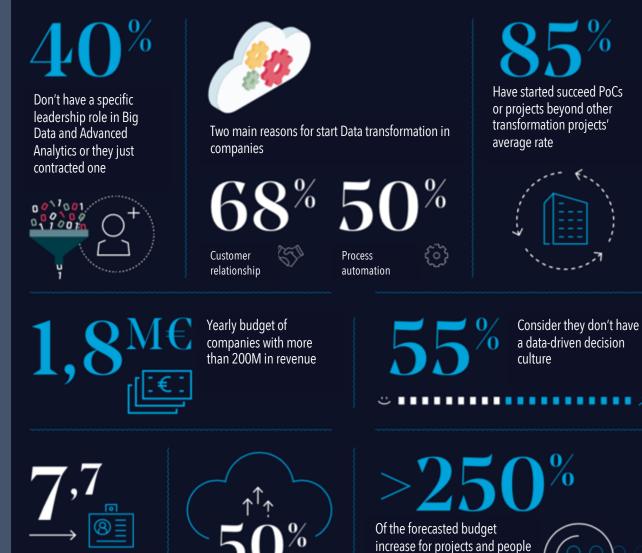
The Spanish case

Companies are aware of Data Analytics and Big Data potential. But they are far from a fully adoption.

Investment is arriving to Data initiatives. But generally people are working on **Proofs of Concept.**

Talent is rare and hard to obtain.

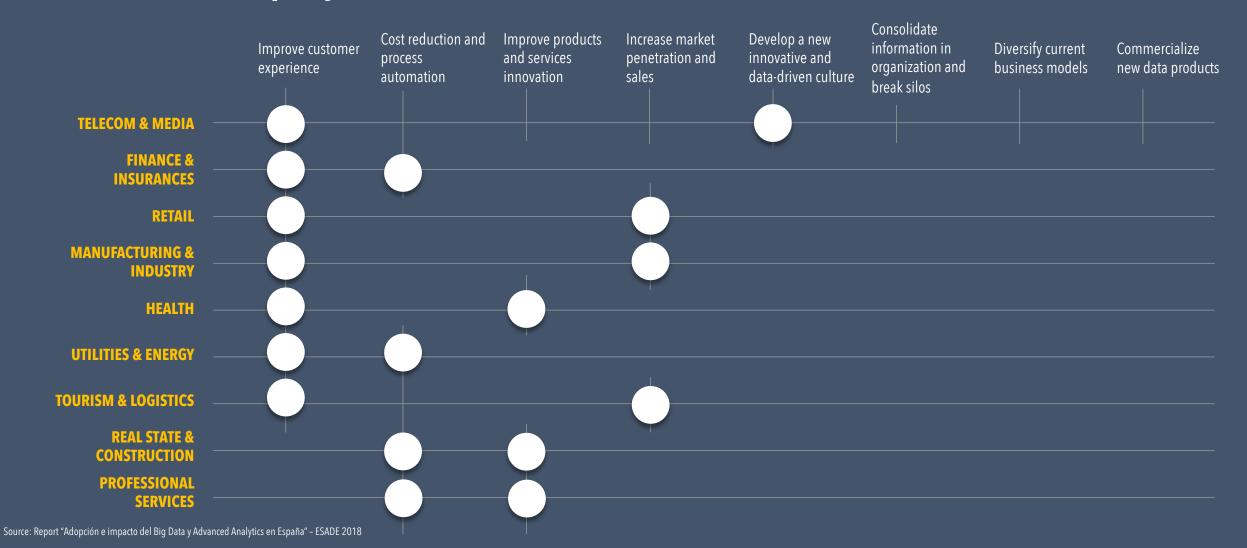
Predominance of **on-premise** architectures, but with a strong cloud **presence**. At the same time, usage of programming for analysis and tools for visualization



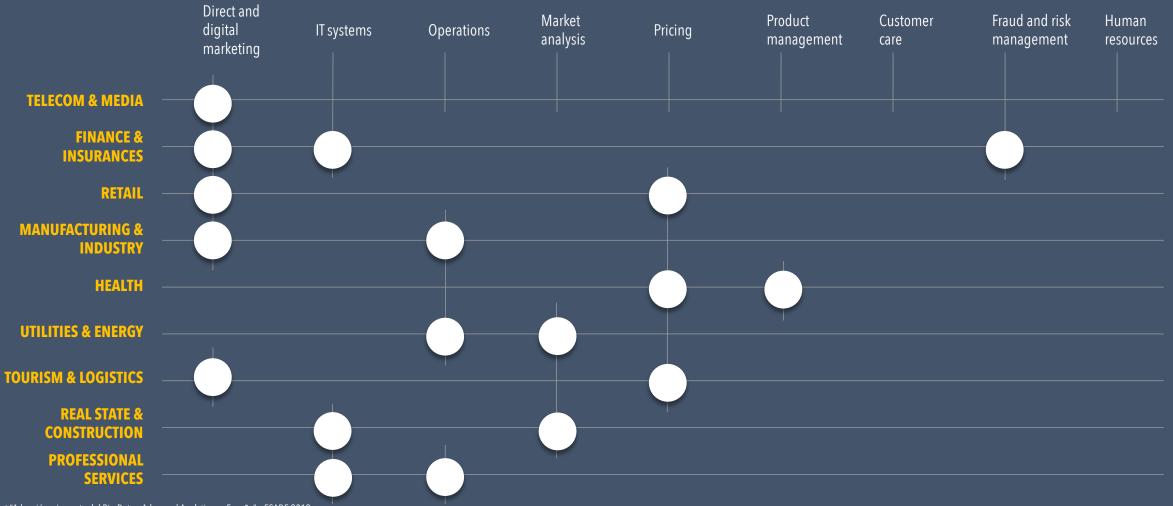
On average difficulties to contract an analytical profile (10 is very difficult)

Use CLOUD partial or completely to data storage dedicated to Big Data in next 3 years

Improve customer experience is the first motivation to be a Datadriven company



Digital marketing is the most analytical demand from Business Units



Source: Report "Adopción e impacto del Big Data y Advanced Analytics en España" - ESADE 2018

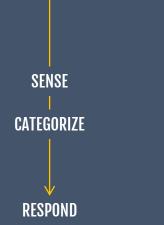
How can I use Data to take the right decisions?

Data and emotion – The situations your company has to deal with

Simple

The relationship between cause and effect is **obvious and proven**. Best practices exist, and should be researched and applied.

For example, it's obvious that when healthcare providers in hospitals wash their hands frequently, this reduces the spread of disease



Complicated

The relationship between cause and effect **requires analysis or some other form of investigation** and/or the application of expert knowledge.

For example, web developers have to test various website designs to see which result in fewer abandoned shopping carts

SENSE

ANALYZE

RESPOND

Complex

PROBE

SENSE

RESPOND

The relationship between cause and effect is **unknown**. We can see it only in retrospect, not in advance.

For example, pharmaceutical research teams have to explore multiple compounds to determine their impact on disease conditions.

Chaotic

The relationship between cause and effect is **unknowable**. There is no discernible relationship between cause and effect, and there may never be.

This, for example, is the situation facing medical emergency or senior leadership teams experiencing an unanticipated disruption to their supply chain.



Data and emotion – How to act in front of each situation

Simple

Automate? Yes

Frequency: Every day

Quantity: Many

Relation between cause and effect: Known to all in advance Approach: Sense, categorize and respond

Technique: Best practice

Inputs & variables: Few

Algorithm or heuristics? Algorithm

Data or instinct? Data

Who does it best? Machines

Tactical, strategic or operational: Operational and tactical Examples: Interest calculation, credit scoring

Yes
Frequent
Many
Requires analysis but can be known
Sense, analyze and respond
Good practice
Start with lots, end with less
Combination
Both
Machines plus human experts
Operational and tactical

Predicting employment or academic

success

Complicated

Complex Partially Frequent Many Only known in retrospect Probe, sense and respond Emergent practice Many Combination Both Human experts Tactical or strategic Developing software

Chaotic

No Frequent Many Not discernible Act, sense and respond Novel practice, experimentation Many and interacting Heuristics Emotion Human experts with emotional intelligence plus machines Strategic Responding to crises

Data and emotion – Dealing with fear and anger

Daniel Khaneman's bestseller called "Thinking, fast and slow"

System 1 based on intuition – Fast, automatic, frequent, emotional, stereotypic, subconscious

System 2 based on reasoning – Slow, effortful, infrequent, logical, calculating, conscious

Applied to evidence-based business scenarios, system 1 means that any interaction that conveys an implied criticism of a person's current work can lead to immediate resistance. This is the source of employee's defensive and unresponsive attitudes

Data may be nonjudgmental and unemotional, but when people are put in the mix, the results are far from guaranteed



Data and emotion – Cognitive bias and logical fallacies

Cognitive bias

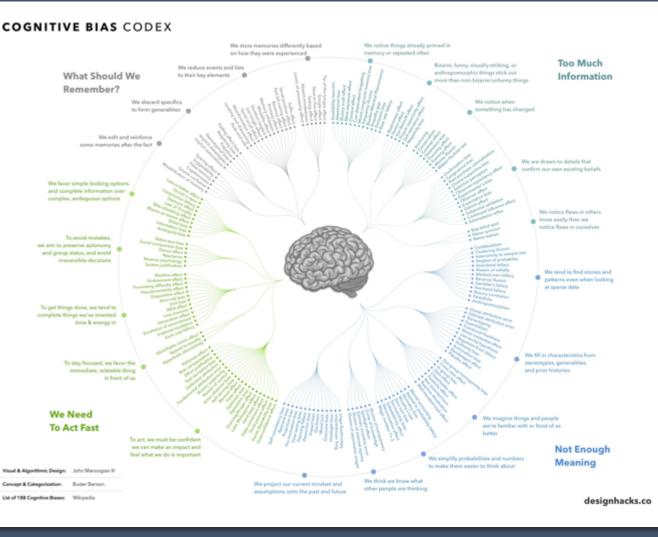
Cognitive biases are our default inclinations towards certain kind of thinking when we interpret and process information from the world around us. Everyone has biases and they affect greatly our behavior, decisions and judgements.

It's about **INTERPRETATION**

Logical fallacies

Logic fallacies are mistakes in arguments - done deliberately or by accident. These mistakes include misuse of evidence, misuse of language, erroneous line of reasoning and distortion of an issue. Logical fallacies are "nonsequiturs", meaning that the conclusion doesn't follow from what preceded it.

It's about **COMMUNICATION**



Data and emotion – Some famous and dangerous Bias

Overconfidence

Also called the **Dunning-Kruger effect**. The more ill-informed and incompetent someone is, the more confident they are of their position. In contrast, the more informed a person becomes, the less confident they tend to become.

Benjamin Franklin effect

People reason that they help others because they like them, even if they do not, because their minds struggle to **maintain logical consistency between their actions and perceptions**.

Validation by frequency effect

The more times you listen to a fact, even if it is a lie, the more predisposed it is to validate it. The basis of the current trend of **FAKE NEWS**

Peltzman effect

Better to lower a small risk to zero than larger profit assuming risk or the the tendency to take greater risks when perceived safety increases.



Data and emotion – Other cognitive bias or the things you probably do

1. Anchoring Bias

People are **over-reliant on the first piece of information** they hear.

In a salary negotiation, whoever makes the first offer establishes a range of reasonable possibilities in each person's mind

2. Availability heuristic

People overestimate the importance of information is available to them.

A person might argue that smoking is not unhealthy because they know someone who lived 100 and smocked three packs a day

3. Bandwagon effect

The probability of one person **adopting a belief increases** based on the number of people who hold that belief.

This is a powerful form of groupthink and is reason why meetings are often unproductive

4. Blind-spot

Failing to recognize your own cognitive biases is a bias itself.

People notice cognitive and motivational biases much more in others than themselves

5. Choice-supportive

When you choose something, you tend to **feel positive about** it, even it that choice flaws.

Like how you thing your dog is awesome, even it bites people every once in a while

6. Clustering illusion

This is the tendency to **see patterns in random events**. It's key to various gambling fallacies.

Like the idea that red is more likely to turn up on a roulette table after a string of reds

7. Confirmation

We tend to listen only to information that confirm our preconceptions.

One of the many reasons it's so hard to have an intelligent conversation about climate change

8. Conservation

Where people **favor prior evidence over new evidence** or information that has emerged.

People were slope to accept that the Earth was round because they maintained their early understanding

9. Information

The tendency to **seek information when it doesn't affect action**. More information is not always better.

With less information, people can often make more accurate predictions

10. Ostrich effect

The decision to ignore dangerous or negative information by burying one's head in the sand, like and ostrich.

Research suggests that investors check the value of their holdings significantly less often during bad markets

Data and emotion – Other cognitive bias or the things you probably do

11. Outcome

Judging a decision **based on the outcome** rather than how exactly the decision was made in the moment .

Just because you won a lot of money in Vegas doesn't mean gambling your money was a good decision

12. Zero - risk

Sociologists have found that **we love certainty** even it is counterproductive. Eliminating risk entirely means there is no chance of harm being caused.

13. Placebo effect

When **simply believing** that something will have a certain effect on you causes it to have that effect.

In medicine, people given fake pills often experienced the same physiological effects s people given the real pills.

14. Pro-innovation

When a proponent of an innovation tends to **overvalue its usefulness** and undervalue its limitations.

Sounds familiar Silicon Valley?

15. Recency

The tendency to weight the **latest information more heavily** than older data.

Investors think the market will always look the way it looks today and make unwise decisions.

16. Salience

Our tendency to focus on the **most** easily recognizable features of a person or concept.

When you thing about dying, you might worry about being mauled by a lion, s opposed to what is statistically ore likely, like dying in a car accident.

17. Selective perception

Allowing our expectations to influence **how we perceive the world**.

An experiment involving a football game between students from two universities owed that one team saw the opposing team omit more infractions.

18. Stereotyping

Expecting a group or a person to have certain qualities without having real information about the person.

It allows us to quickly Identify strangers s friends or enemies, but people tends to overuse and abuse it.

19. Survivorship

A error that comes from **focusing only on surviving examples**, causing us to misjudge a situation.

For instance, we might think that being an entrepreneur is easy because we haven't heard of all those who failed.

20. Barnum effect

People accept general and vague information when they are led to believe that the **information has been specifically tailored** to be about them.

Data and emotion – Some relevant logical fallacies

1. Argument from incredulity

This is basing an argument on personal disbelief.

This provokes that a decision cannot go forward because it contradicts the point of view of the misinformed individual.

2. Correlating proven causation

This is a faulty assumption that a correlation between two variables implies that **one causes the other**.

So, the action is taken based on a mistaken premise.

3. Base rate fallacy

This is making a probability judgment **based on conditional relationships**, without taking into account the effect of prior status.

The starting conditions are misjudged, leading to unreasonable or invalid expectations.

4. False authority

This is **using an expert of dubious credentials**, or using only one opinion to sell a product or idea.

Wrong solutions are adopted for the wrong problems because they were recommended by an "authority."

5. Anecdotal fallacy

People use a personal experience or

an isolated example, instead of reasoning or compelling evidence. An anecdote is not data.

This extrapolates from a small set of anecdotes

6. False dichotomy

Two alternative statements are held to be the only possible options, when in reality, there may be other options.

Leaders force a decision without looking at other alternatives..

Fallacies have a more negative connotation than bias

Which are the rules or principles to go in the right direction? How can I get the value from Data?

Mantras for a Data-driven organization



Data driven

Adopt an experimental mindset

- 1. Challenge data-decision making
- 2. Anticipate unintended consequences of metrics
- 3. Experiment with new data and analytical models



Privacy

Be the guide an guardian of your customer's data

- 1. Privacy, as we known, it no longer exist
- 2. Leverage transparency to create trust
- 3. Treat customers' data as they want it to be treated



Artificial Intelligence

Automate the manual | Promote the creative

- 1. Algorithmic decision making is inevitable
- 2. Focus on augmentation, not replacement
- 3. Play to the respective strengths of AI and humans

VALUE PYRAMID

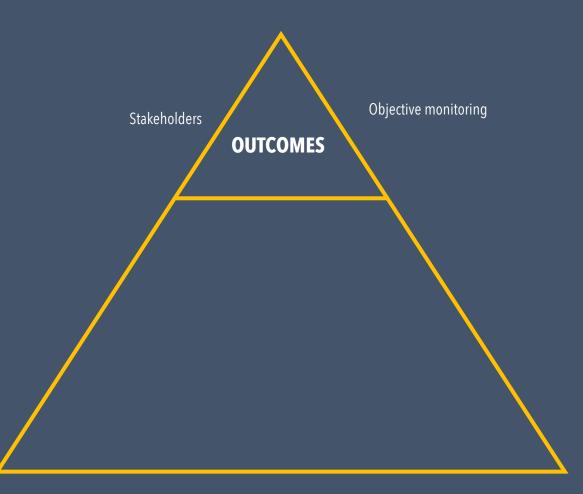
Connecting Data and Analytics to Business value

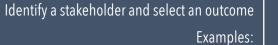
Bringing business value from Data Analytics is not an easy thing. Hundreds of small problems can occur and provoke a misalignment between technology and business.

We need to draw a consistent path then.

First, we should start **identifying the needs and problems** are impacting most in our business co-creating with our stakeholders (Regulators, investors, suppliers/partners, community, consumer, employees...)

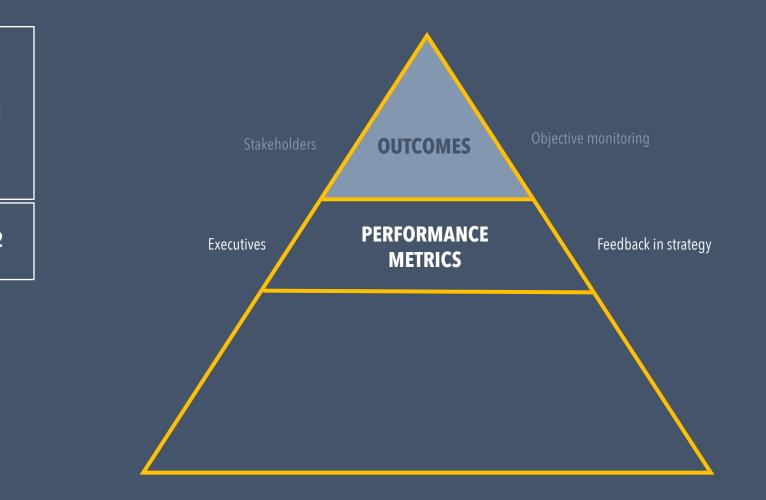
Second, we need to recognize the key elements of any use case identified. We need to recognize **value** (What is the question, business problem or target outcome? How is value realized?). We need to recognize **information** (What data or data sources e involved?). And we need to do the same with **analytics** (What analytical or data science methods are applied to the data) Once we've done that, it's time to move along the **value pyramid**...



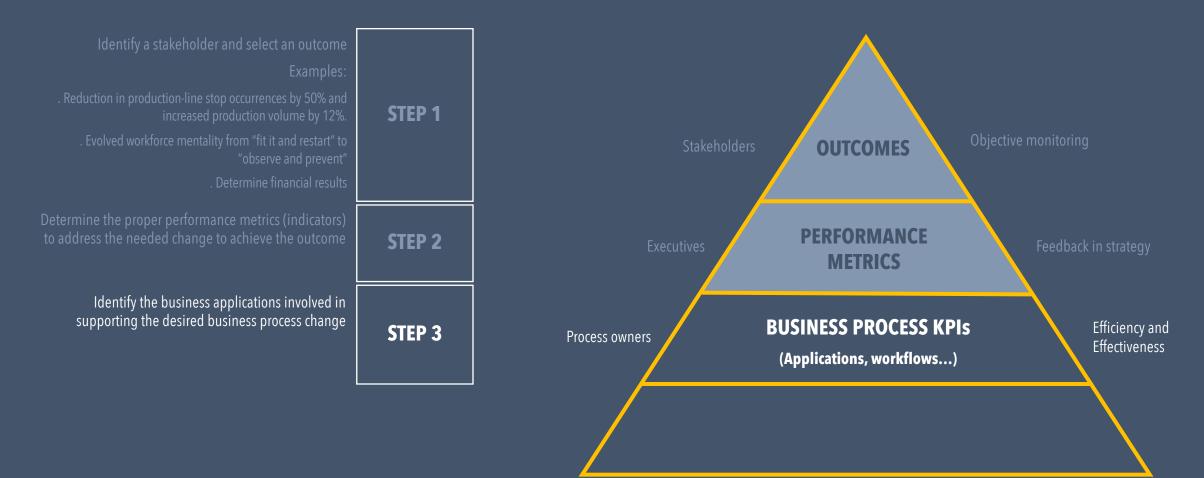


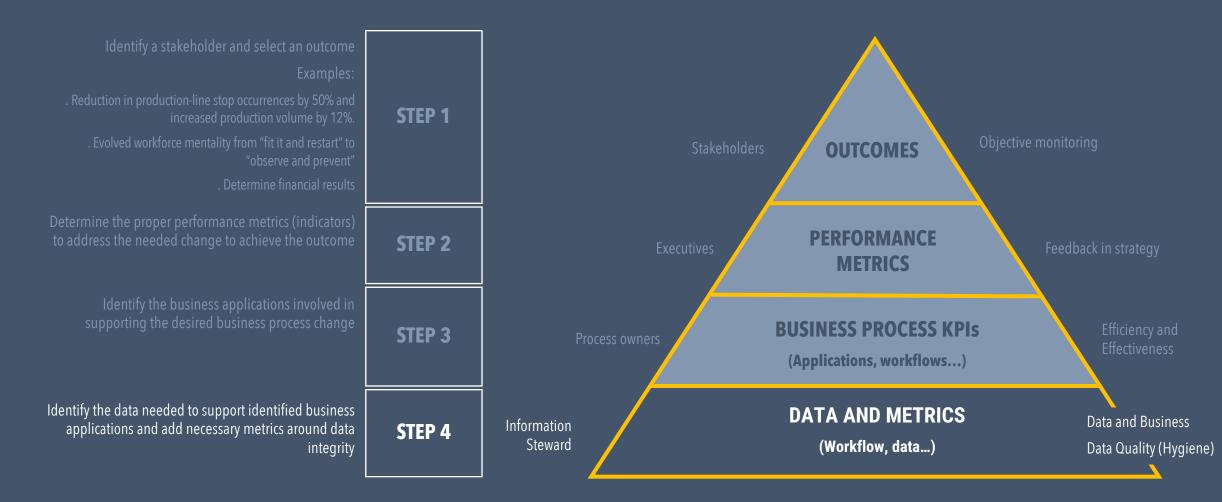
- . Reduction in production-line stop occurrences by 50% and increased production volume by 12%. . Evolved workforce mentality from "fit it and restart" to
 - "observe and prevent"
 - . Determine financial results

STEP 1

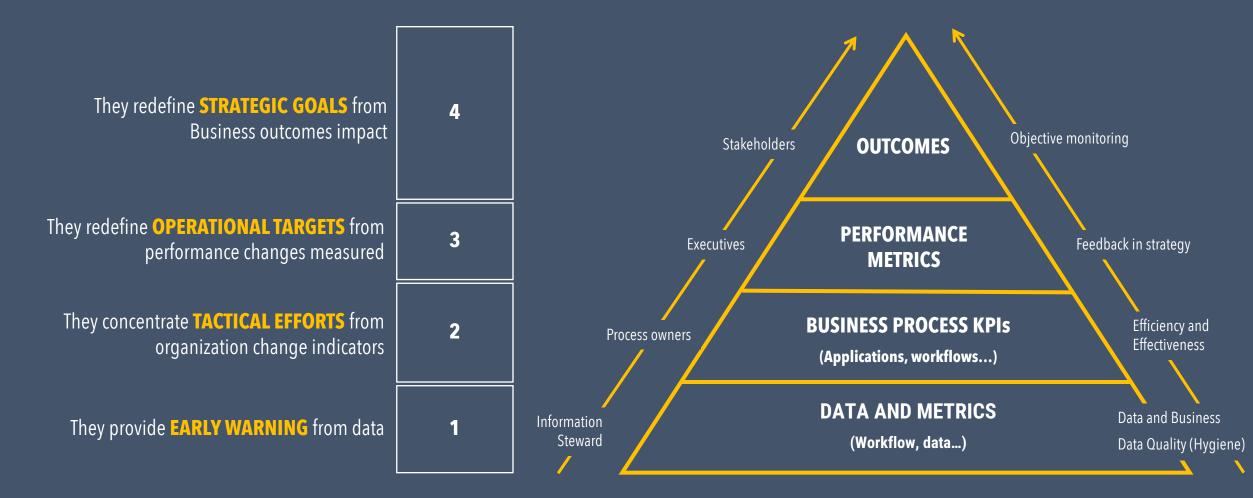








Connecting Data and Analytics to Business value – Bottom Up feedback



All this stuff seems quite complicated to manage. Is it easy to drive and control?

Sounds familiar?



Other consequences of a bad Data Governance

Your meetings dissolve into data brawls

Your decisions are primarily made by associated staff who owns the IT systems.

Your data availability and collection are **inconsistent**. It depends on third parties' good deeds.

Your data usability and quality are **not guaranteed**. You never know that's the most accurate or current.

Your data integrity is **inconsistent**. Maybe you're using a local duplicate and old dataset because there's no unique data policy.

And so forth...

So, a trustworthy data, a common understanding, a complete traceability, and a transparent data ownership is needed



Data governance inside the organization is...



🔆 27 tanka

୍ଲ 🍮

Data governance for users is...

A system of record for Data assets that should be the authoritative source of information for any given data asset used by/valuable for the organization

FIND	Know where
the dat	a comes from

UNDERSTAND | Know what the data means

TRUST | Know that the data is right

Catalog
Data dictionary

Business glosary
Reference data

Policy manager
Data helpdesk

3. Stewardship

Steward Dashboard. • 1<0 My Tasks & Issuer **Quick Actions** 4 Tanks 124 12.5K 240 39 Access Name for Maturity Date is not shown on PPB Base Identify and Link Critical Data Element 4 months ap 793 Assets Per Domai 47 to: PRY/HG-DOAR On the left pane, po to = Show A Stewardship Most Viewed 27 36 14 10 realit Hisk Belling and Customer Del 4 et rate BETWEEN (NO. 20) Materia d Party Credit Check Beference Data · Acception 195 •) Pending Appr Counterparty Ball Rating Candidate uationer 1 Customer Business Giosse

800888

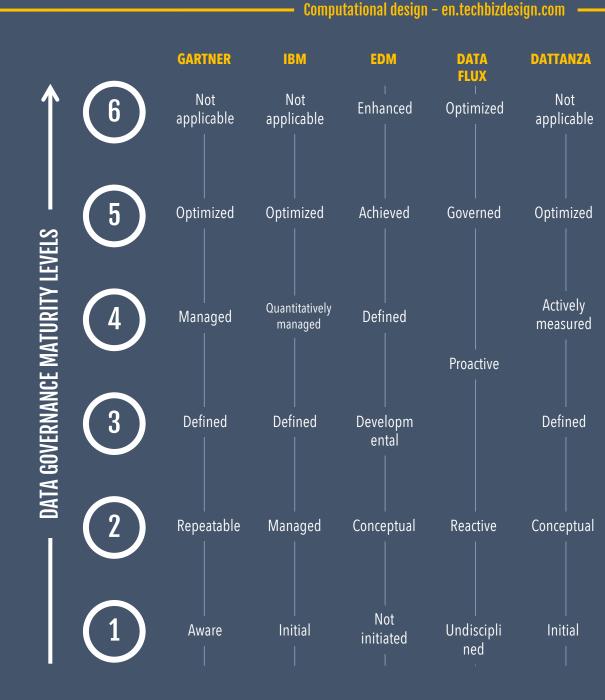
Collibra customers achieve 510% ROI with their data governance and catalog initiatives

The Data governance path

There are several approaches to face a Data Governance maturity model. Gartner, IBM, CMM, EDM... but most of them put the emphasis on same things.

. Process and the nature of the outcomes with each achieved process state

- . Adoption by People, Process and Technology
- . Implementation of capabilities along with Risk and related Benefits
- . Perceived data value from non-monetization to monetization data
- . Data being traversed from being a transactional asset to an enterprise asset
- . Implementation of Org structure, Policy, Lineage, Metadata, Funding, and Culture Change
- . Effectiveness of Accountability, Formalization, Principles of managing and governing data



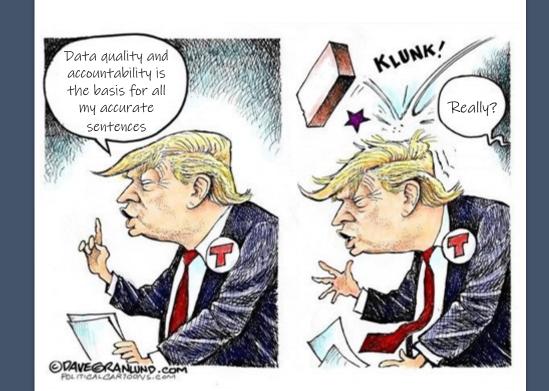
Data Governance first level - AWARE

Accountability

Executive level accountability is not defined. Scope of System Owners (stewards / owners) are not defined or named.

Quality

Profiling or data quality measures of data elements are not in place or data quality standards are not published.



Metadata

System characteristics are not defined or documented. Business, technical and operational metadata is not effectively cataloged.

Provisioning

Data is distributed on a reactive basis with little to no enterprise planning, control or governance.

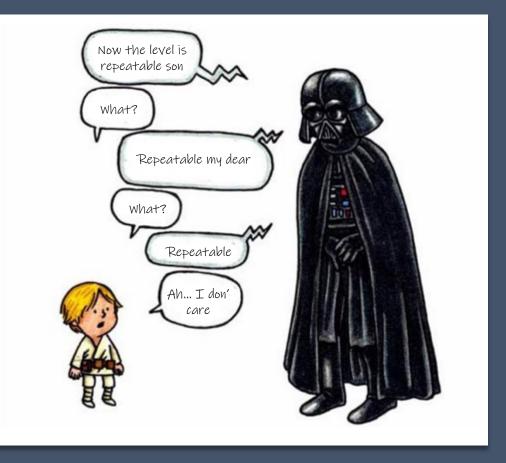
Data Governance second level – REPETEABLE

Accountability

Scope of **System Owners is defined**, and stewards / owners are named.

Quality

Key business elements are identified and data quality standards are created for them based on analysis of profiling or data quality measurement results.



Metadata

Baseline documentation for data stores, data flows, and data element definitions are available.

Provisioning

Registration as a data provider is complete. All of the system's business domains and provisioning roles are documented. The data provider assessment information is complete.

Data Governance third level - DEFINED

Accountability

Executive level accountability is defined by Enterprise Governance.

Quality

Key business elements are measured against data quality standards and data quality reports are published on an established measurement schedule.



Metadata

Documentation for data lineage, data stores and data element definitions are maintained and available to the enterprise.

Provisioning

SLAs with data consumers are in place; all data flows into and out of system are documented. Projects comply with enterprise Data Provisioning Strategy Framework and Guidelines.

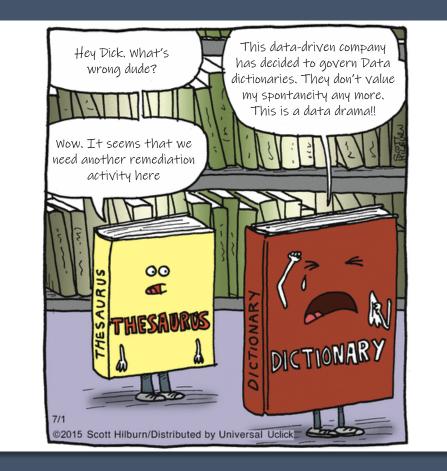
Data Governance fourth level – MANAGED

Accountability

Local Data Governance bodies are chartered and routines are in place.

Quality

Data quality goals are in place and drive **remediation** activities.



Metadata

Data Dictionaries are governed. A **Business Domain Language** is governed and mapped to data elements.

Provisioning

Data lineage is documented for all prioritized data flows involving the system. Target provisioning points are designated and a domain provisioning roadmap is in place.

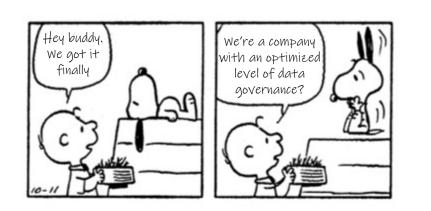
Data Governance fifth level – OPTIMIZED

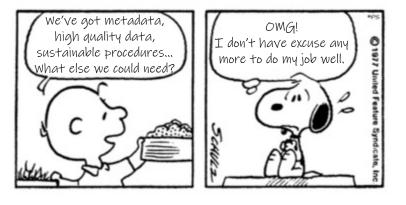
Accountability

Enterprise and Local Data Governance sustainability routines are in place.



A data quality response plan with defined thresholds for key business elements and data quality self-monitoring activities are defined and followed.





Metadata

Metadata is easily accessible across domains. The BDL is mapped to the CBL.

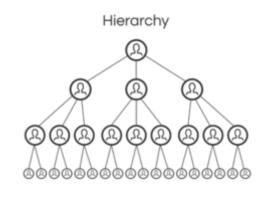
Provisioning

Data provisioning and consumption occurs according to the **domain roadmap**. **Provisioning governance** is in place and drives ongoing funding and execution decisions.

A shift in Data Governance is happening – From hierarchies to networks

HIERARCHICAL DATA GOVERNANCE (SYSTEM OF RECORD)

- . CDO as a Coordinator: Inward-oriented / Traditional Data / Service
- . Defensive: Risk-driven
- . Scarcity: Few consumers, few producers
- . Compromises on old obsolete cost assumptions of digital power
- . Use of digital optimizes to some extent
- . Not scalable for big data by larger 'data scientist' populations



NETWORKED DATA GOVERNANCE (SYSTEMS OF ENGAGEMENT)

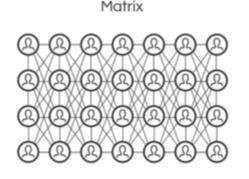
. CDO as an Experimenter: Outward / Big Data / Strategy

. Offensive: Value-driven

. Abundance

. Many Producers - Data Democratization | Eliminate Breadlines | Consumerization of BI and cheap digital power | Many serve many | Supports customer

. Many Consumers - Data Amazonification | Access, SLA, Trust, Secure Cloud...



Who's the CDO?

It's the abbreviation of **Chief Data Officer**

He/she takes care of Analytics excellence, Information management excellence and leads change for impact

He/she defines strategy, applies best methods, embraces cutting-edge technologies and moves organization forward in data-driven maturity levels

Her responsibilities are:

- . Enterprise Data Strategy
- . Data Governance and Management
- . Data Analytics
- . Data Architecture
- . Data Culture

"The executive suite needs someone who can oversee the strategic business application of its information assets enterprise-wide"

Michelline Casey - Federal Reserve Board CDO

Coming soon

That's all Folk.

DATA ANALYTICS AND BIG DATA – INSIDE THE ORGANIZATION