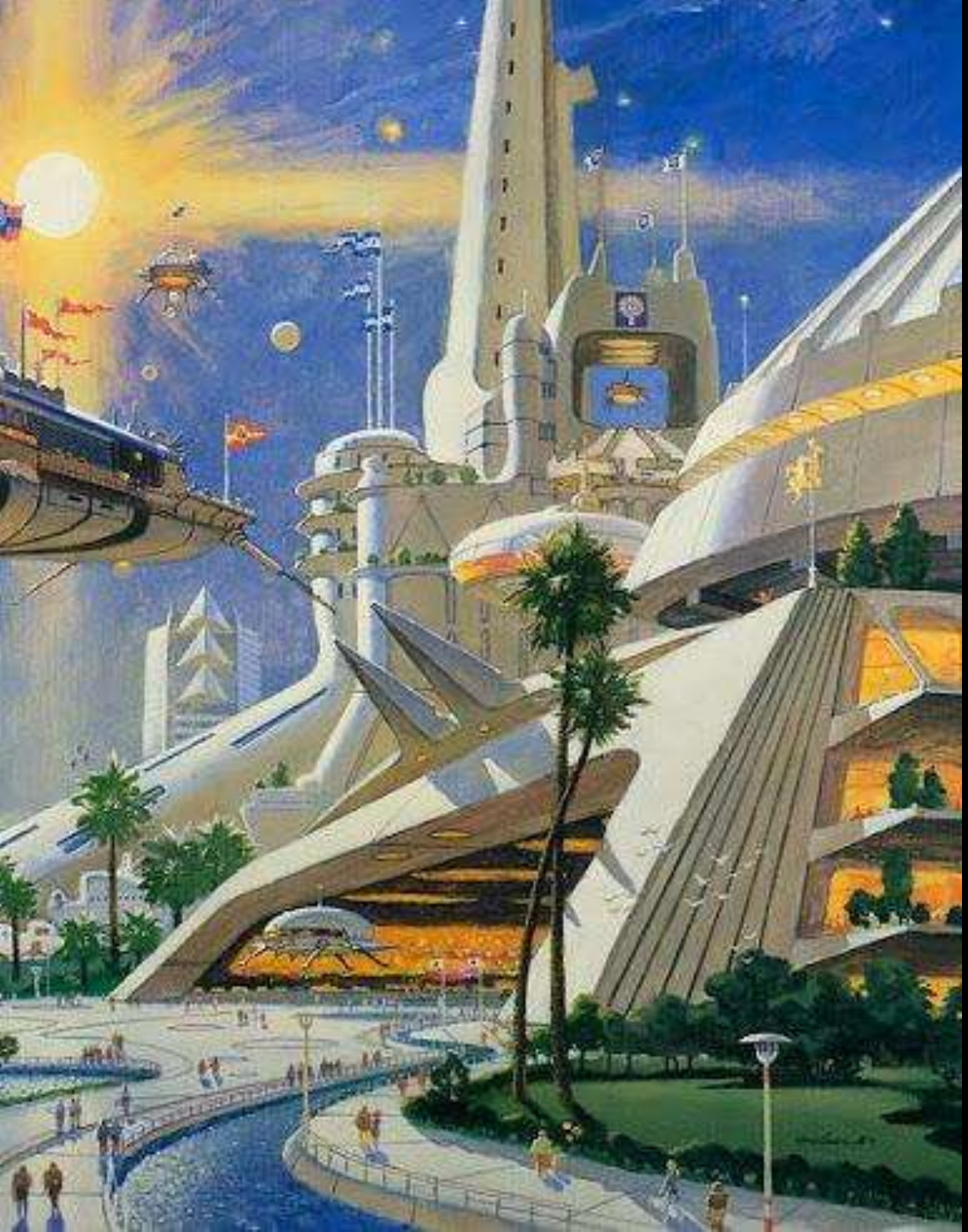


Architecting a Data Platform for Enterprise Use

Strata New York

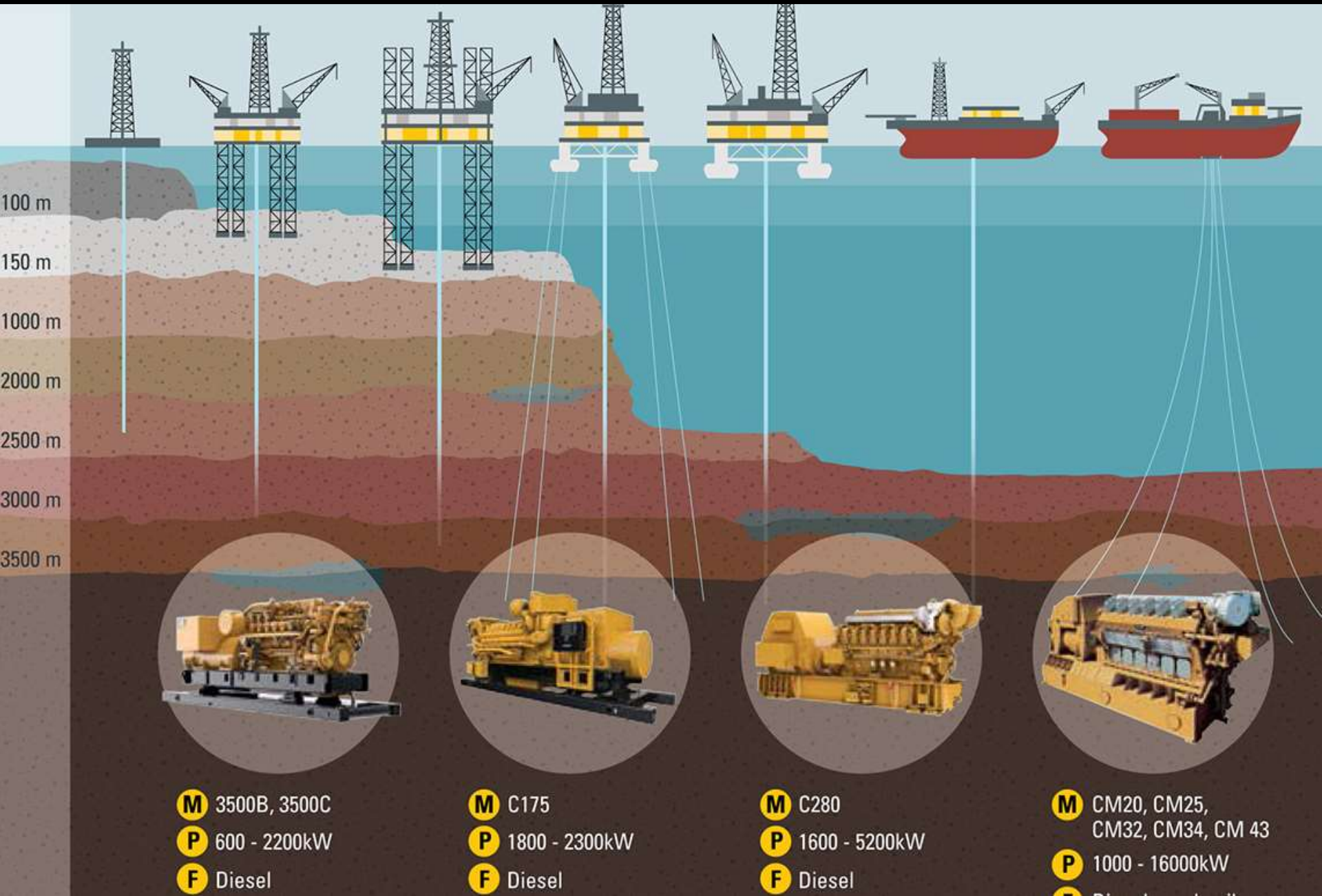
September 2019

Mark Madsen
Todd Walter

Why are we talking about architecture?


The market shifted from not enough data in the 90’s to too much data: the problem has become managing not just size, but scope and variety

More complex needs drive more complex technology

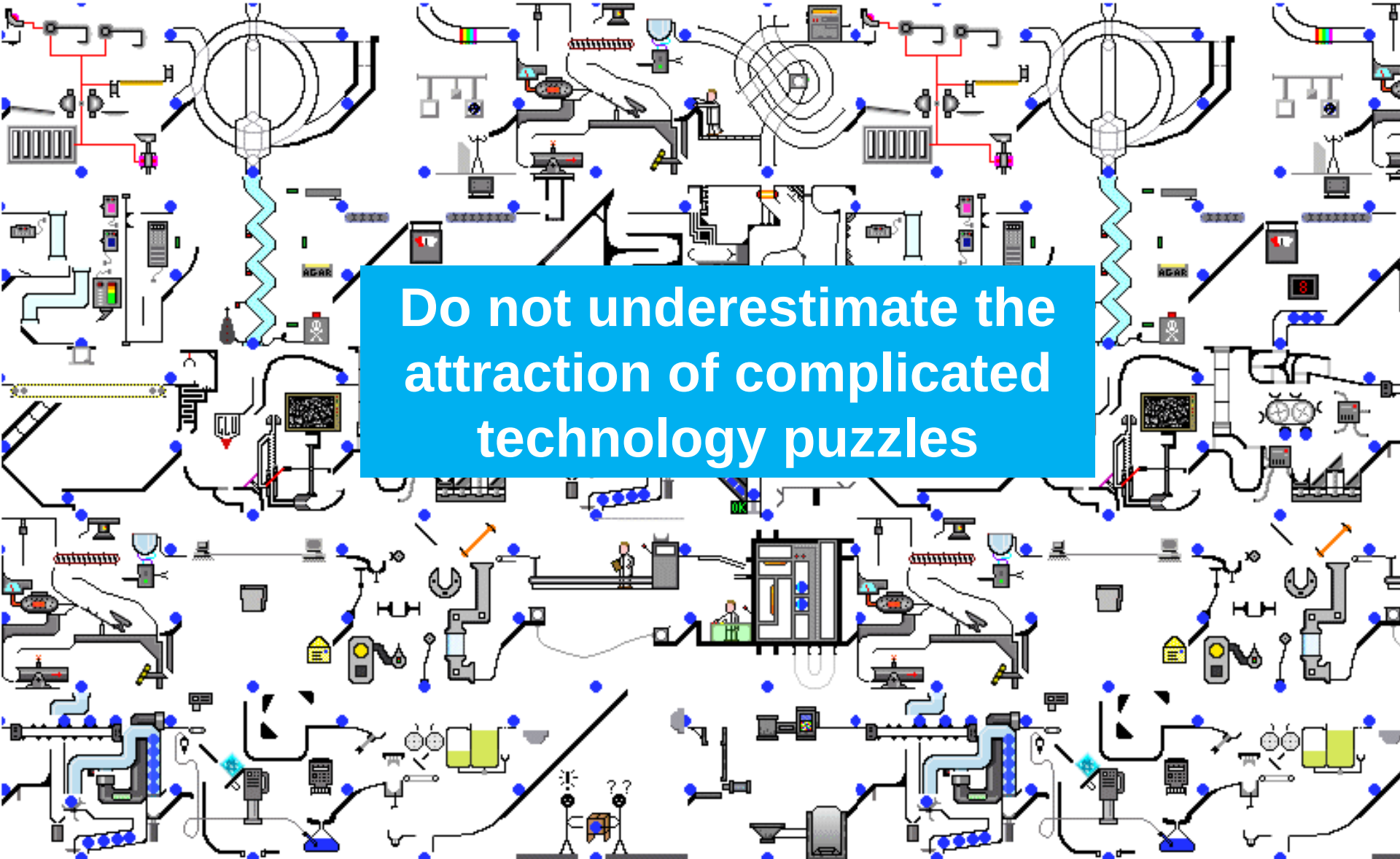


Market hype and IT workforce skill gaps lead to FOMO

The pressure on IT to “just buy something” is high. The usual IT response is based on procurement, not innovation or integration. The data infrastructure solution tends to be: buy tools, collect data.

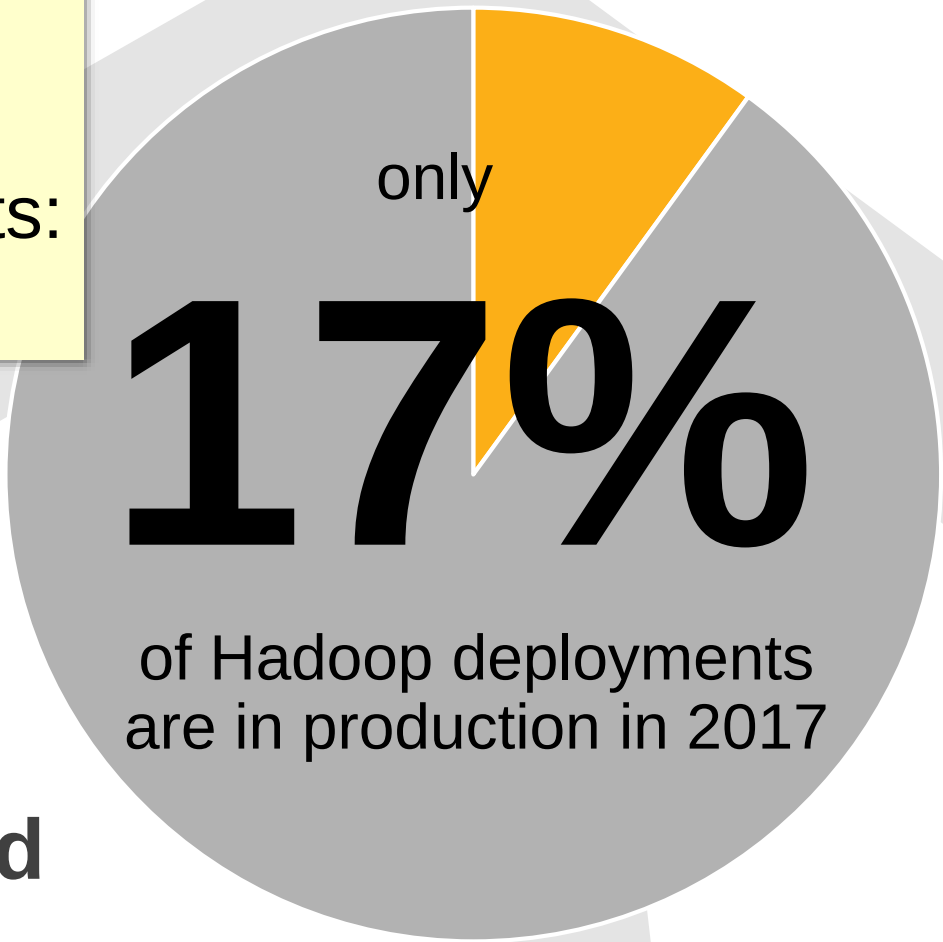
Development accumulates in a disorderly fashion

The end result in the IT landscape is complexity



A McKinsey survey this year asked executives if their company had achieved a positive ROI with their big data projects:
7% answered "yes"

Gartner Finding:
in 2017



Gartner statement in 2018:
only 15% are reported to be successful

Survey Analysis: BI and Analytics Spending Intentions, 2017

Gartner

Market and IT complexity requires a change in strategy

IT complexity means we should focus on **simplifying**

Diverse but narrow analytic needs mean we must focus on identifying **business value** and use cases

Many diverse needs across multiple projects means we must shift emphases from technology to the **data ecosystem** because more components are required

- Link shared data and infrastructure across multiple opportunities, to avoid one-off solutions
- Functional silos may be ok, but data silos are not

Third Nature


Use


Use
Over time


Use
Over time
By people

Bricks are not buildings

We don’t think this

is equivalent to this

Architecture is not technology. It’s not a product you can buy.

Third Nature

Blueprints are not architecture.
Architecture is not…

Technical wiring diagrams

Product lists

Pretty pictures

Hand-waving abstract statements and rules

A thing you can purchase

…so what is it?


What is this?

Architecture is an abstraction – a pattern that supports a purpose

You need purpose, therefore focus business goals, outcomes, use cases

Architecture is not Static – it is a Process

Rarely does anyone talk about a core problem: preexisting conditions.

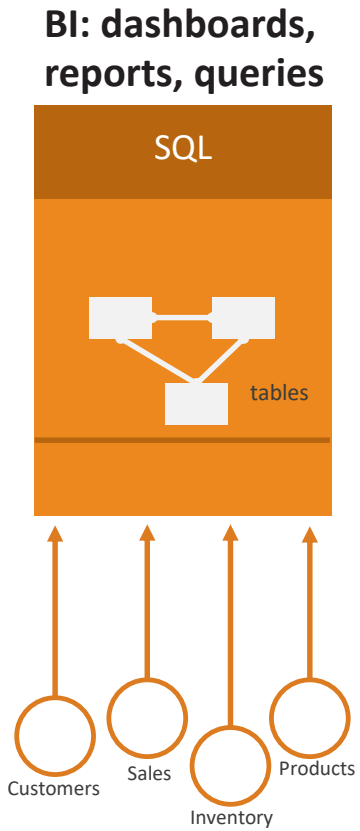
You have something new. How does it affect the old?

- Replaces the old?
- Adds to what you have?
- Overlaps with the old, forcing you to make decisions about what parts to keep, change, throw away?

The heart of this problem is the *process* of architecture: integrating changes to systems over time. The integration is not purely technical, it's practices of use, operation, deployment.


HISTORY: HOW DID WE GET HERE?

Where we started: the data warehouse and BI

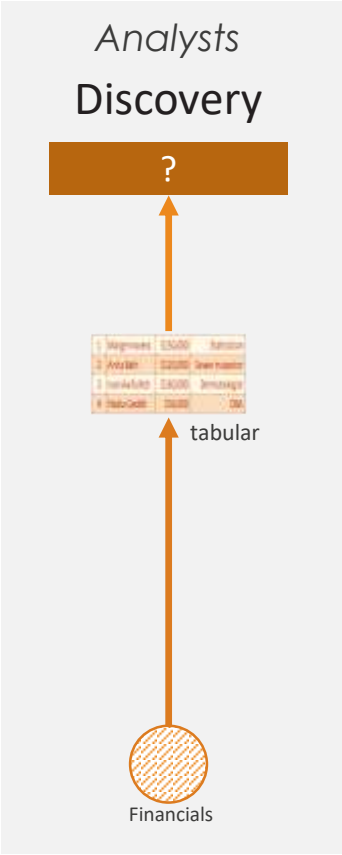


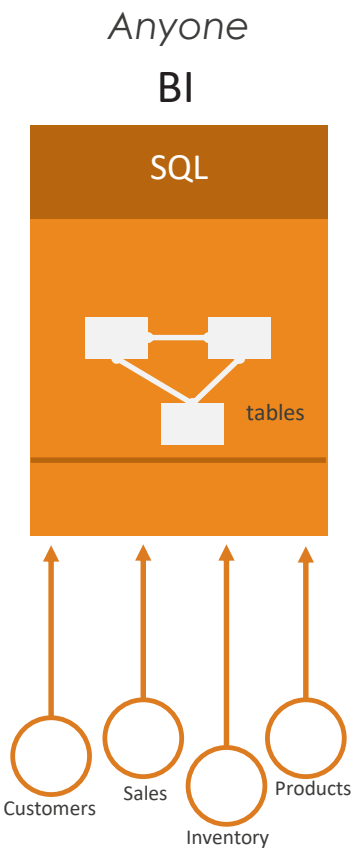
The data warehouse solved a key problem: access to data from multiple OLTP systems to provide a unified view of key information.

It is built on some assumptions: you must model the data before use, the data must be cleaned first, the data must be in tables.

The DW is built for repeatable data use, not for one-time uses of information or unknown-value datasets.

After a while, user self-service was required

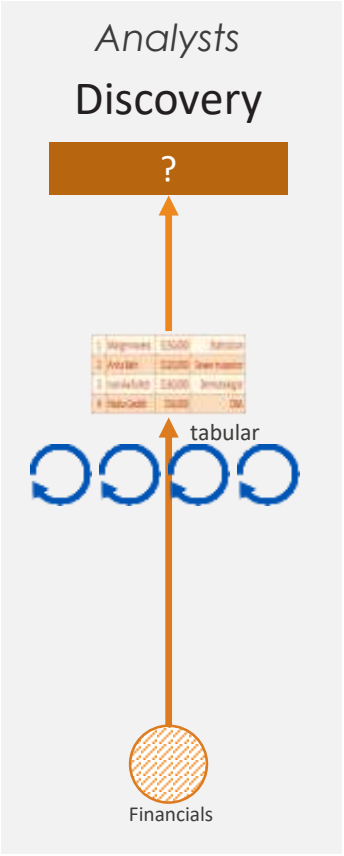


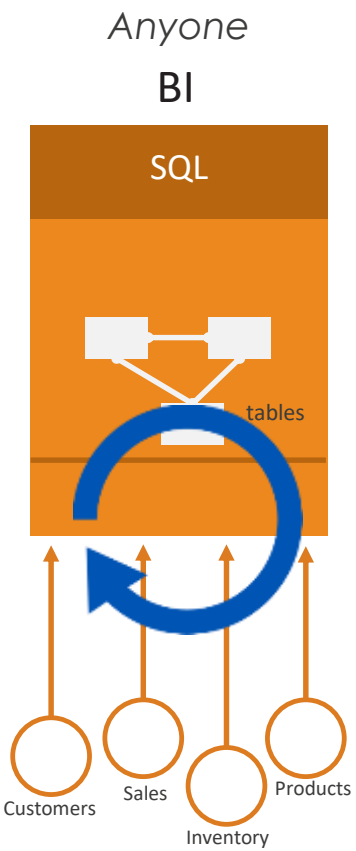


Eventually we reached maturity with the DW, driving an increasing rate of new data requests by departments and individuals.

A backlog of smaller data requests built up around .it We got self-service tools that actually worked.

Why Isn't the Data in the DW? Rush Jobs and Unknown Data

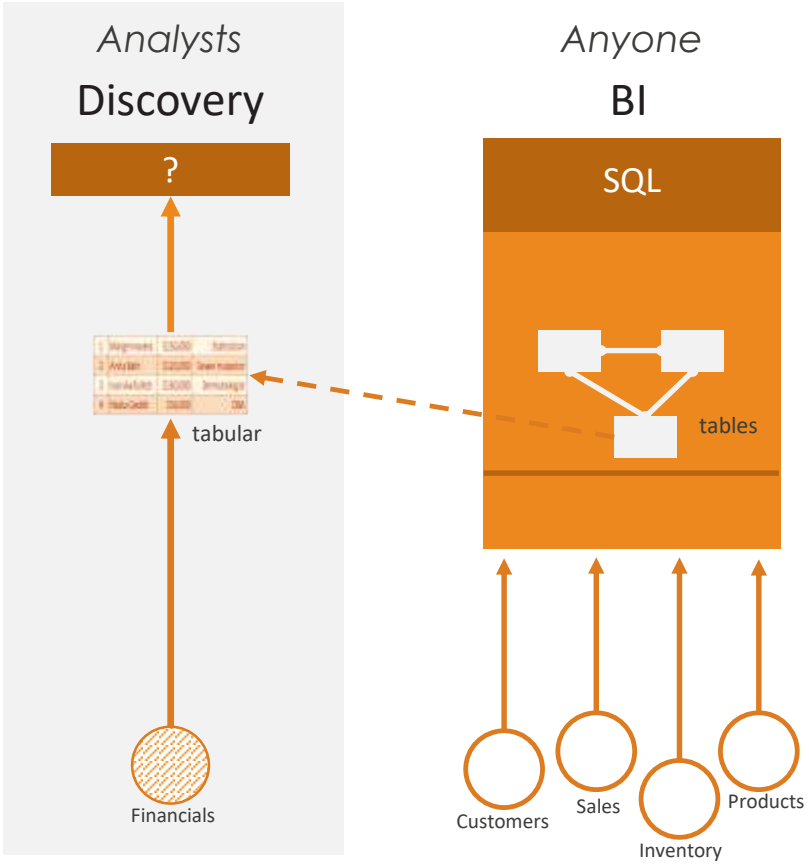




The real problem is time: business analyses are often needed in a week or less. If the data is not in the DW then the analyst has to wait – the industry average for making data available in a DW is 10 weeks.

They need quick access to new data rather than reusable, cleaned, common data. This means they need another way – and self-service tools offer an answer other than "wait."

Data is rarely used in isolation, DW data is often needed

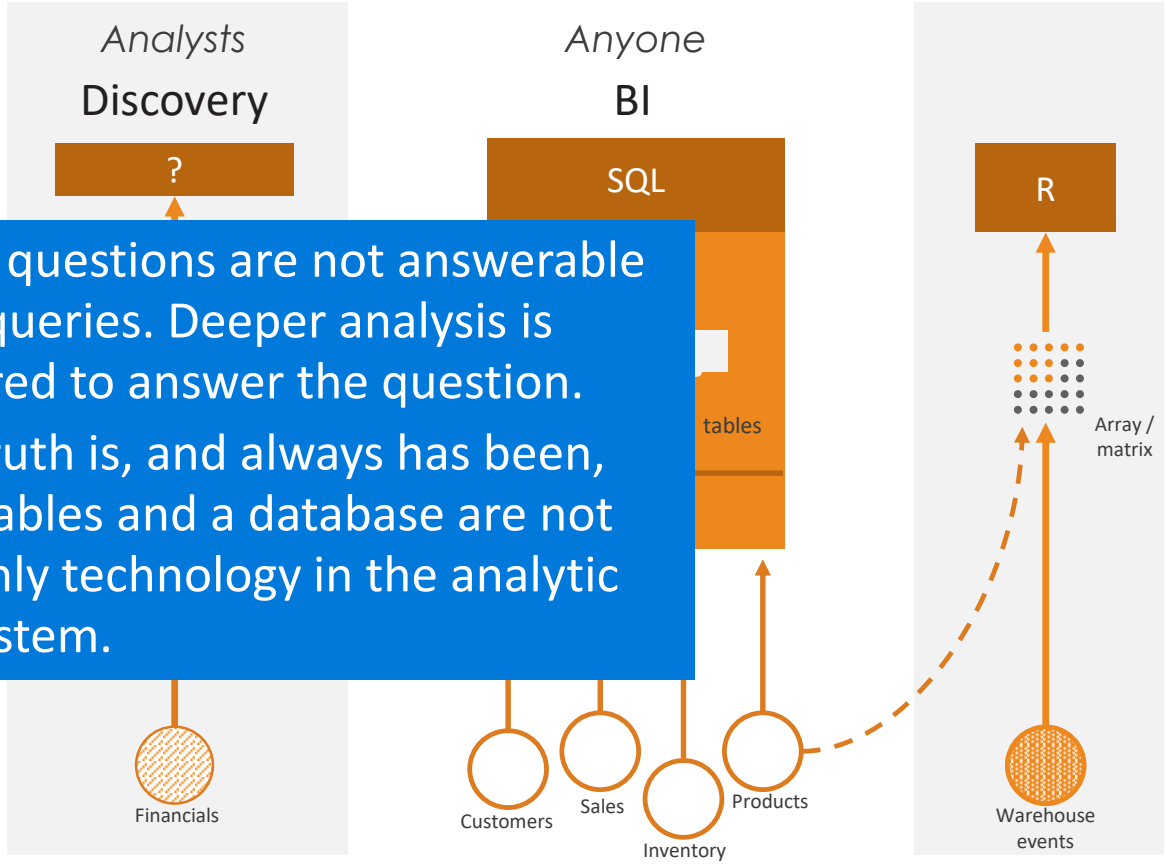


New data usually needs to be linked to existing data.

Users don't just need *access* to data, they need a place to work with and store data too.

Ignore this requirement and you have runaway copies, extracts, and files tied to specific tools, with have no visibility into what is happening.

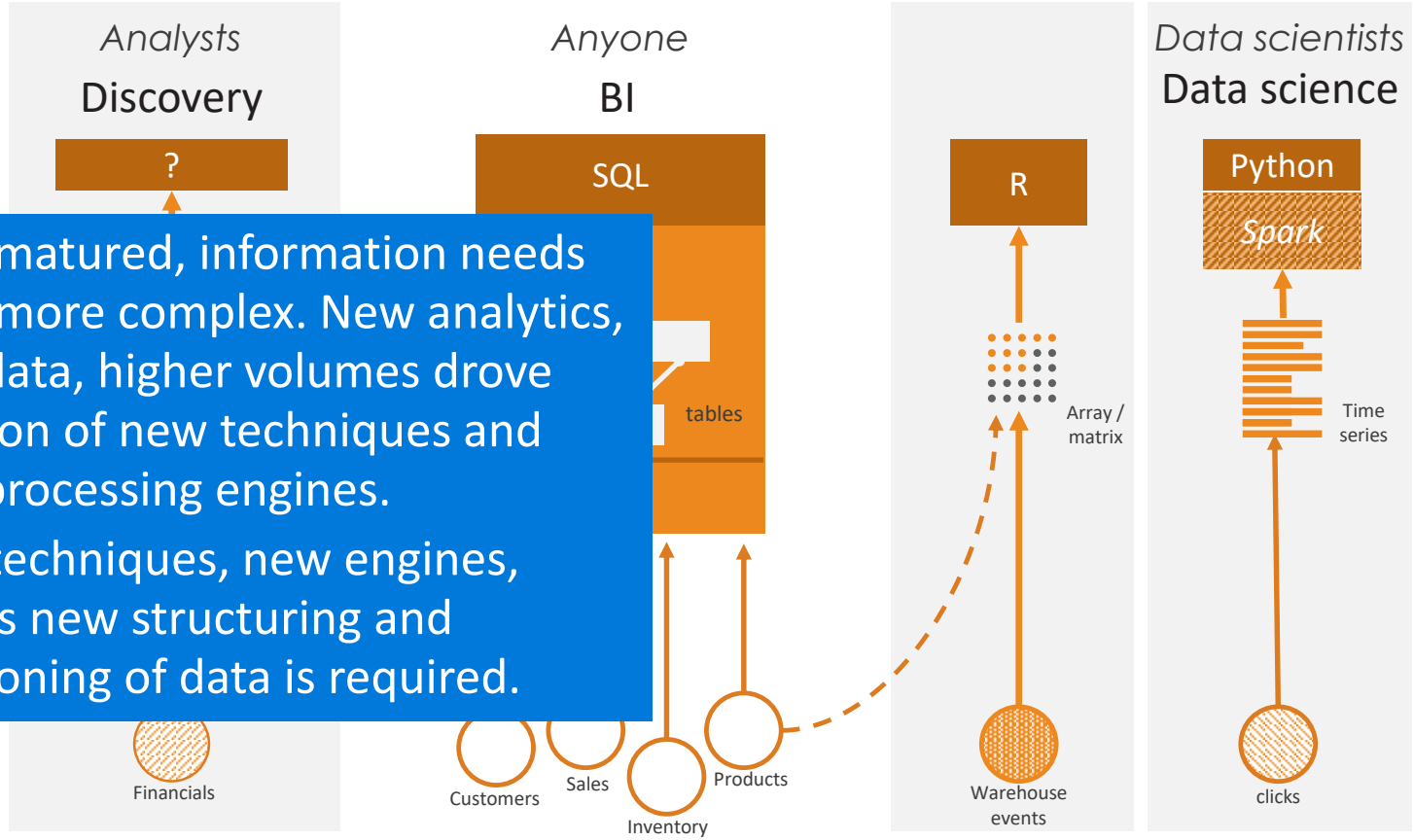
There are limits to what you can do with queries



Some questions are not answerable with queries. Deeper analysis is required to answer the question.

The truth is, and always has been, that tables and a database are not the only technology in the analytic ecosystem.

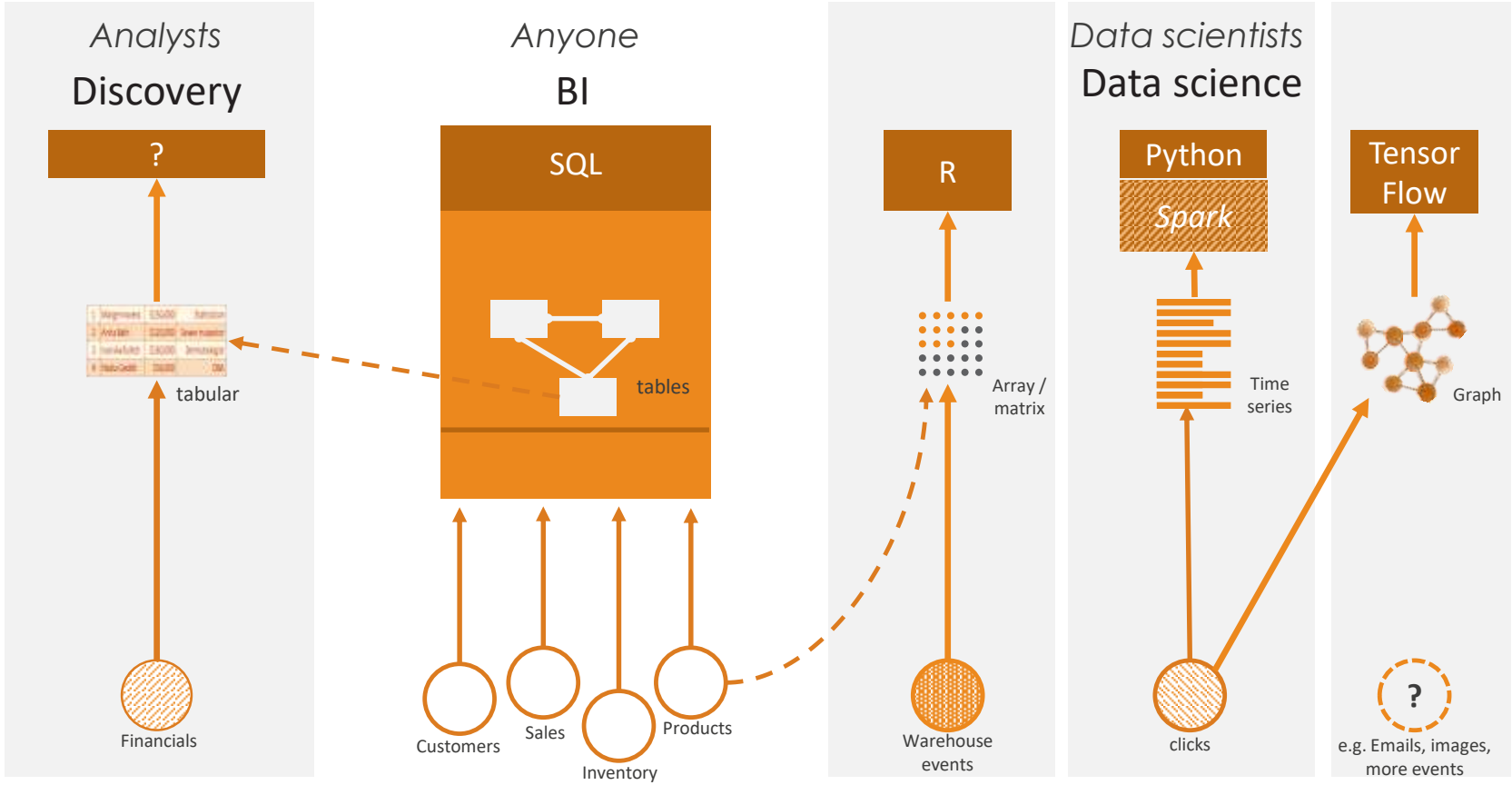
Data Science accelerates, more data, more engines



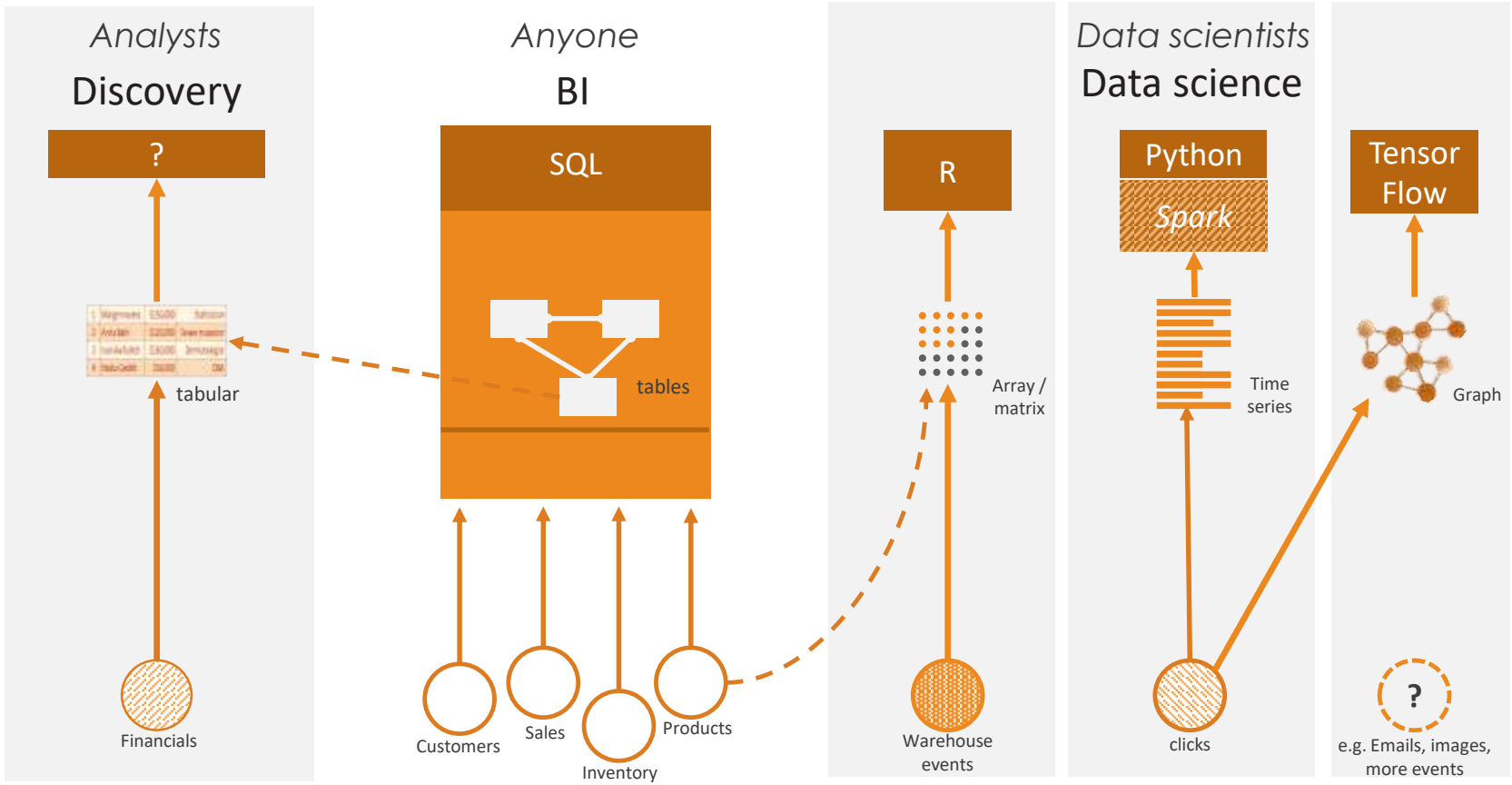
As BI matured, information needs grew more complex. New analytics, new data, higher volumes drove creation of new techniques and new processing engines.

New techniques, new engines, means new structuring and positioning of data is required.

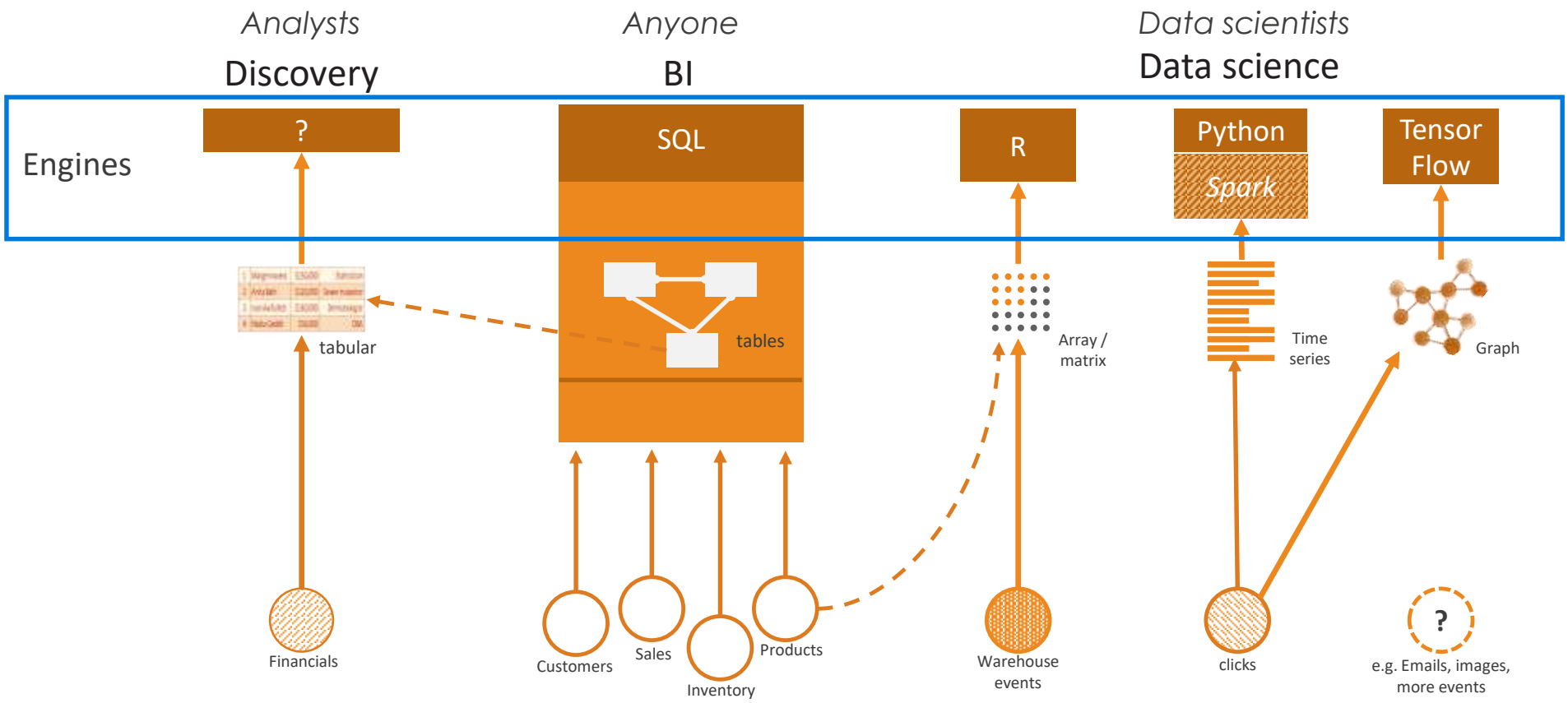
More data, more approaches, technologies arrive monthly



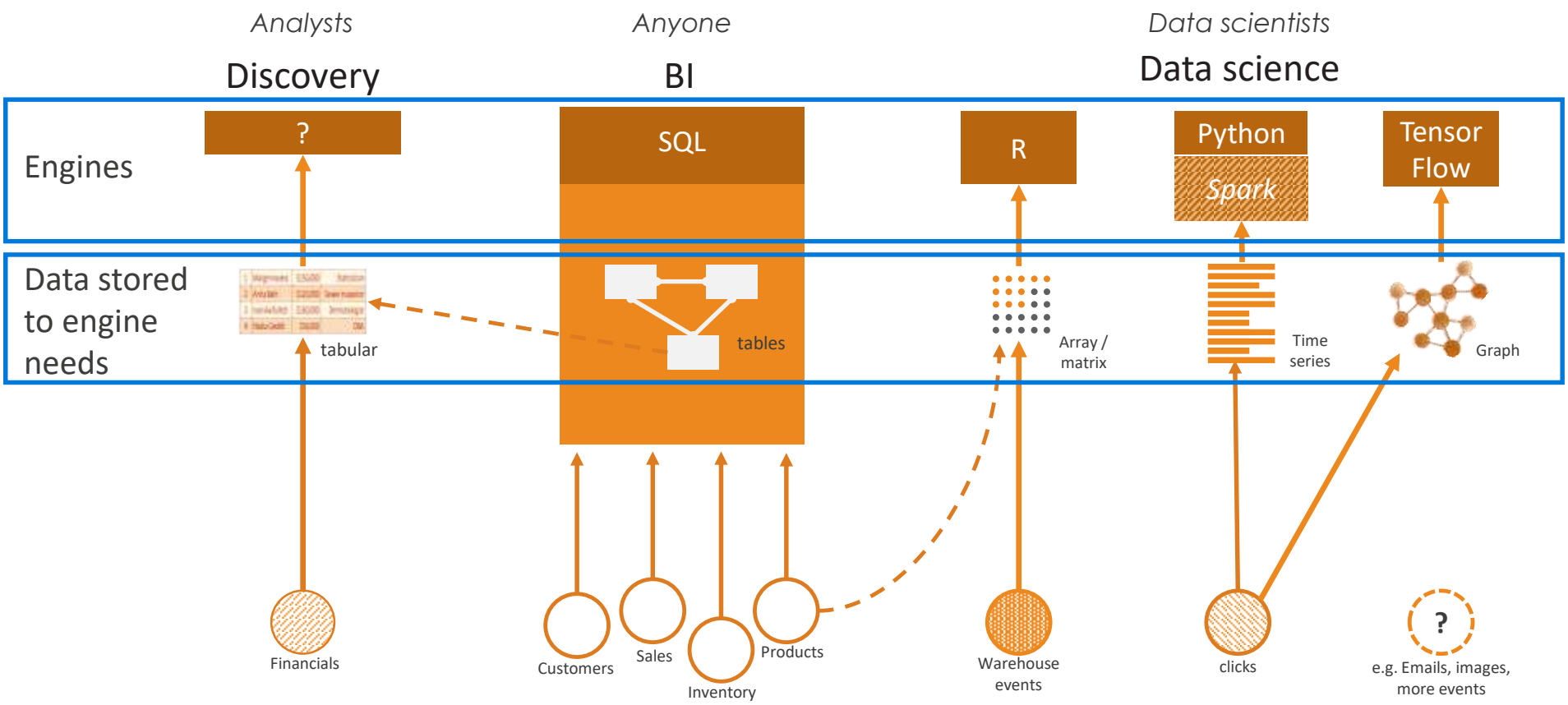
The end result of years of addition: accidental architecture



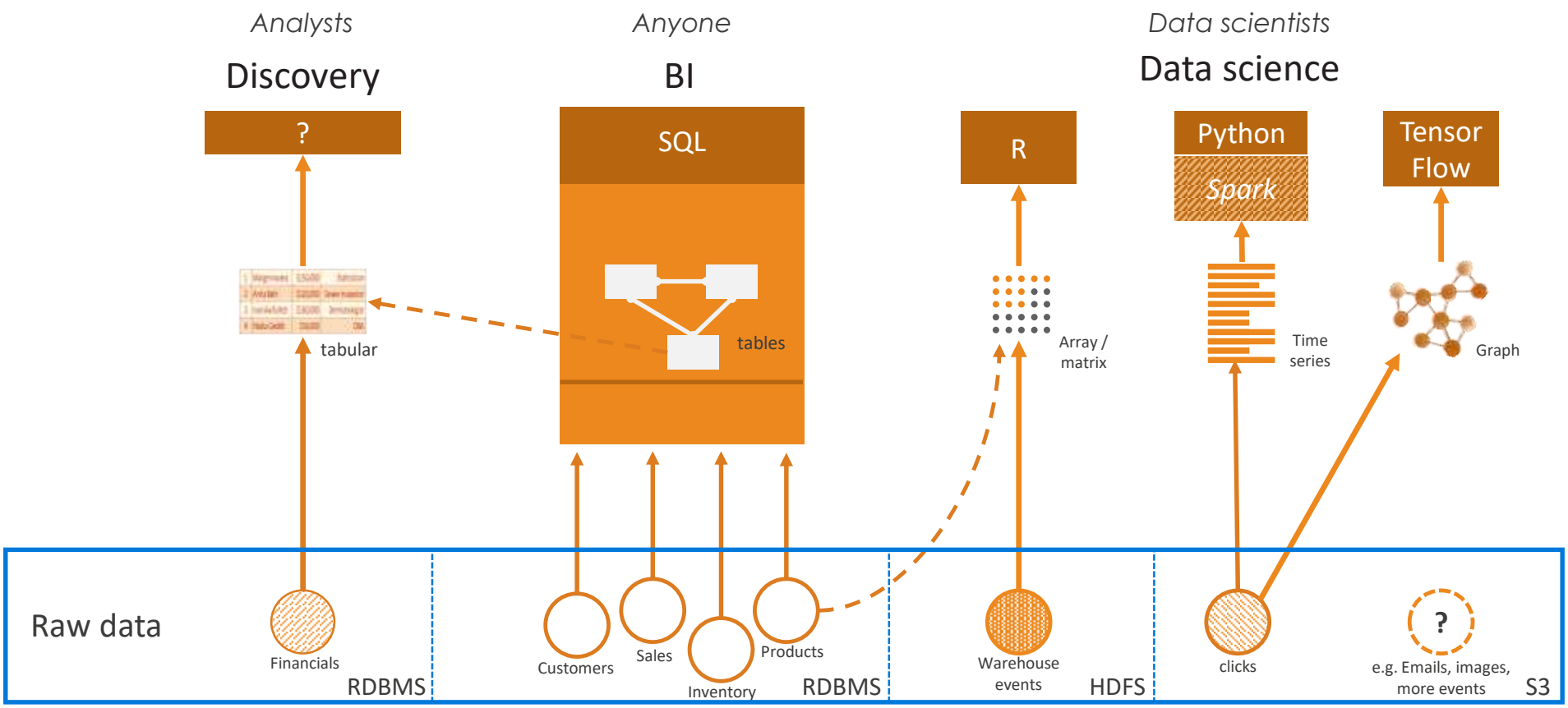
Today's environment has (and still needs) different engines



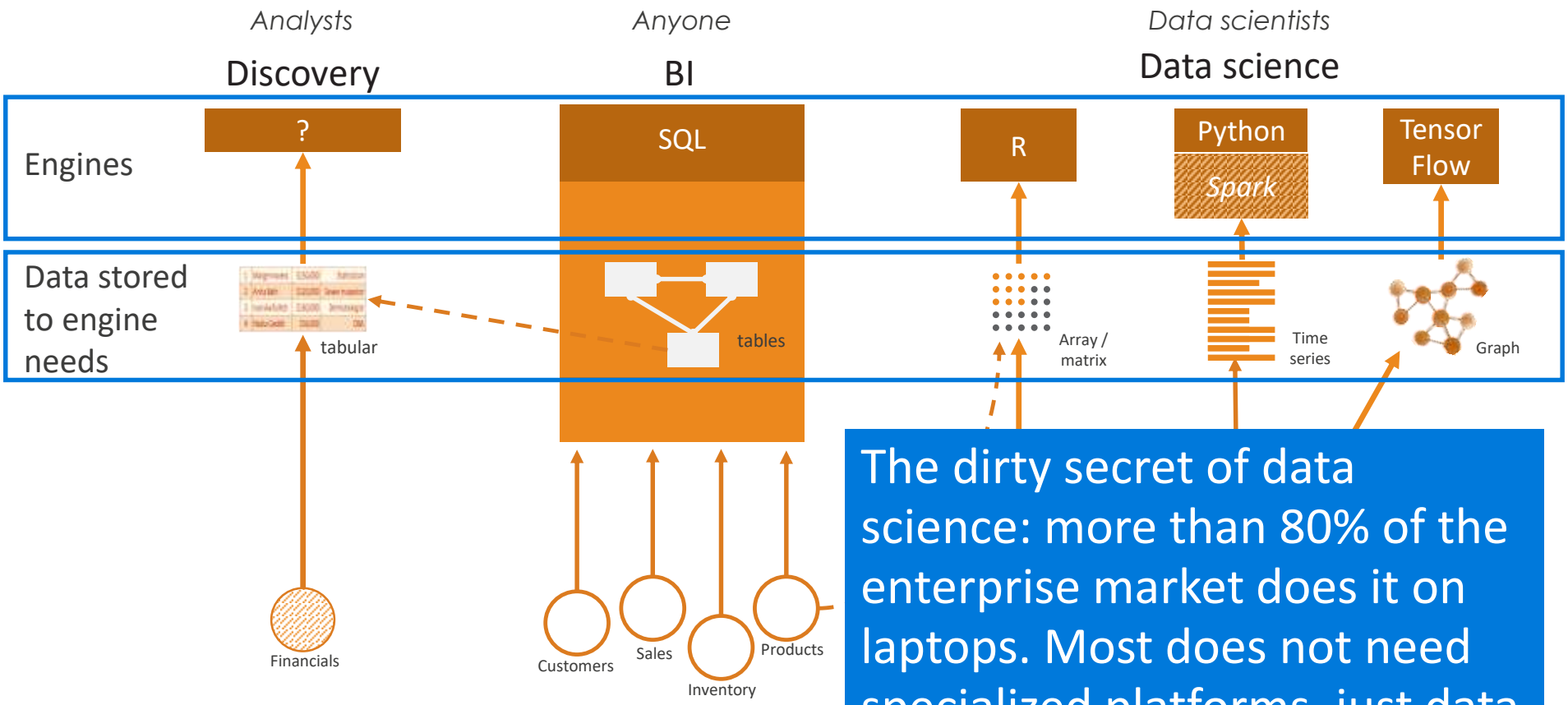
Some engines require specific data structures and positioning



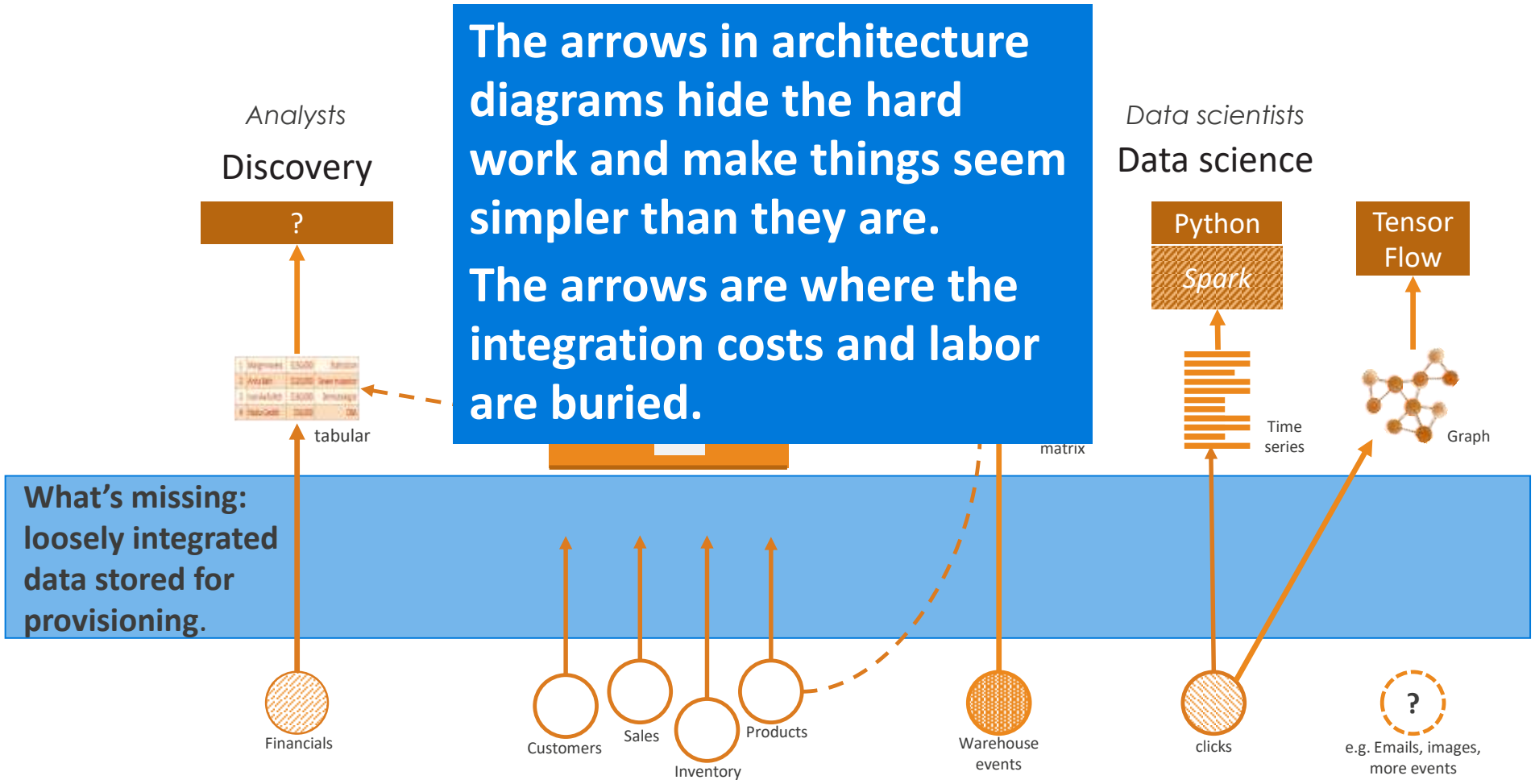
Distributed data is the norm, stored in multiple repository types



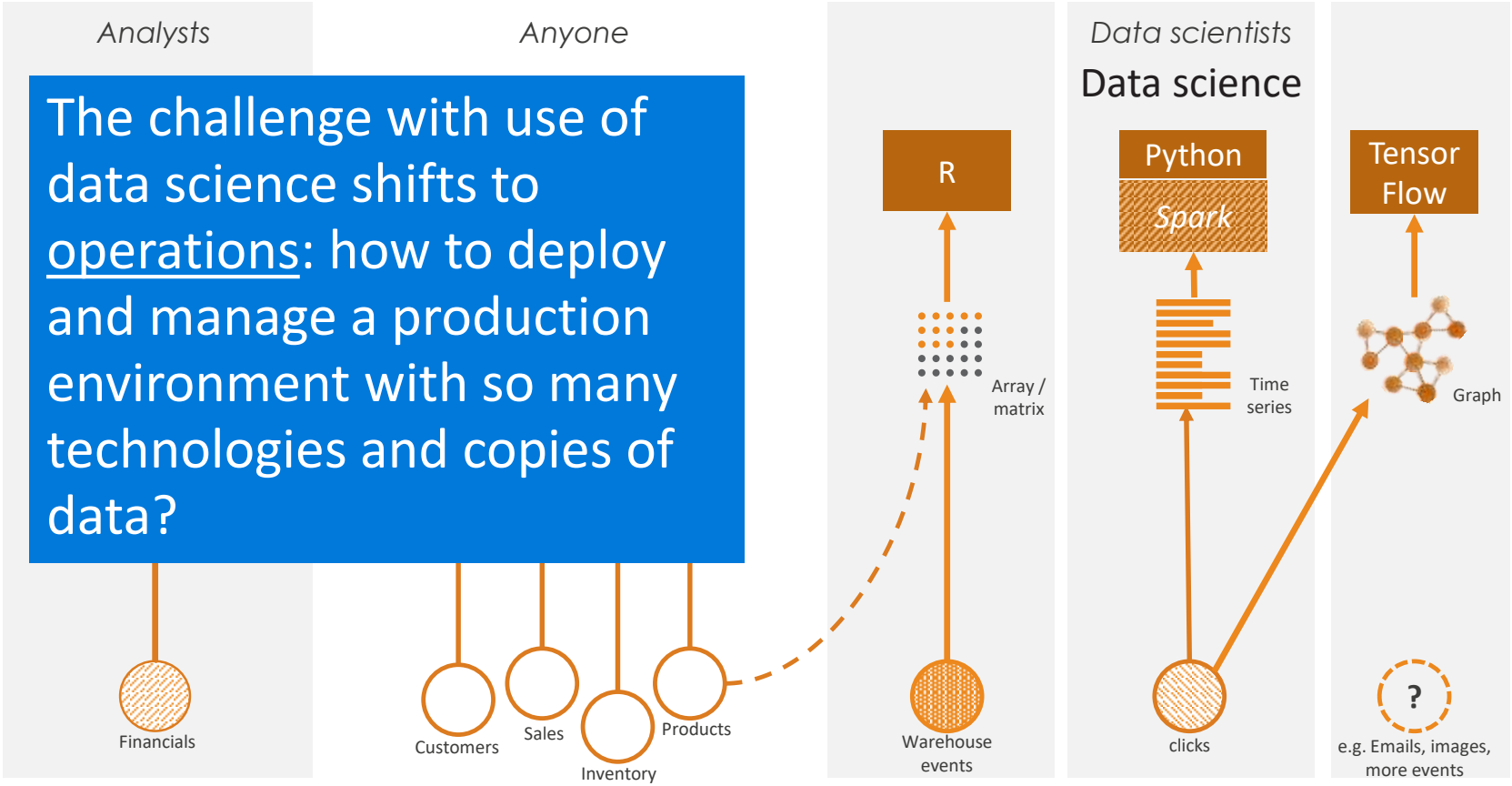
How much of the data science problem is tools vs engines?

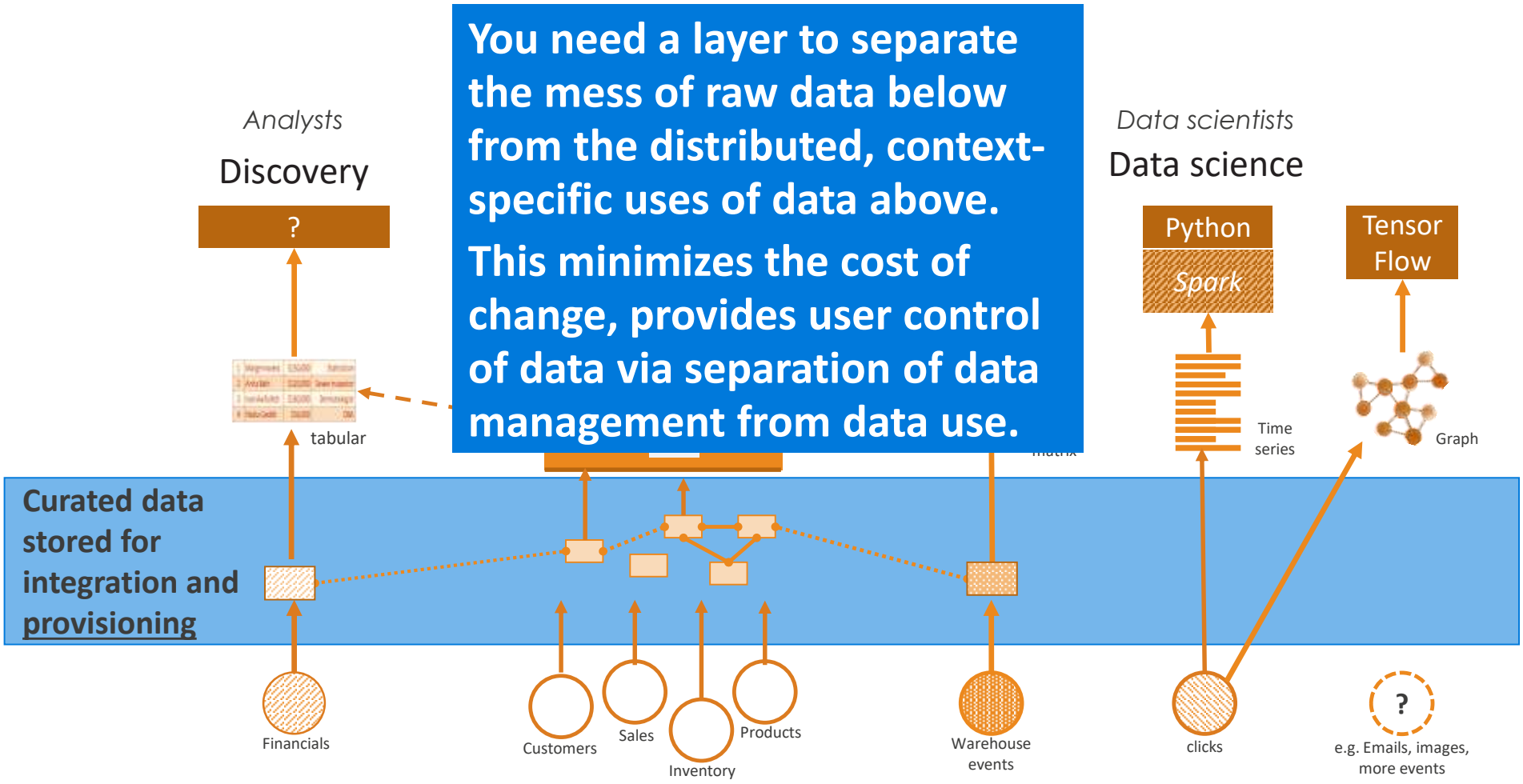


The dirty secret of data science: more than 80% of the enterprise market does it on laptops. Most does not need specialized platforms, just data


The arrows in architecture diagrams hide the hard work and make things seem simpler than they are.
The arrows are where the integration costs and labor are buried.
Analysts
Discovery
?
Data scientists
Data science
Python
Spark
Tensor Flow
tabular
matrix
Time series
Graph
What's missing: loosely integrated data stored for provisioning.
Financials
Customers
Sales
Inventory
Products
Warehouse events
clicks
?
e.g. Emails, images, more events

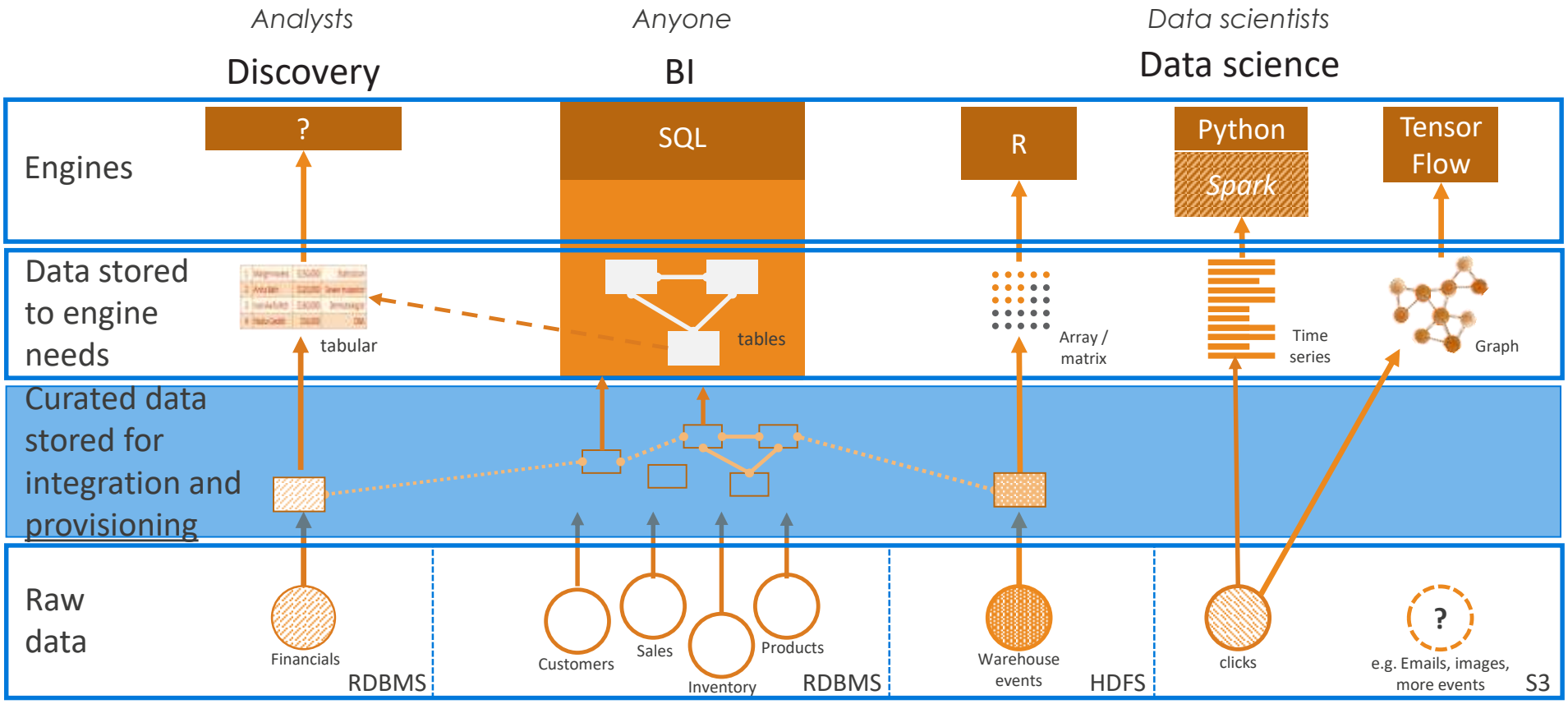
Managing this complexity is a growing challenge



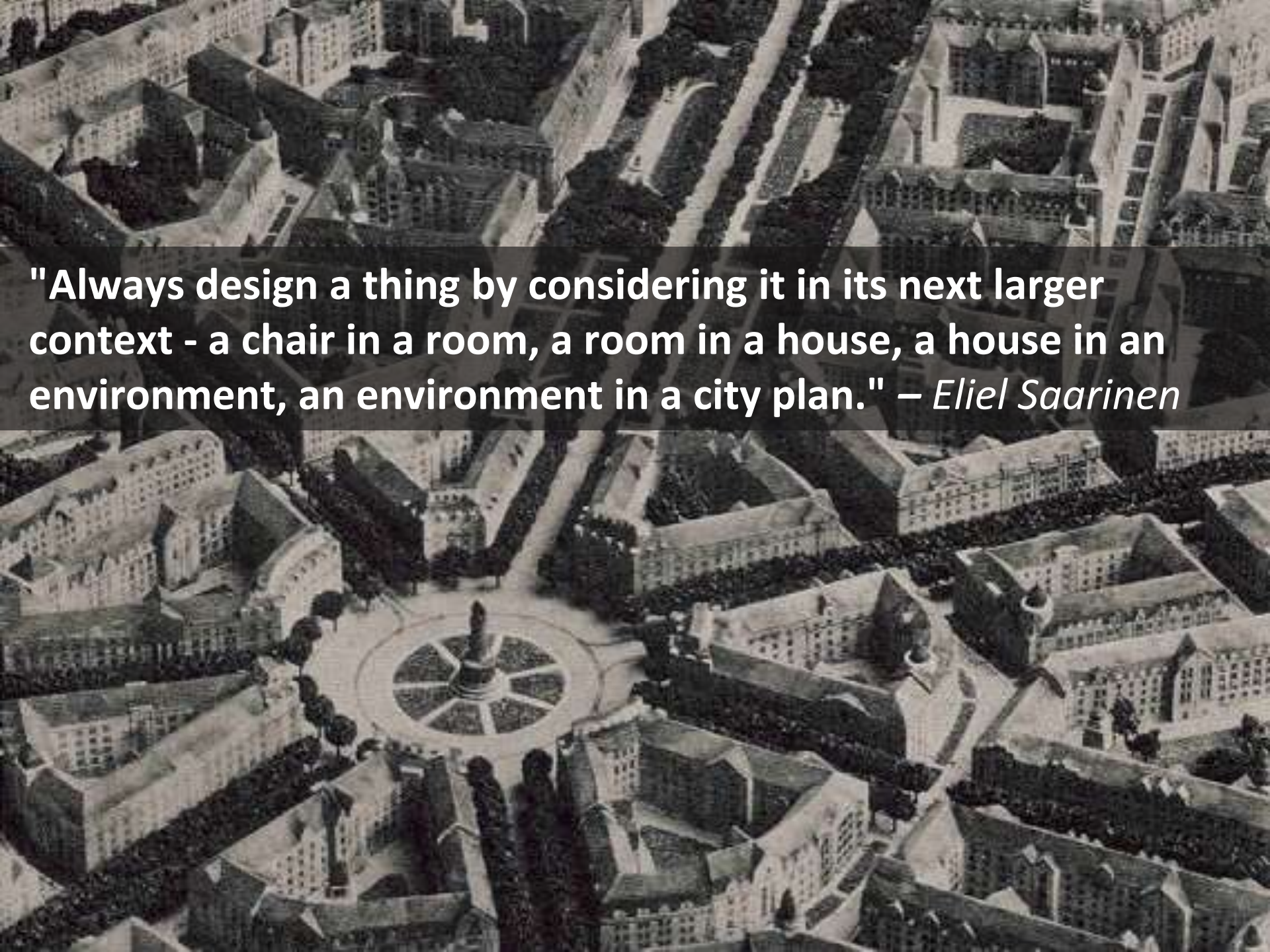


Data architecture is needed to fill the gap

Renovating the accidental architecture requires a transition path to separate data infrastructure from the uses of data



For most organizations, this is your starting point. Not the clean slate of the web companies. It's *renovation*

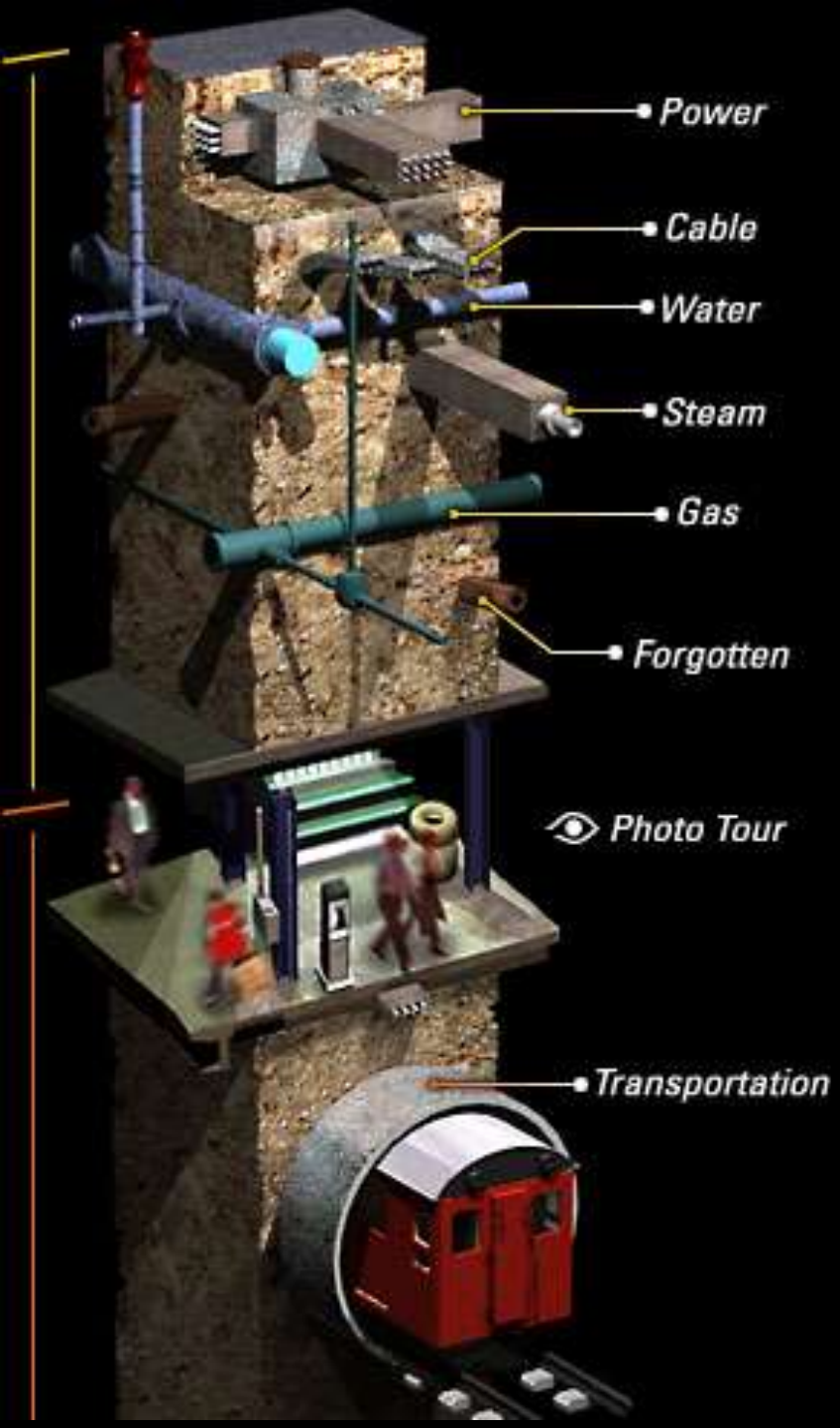


"Always design a thing by considering it in its next larger context - a chair in a room, a room in a house, a house in an environment, an environment in a city plan." – *Eliel Saarinen*


Think of IT as a city
Where does a building fit?


Data science
Streaming analytics
Self-service
/ Discovery
Self-service Data
Data collection
BI (QRD)

Design is the art of separation, grouping, abstraction, and hiding. The fulcrum of design decisions is change. Separate those things that change for different reasons. Group together those things that change for the same reason. — *Uncle Bob Martin*



Key focus for the organization: Infrastructure vs Application

Infrastructure enables value, applications deliver value.

Enable applications by pushing the reusable elements down into the platform.

The infrastructure is a hidden combination of technology, process and methods.

Complexity requires a shift: separate the application from the infrastructure – we are focused on the block, not the buildings

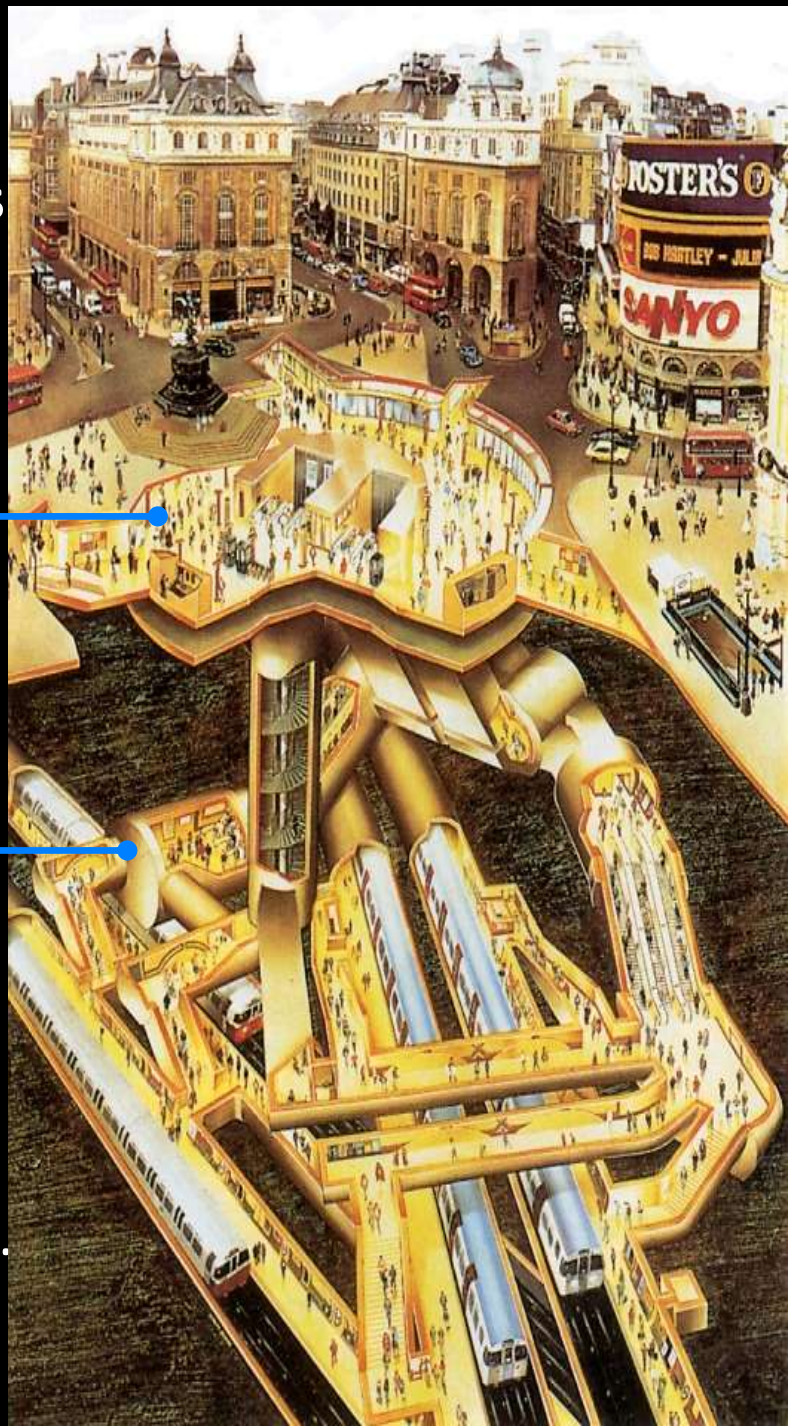
Buildings above: flexibility, repurposing, quicker change above, funded separately

Applications

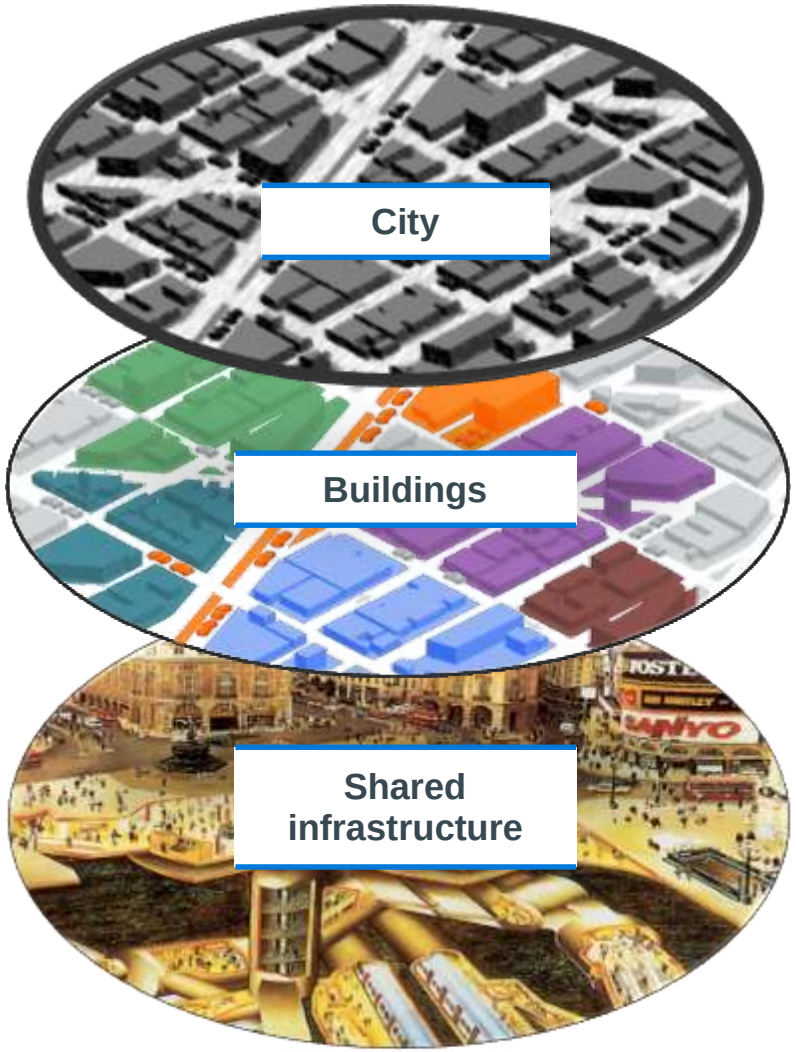
Utilities below: stability, reuse, slow predictable change below, funded centrally

Infrastructure

We built the DW as a single entity that combined the building and the infrastructure in one complex monolith. The same mistake is applied with data lakes.



The bigger picture of what we create



The *ecosystem* is like the city and all of its extended neighborhoods.

The different applications or types of projects are like the neighborhoods with specific types of buildings.

Each individual building (application) has its own unique *blueprint*.

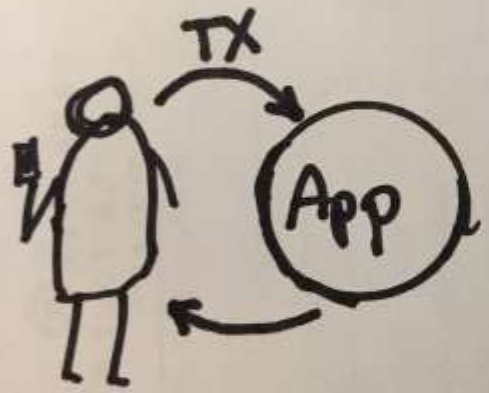
Underlying all the applications is shared data infrastructure, like city services. The shared infrastructure is the foundation of the analytics architecture for a company.

The IT promise: What you see

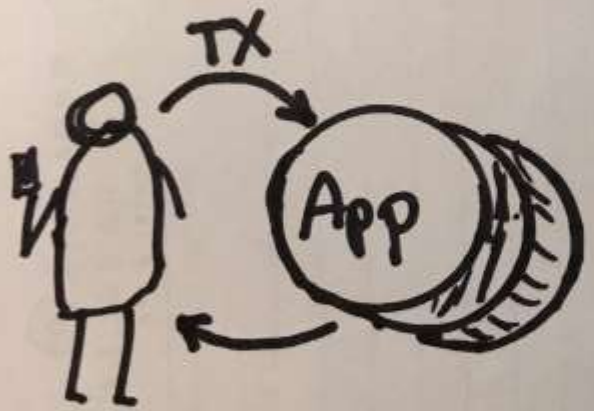
The IT reality: What users see

Who and what are you designing *for*?

How an organization works

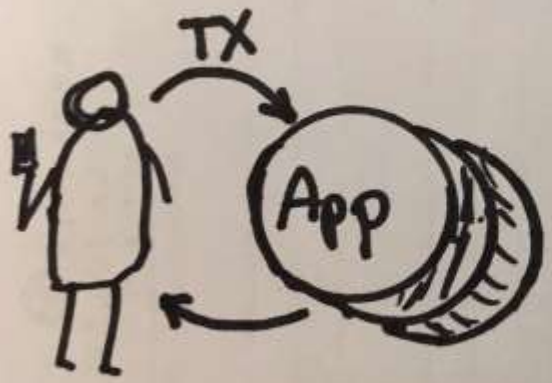


Many applications, many activities

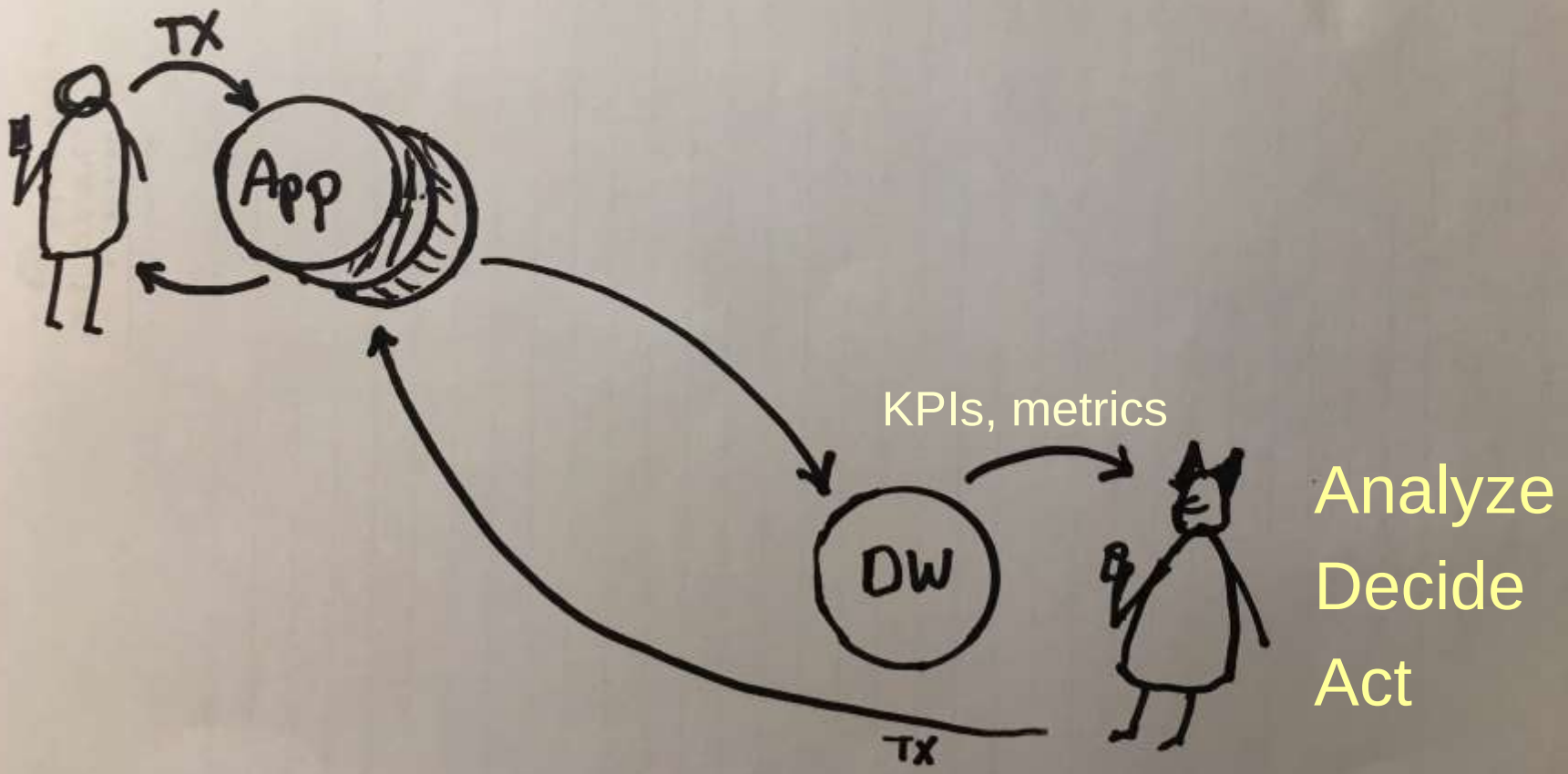


How do you get the full picture?

What does a person do when there's a problem?
One report from each application isn't a sustainable answer



The goal is to make decisions, not get reports
This is the “decision support” model

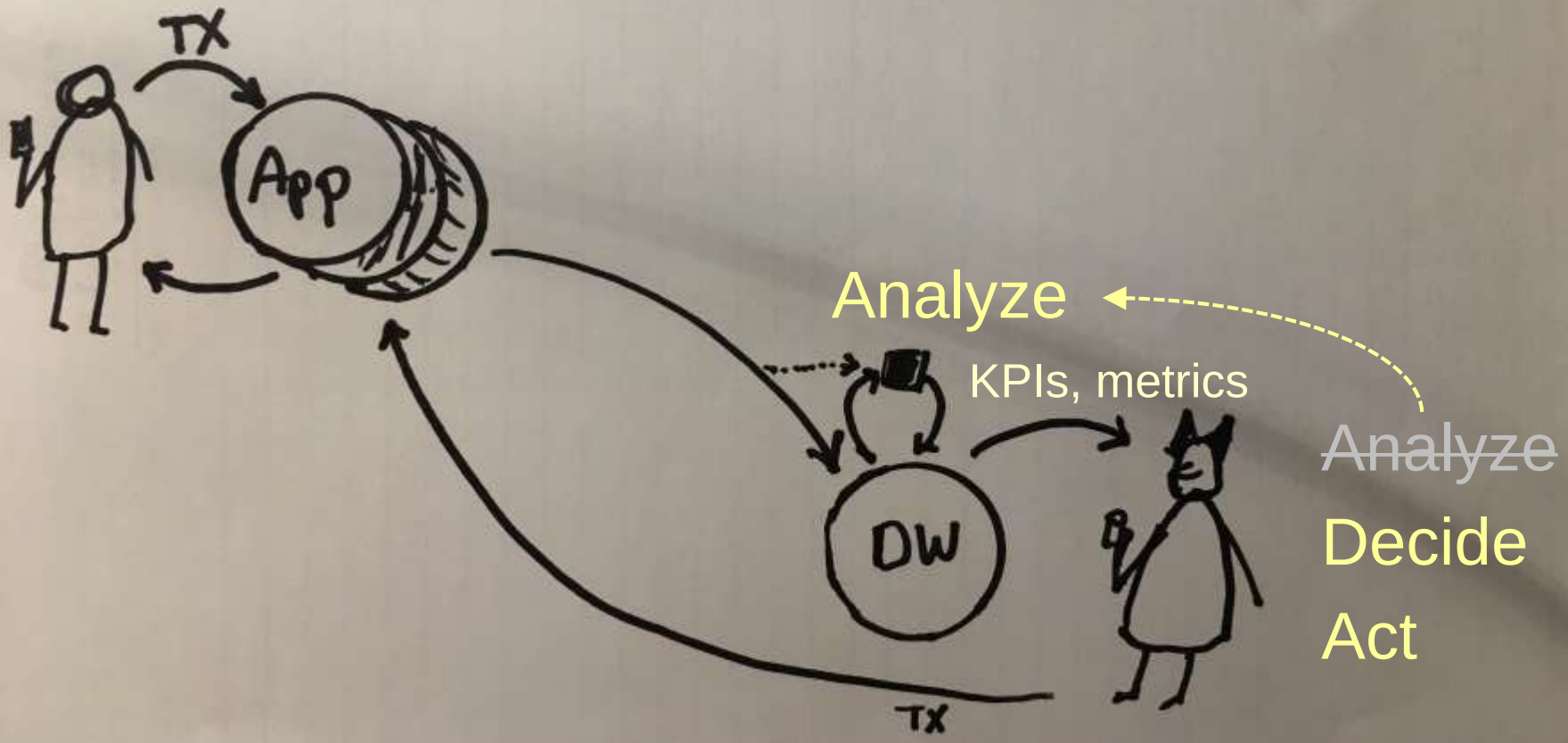


We had batch (and stream) models decades ago

e.g. segmentation, NBO queue, churn, fraud

Usually batch, ran from the DW (but probably not on it), resulting data loaded into the DW for use

Someone oversees and acts on the information

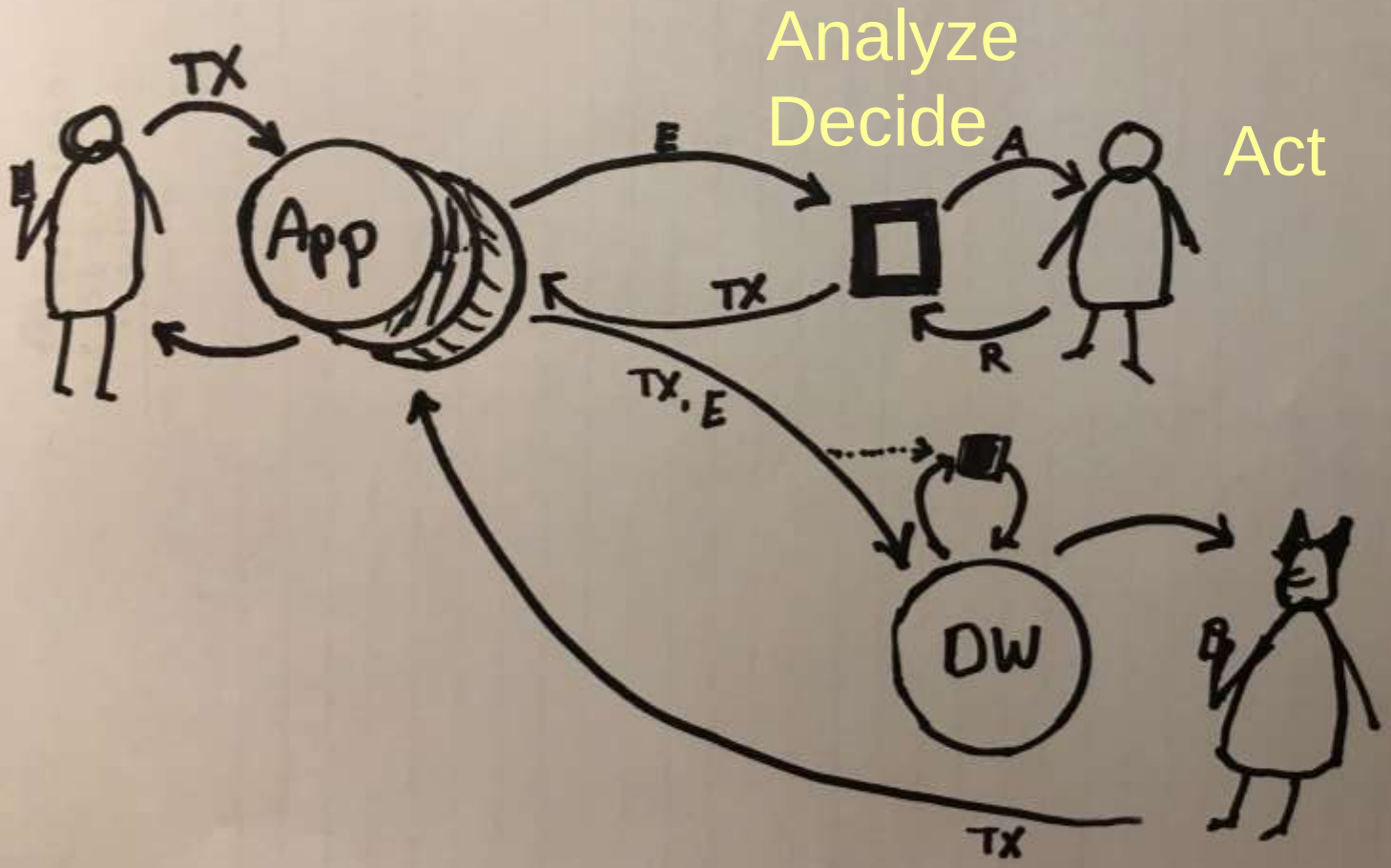


Applying analytics within a process context

e.g. purchasing changes, upsell/cross-sell recommendations

Machines gain agency, humans lose it; “act” is curtailed

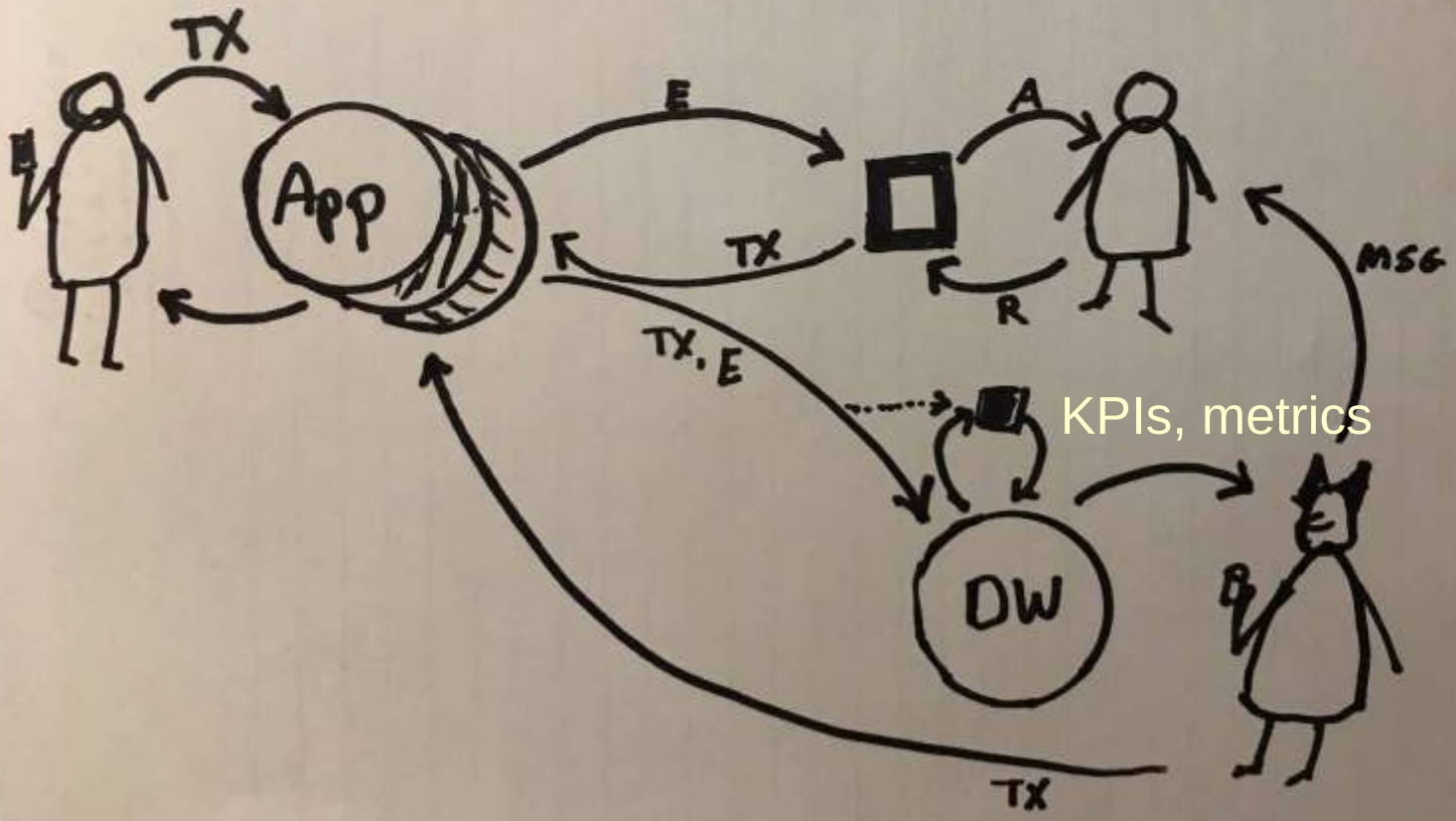
This is the ***human-in-the-loop*** model



When there's a problem, the fix is a message

The model's results should be visible via the KPIs and metrics

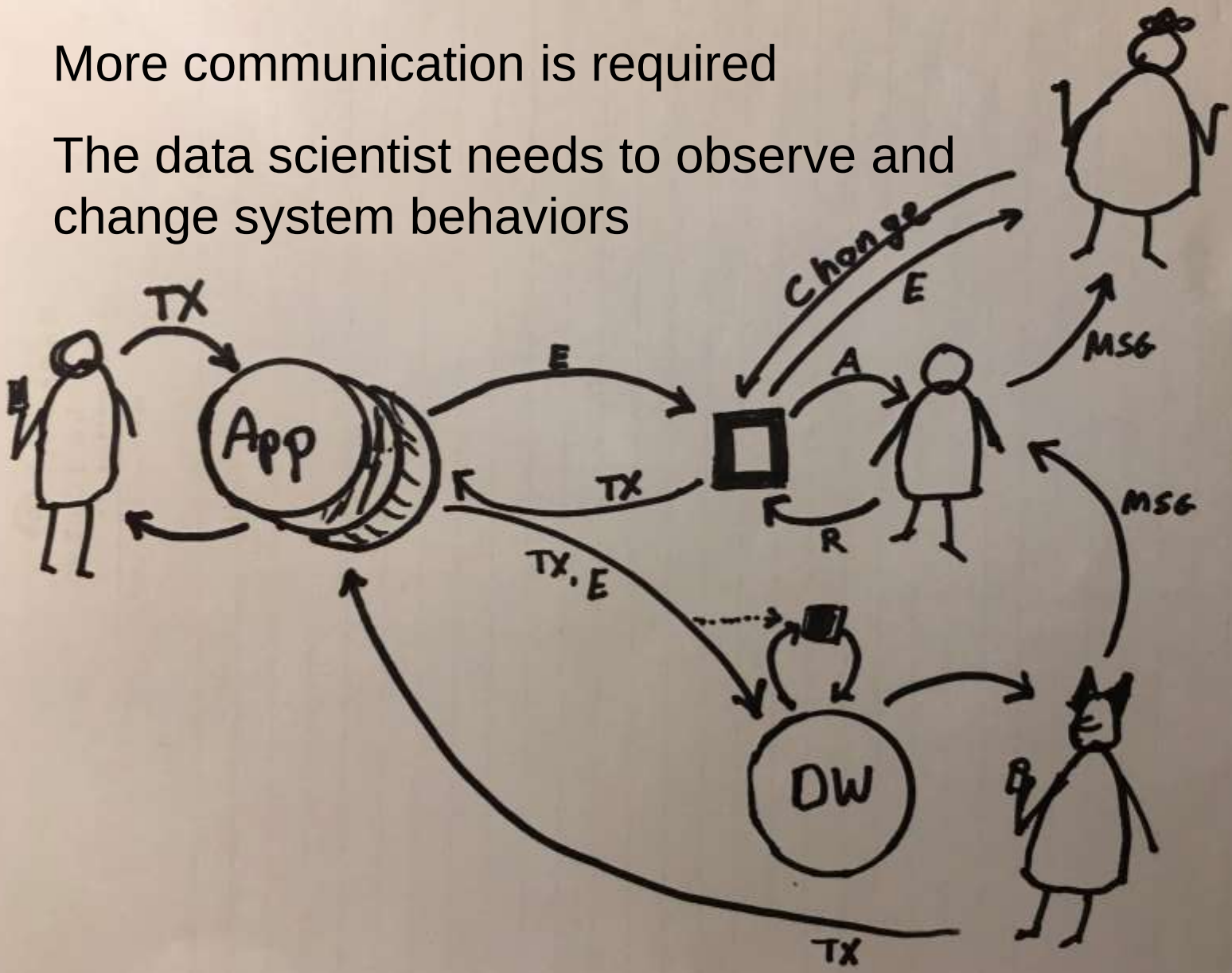
Act: People call people to see what's happening



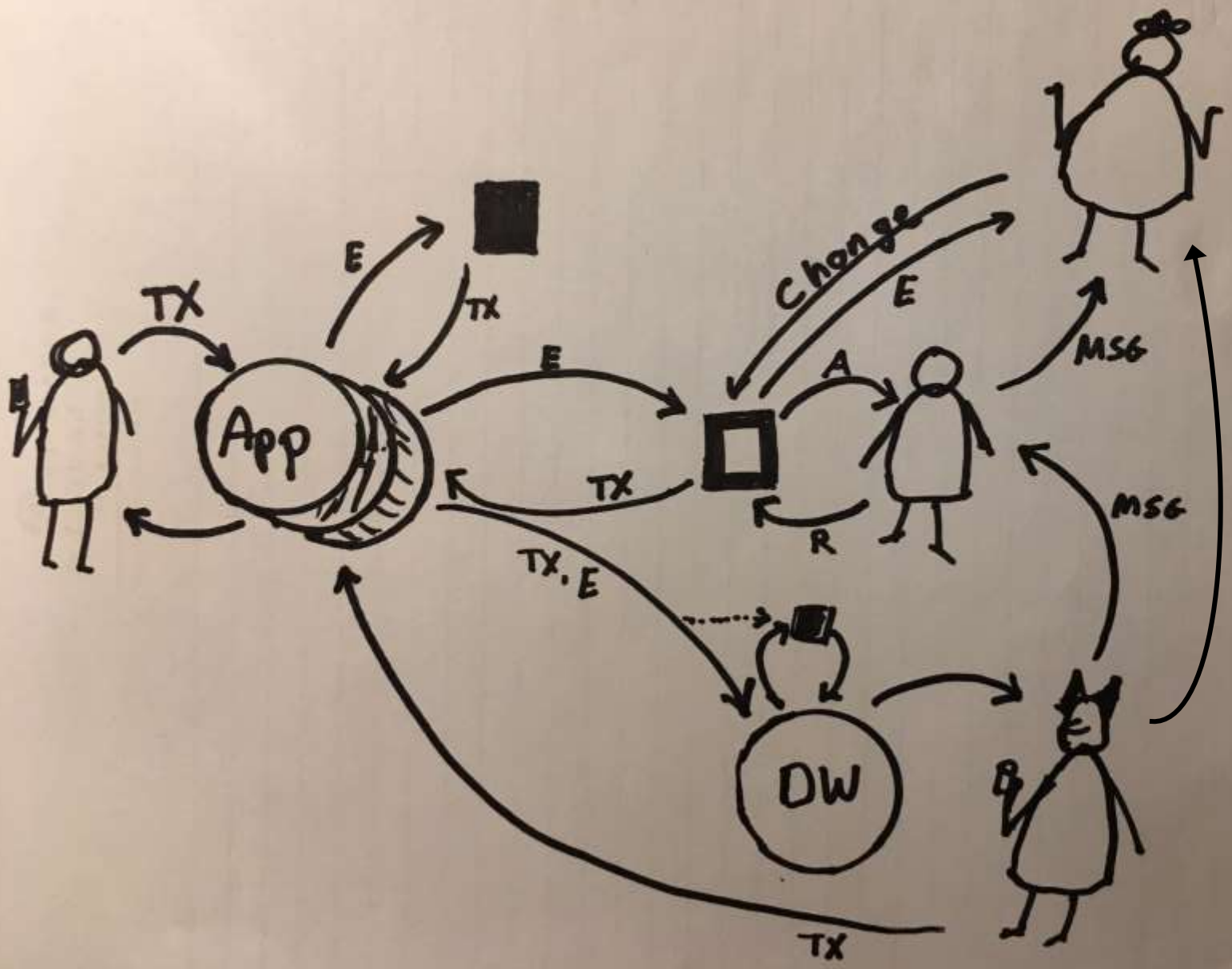
Somebody built the models – the data scientist

More communication is required

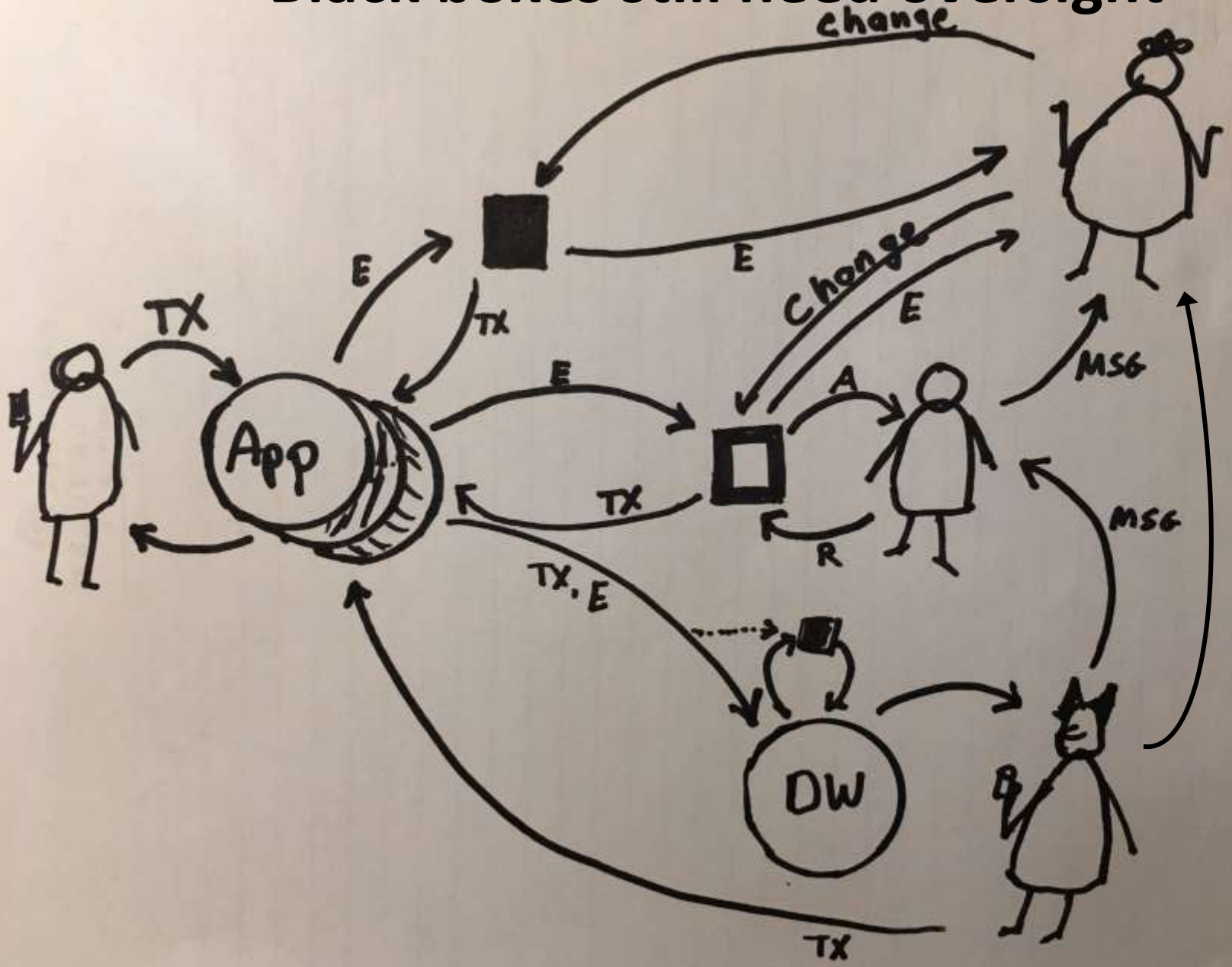
The data scientist needs to observe and change system behaviors



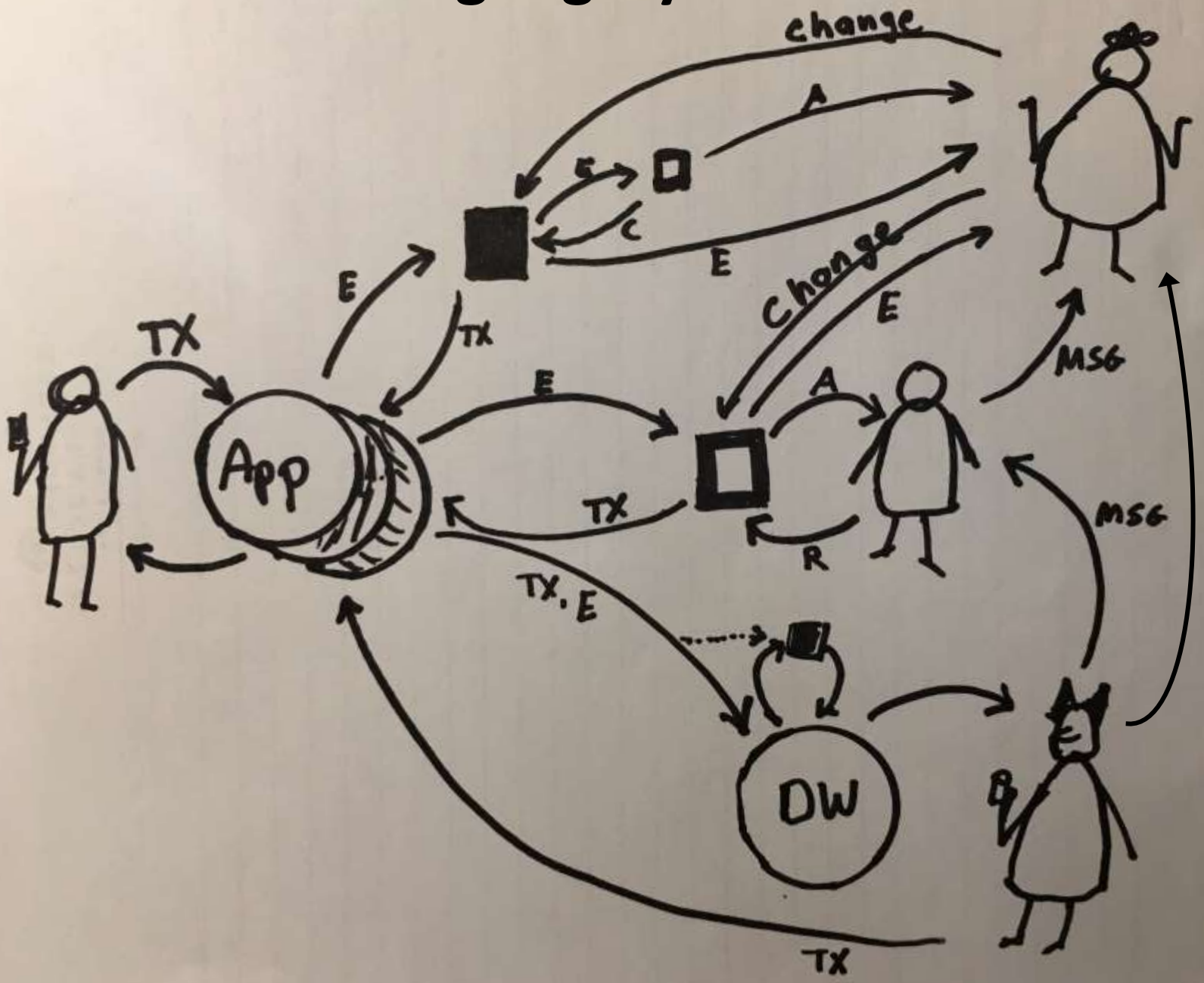
Enter the black boxes – the “autonomous” model



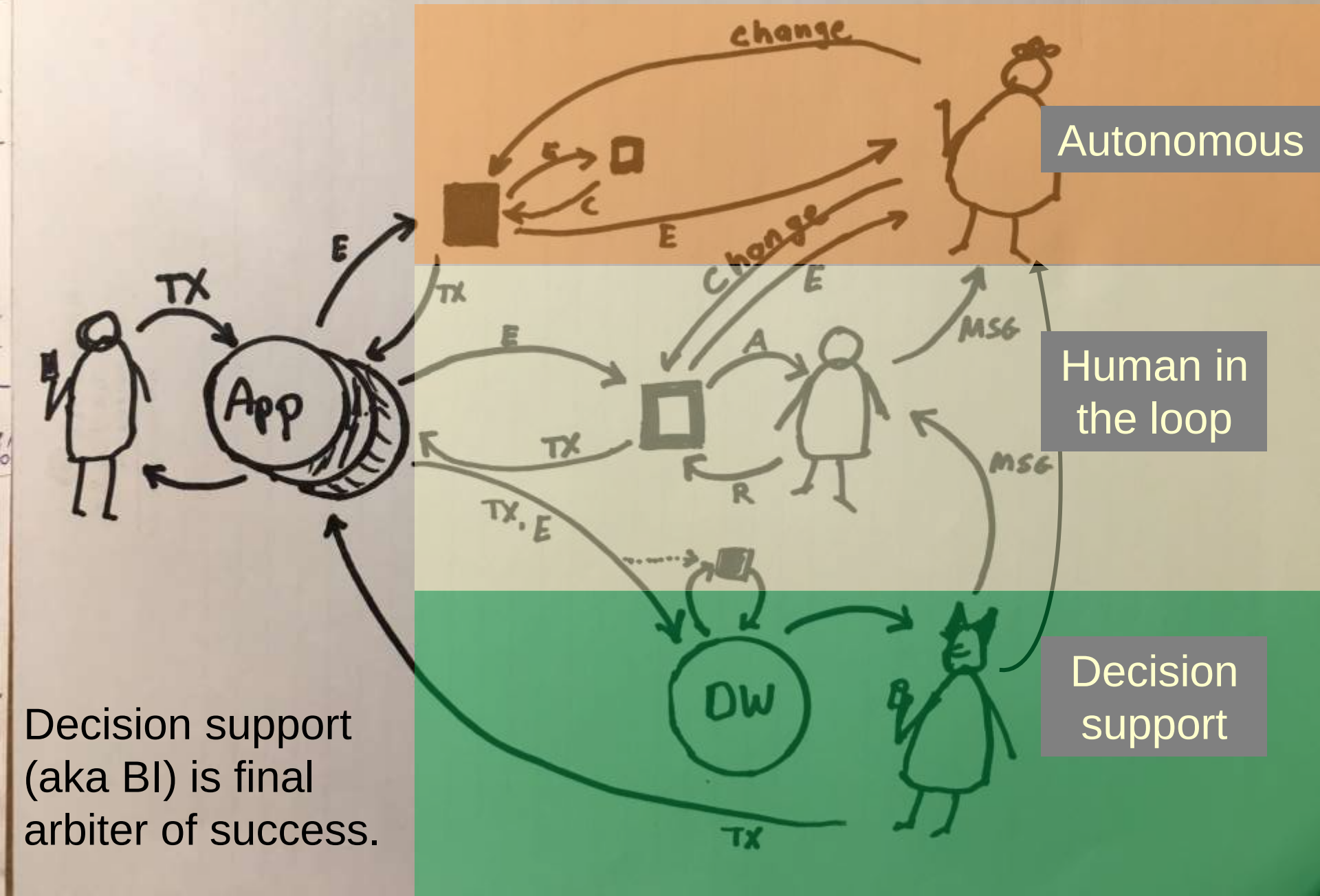
Black boxes still need oversight



Black boxes beget gray boxes because of speed



Three model deployment categories

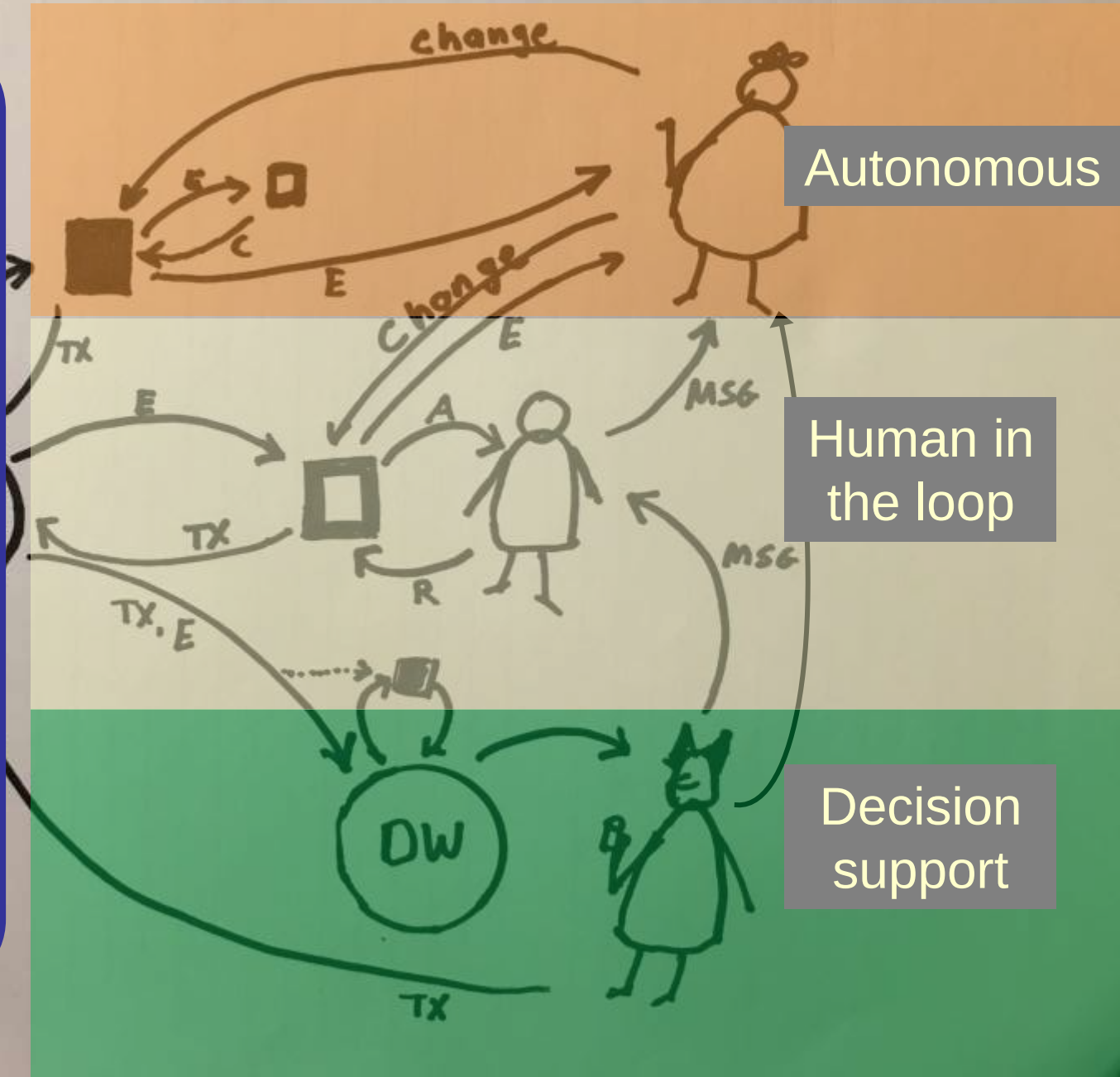


Decision support (aka BI) is final arbiter of success.

Three model deployment categories

All of these independent / separate architectures are dependent on some level of shared context.

That means shared operational data, managed over time.



How to design, extreme #1: Focus purely on business need and agile your way to a shantytown

How to design, extreme #2: design everything first - the users will surely follow

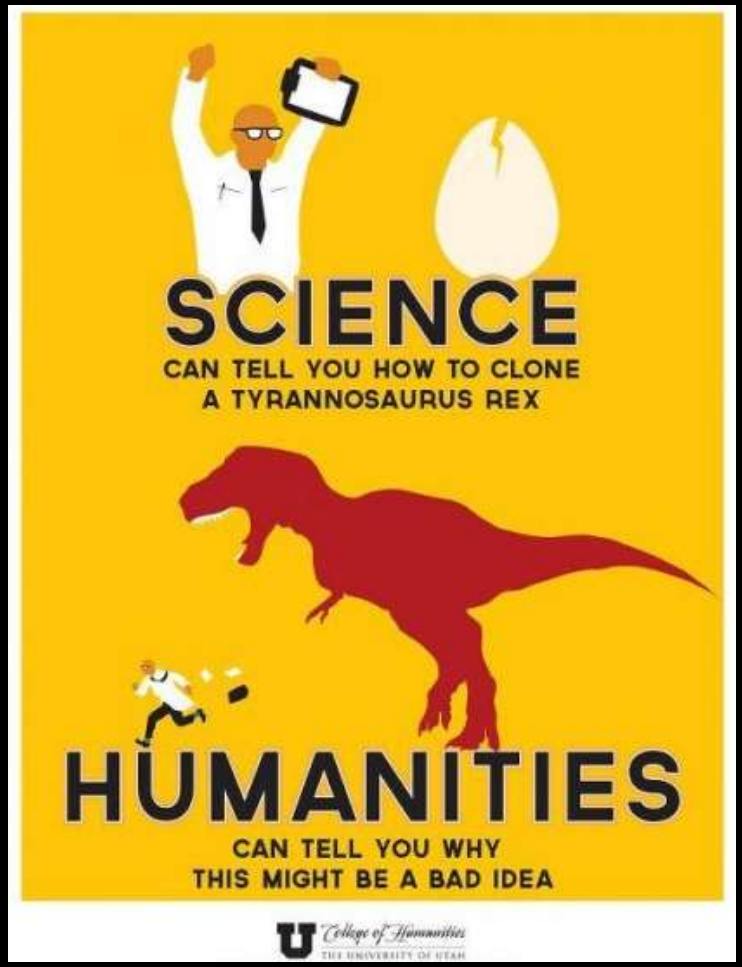

Persisting data is not the end of the line.
If you stop here you win the battle and lose the war

“Begin with the end in mind”

The starting point *can’t be* with technology. That’s like starting with bricks when designing a house. You may get lucky but…

The goals and specific uses are the place to start

- Use dictates need
- Need dictates capabilities
- Capabilities are solved with technology



This is how you avoid spending $2M on a Hadoop and spark cluster in order to serve data to analysts whose primary requirements are met with laptops.

B I

Data use shifted from center to edge, drove greater speed

1. Making decisions at the edge of the organization drives latency of data: cf “active DW”
2. Change is more rapid at the edge, so new data is needed faster than a classic DW architecture can make it available
3. The next “edge” is embedded analytics, which means machine interfaces, machine data, and machine latency: cf “analytic ops” and “embedded ML”
4. Analytics / data science and self-service / discovery share traits: one key element of which is the need for new data and light integration

The analytics process at a high level

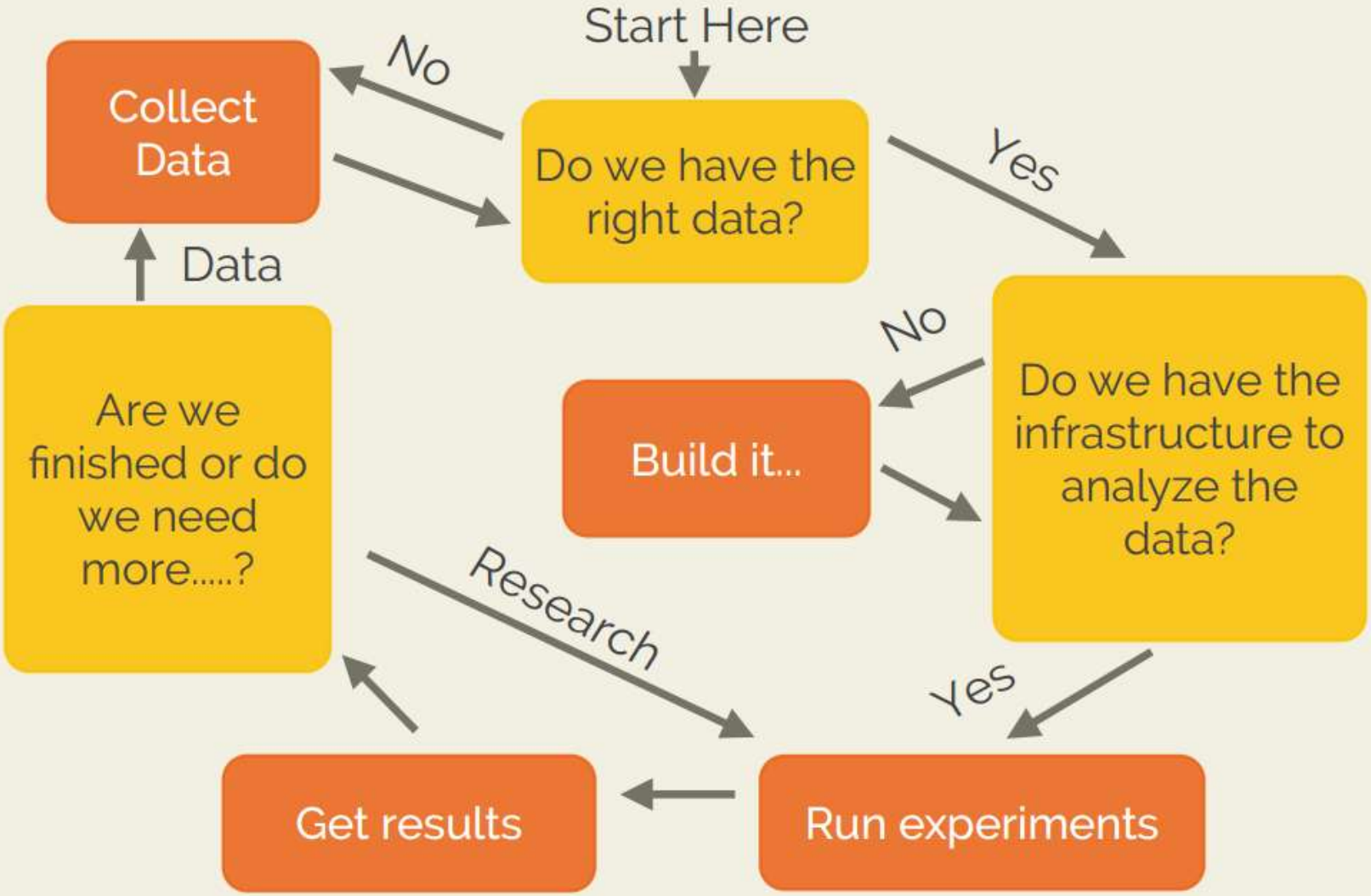
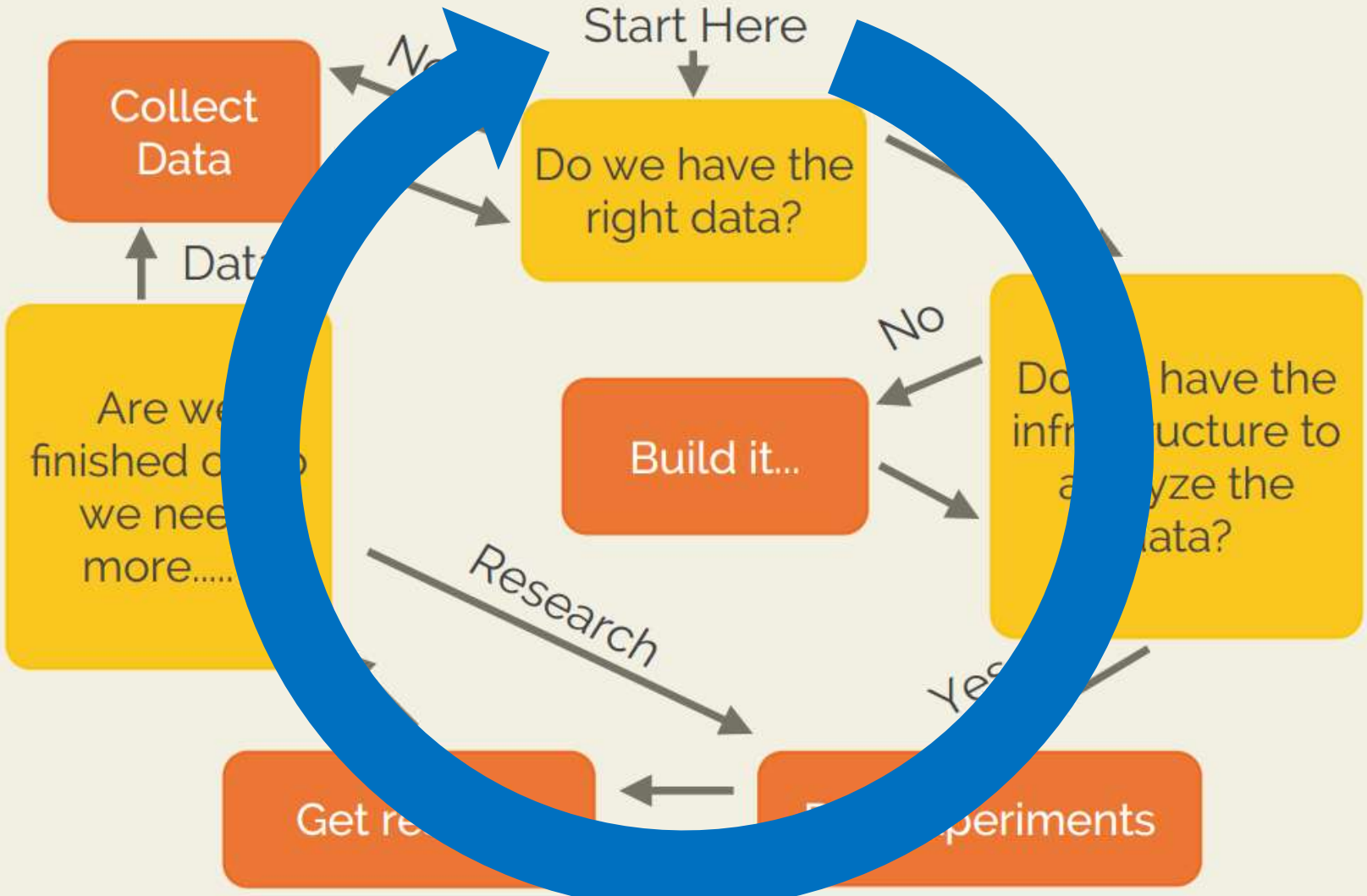


Diagram: Kate Matsudaira

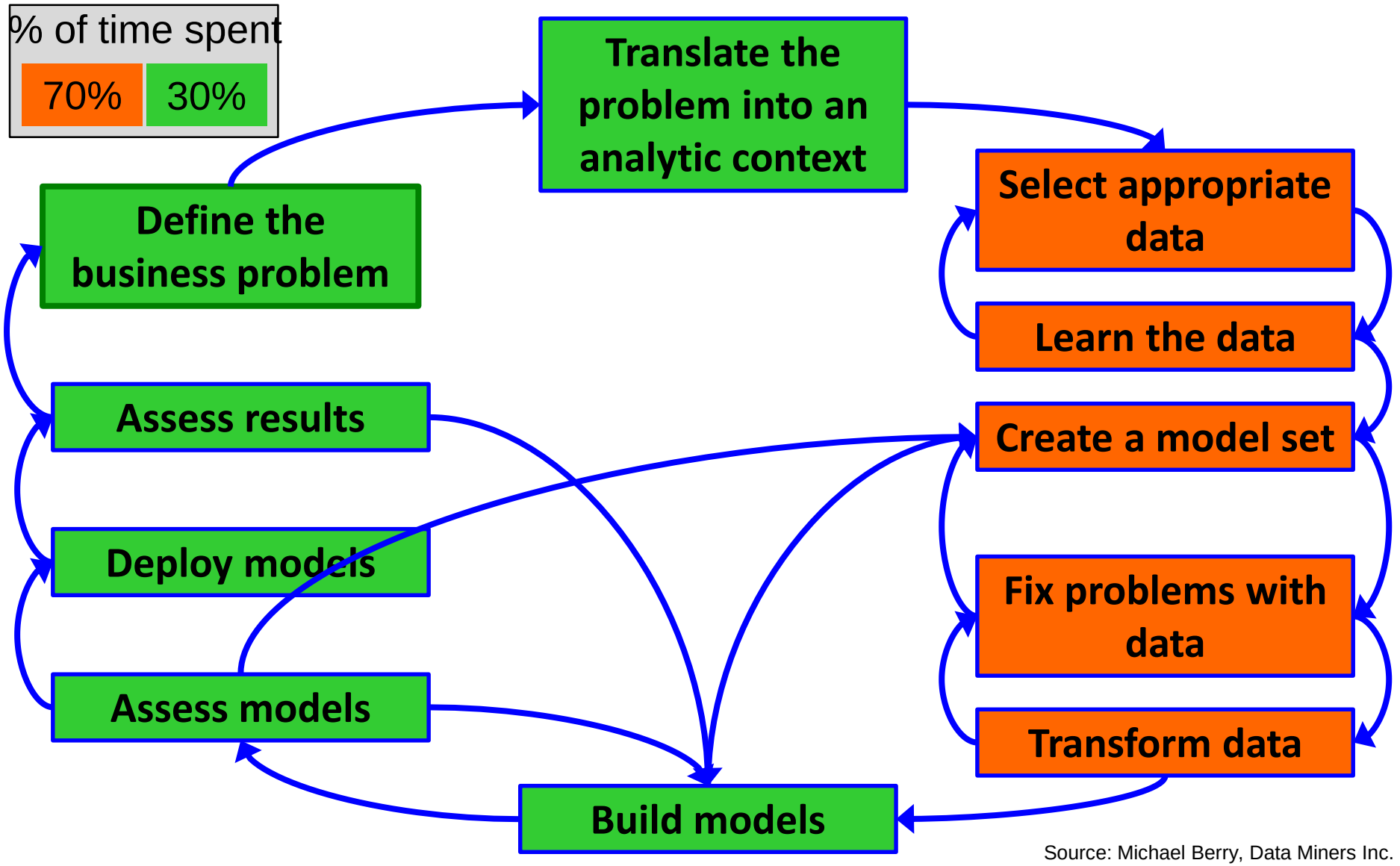
Repeat for each new problem



The nature of analytics problems is researching the unknown rather than accessing the known.

Diagram: Kate Matsudaira

Where do analysts spend their time? *mostly data work*

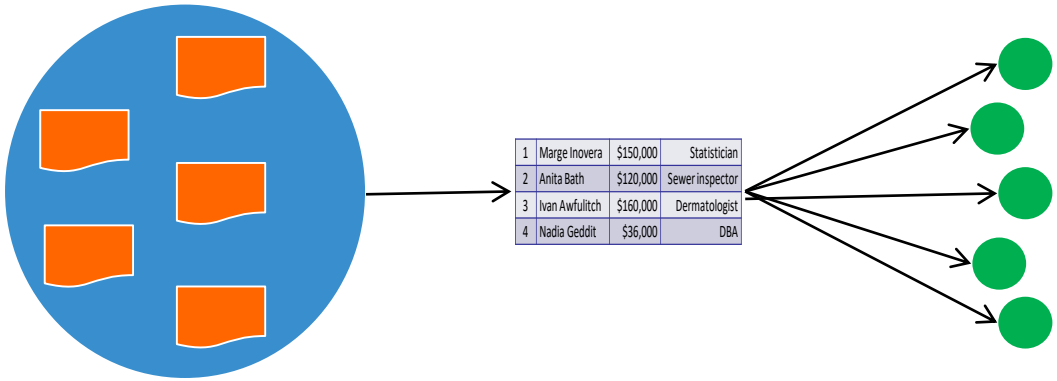


Source: Michael Berry, Data Miners Inc.

Third Nature

The nature of data science and BI differs

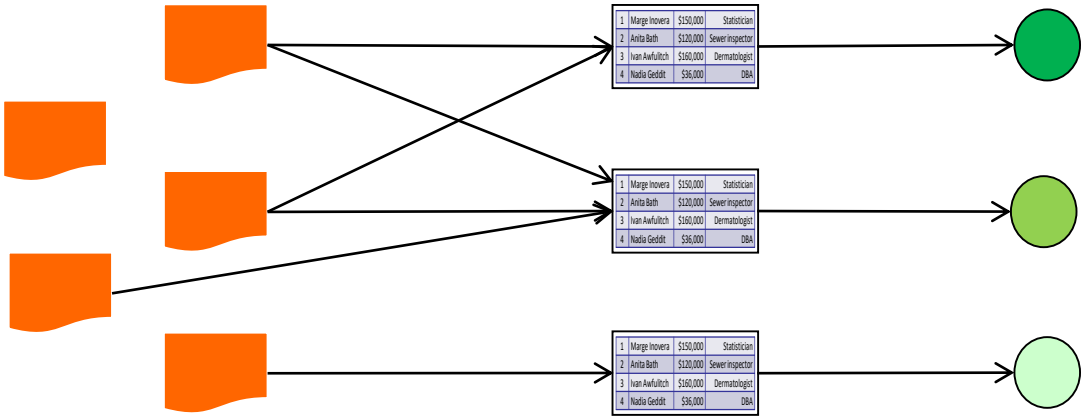
- In BI, the required data is known at the start. One can model the required data in advance.
- Build once, deploy many.
- The same schema can be used by many tools that consume data. The purpose of the schema is to **permit easy data reuse** via query-generating tools.



Source data BI schema BI objects

The nature of data science and BI differs

- In data science, the data is unknown at the start. **The process creates a data model**. The same schema may not be reusable.
- Build once, deploy once is the norm.
- The equivalent to a report is *not* a model. That would be the model's *output.* The equivalent to a model is more like ETL.



Somewhere between the sources and the extract is a point of reuse. Standard models, but not fully integrated data.

Market Solution? Build a Data Lake

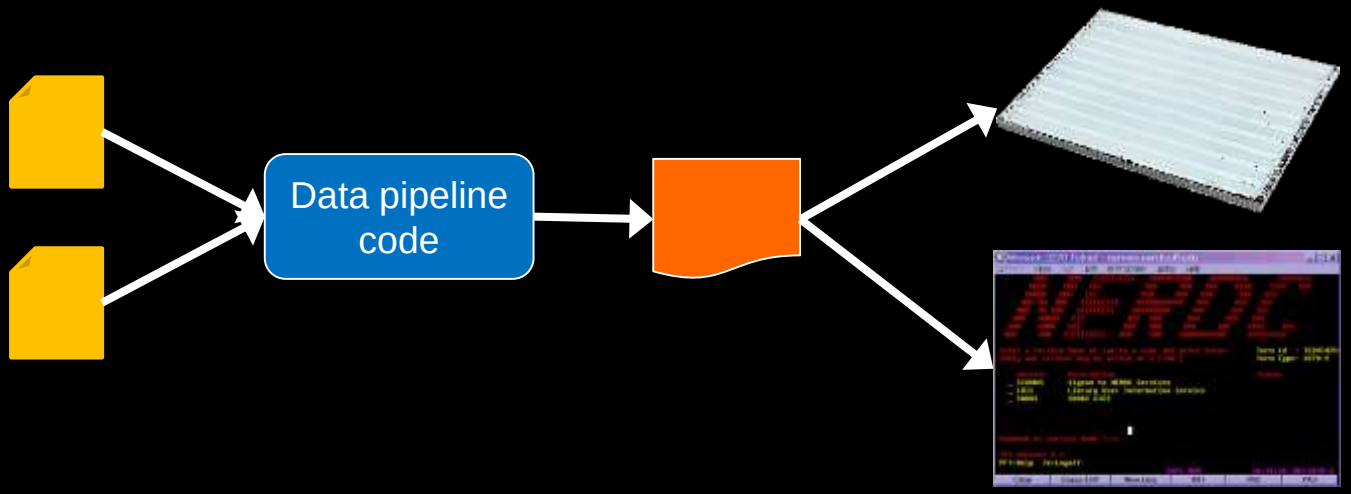
Build silos on a death star. This is an old pattern.

History: This is how BI was done through the 80s

First there were files and reporting programs.

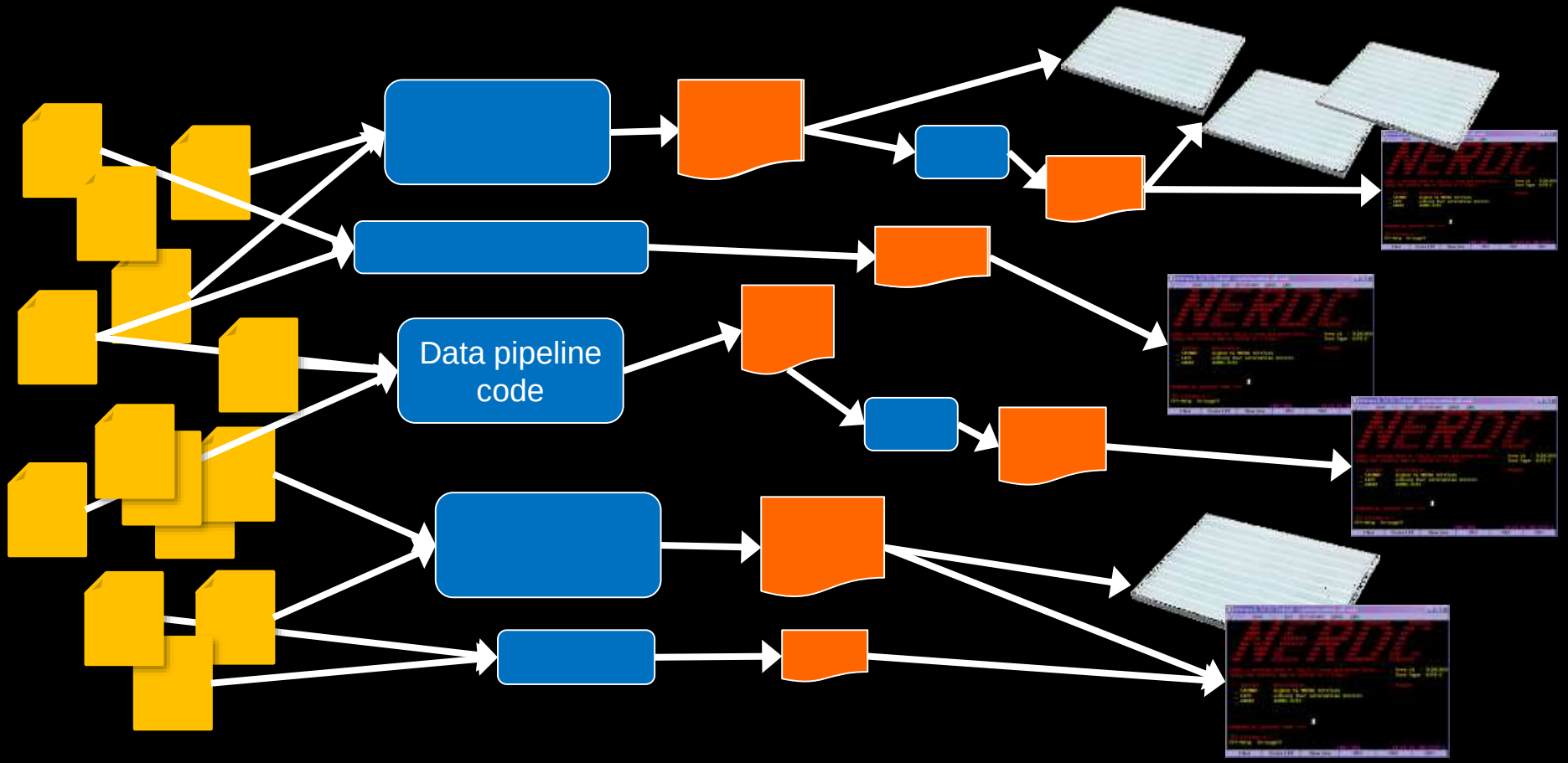
Application files feed through a data processing pipeline to generate an output file. The file is used by a report formatter for print/screen. Files are largely single-purpose use.

Every report is a program written by a developer.



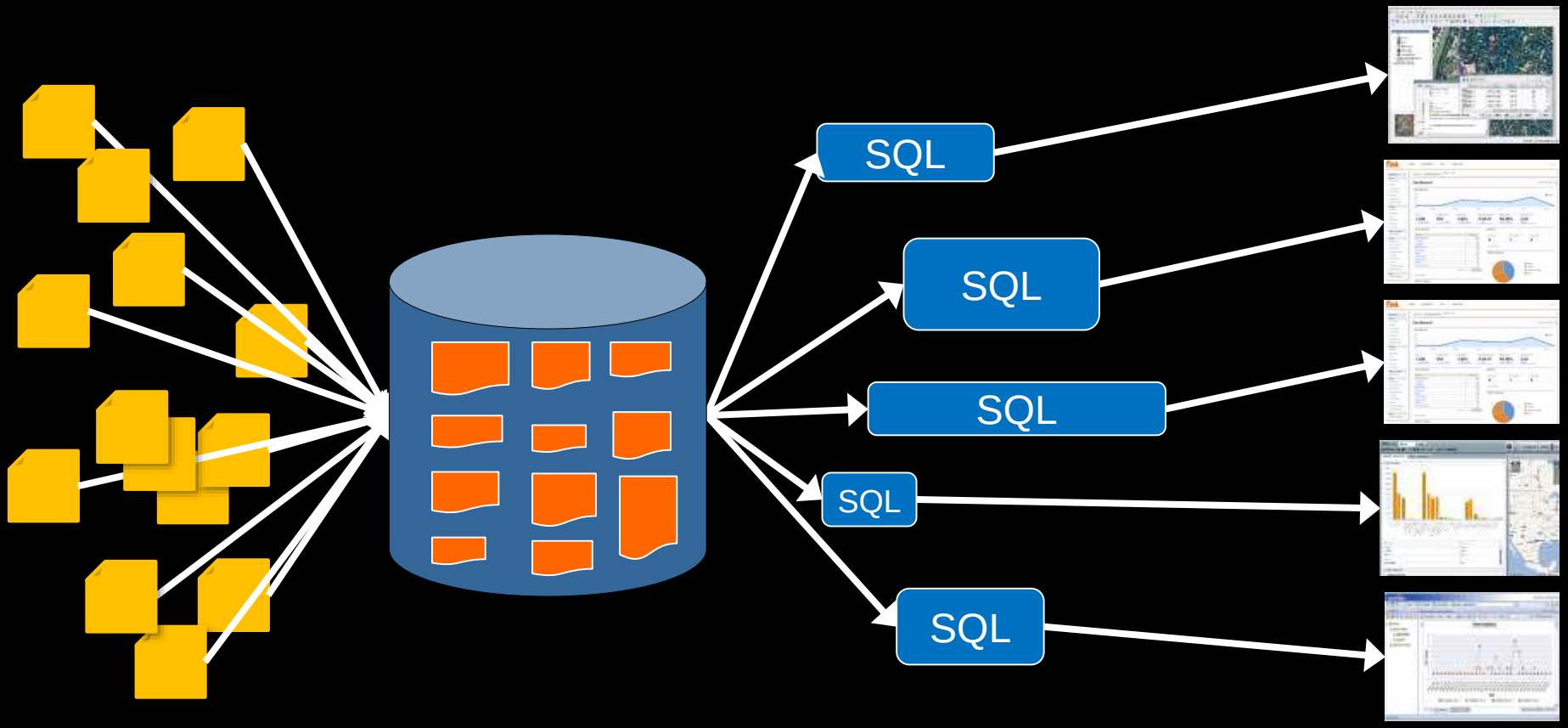
History: This is how BI ended the 80s

The inevitable situation was...



History: This is how we started the 90s

Collect data in a database. Queries replaced a *LOT* of application code because much was just joins. We learned about “dead code”

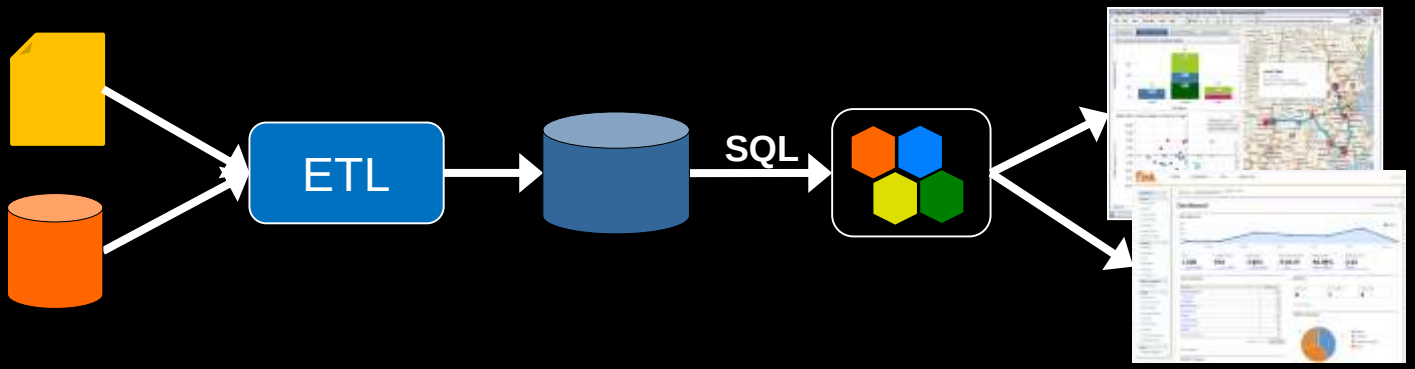


BI evolved to hiding query generation for end users

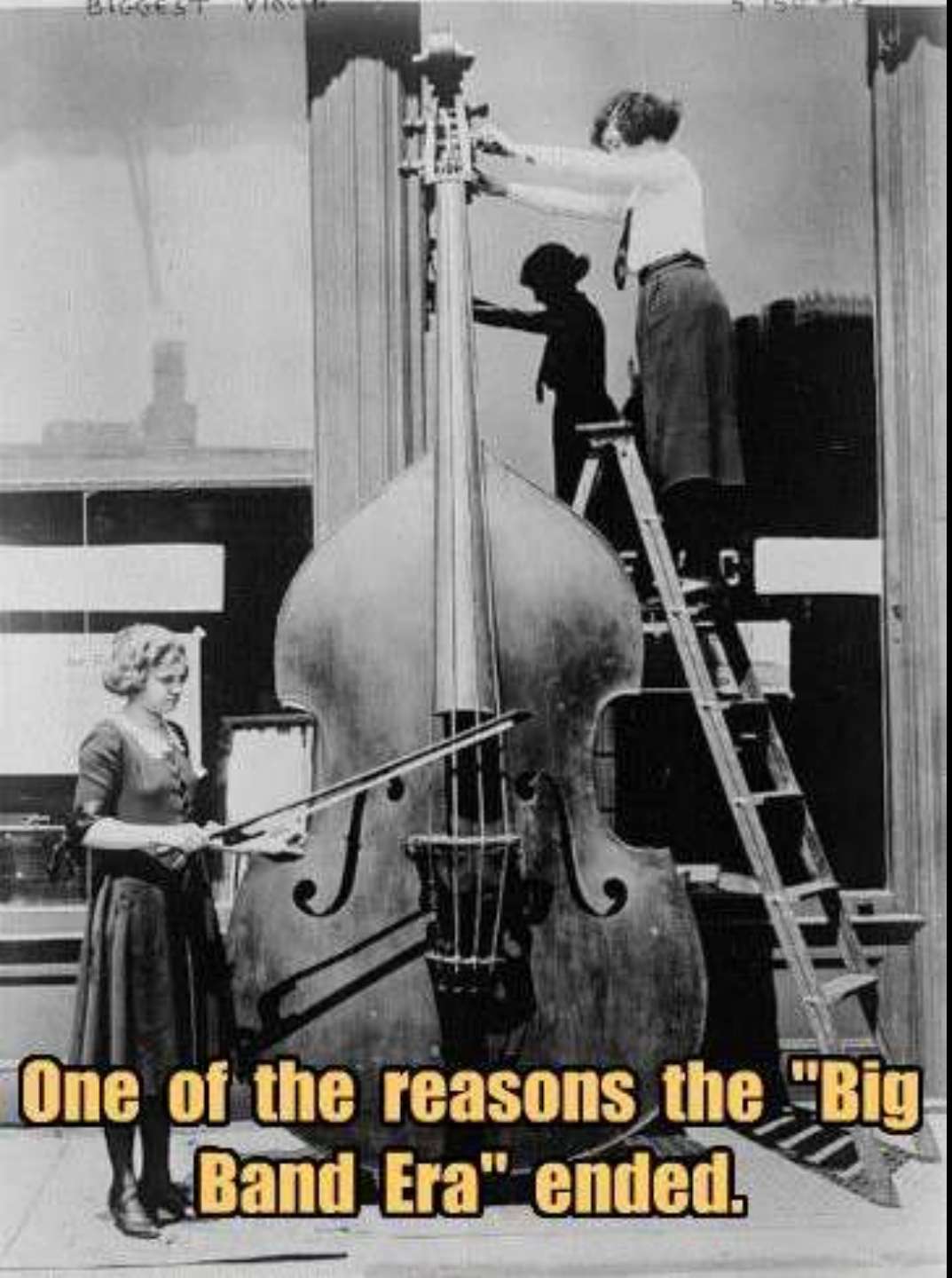
With more regular schema models, in particular dimensional models that didn't contain cyclic join paths, it was possible to automate SQL generation via semantic mapping layers.

We developed data pipeline building tools (ETL).

Query via business terms made BI usable by non-technical people.



Life got much easier…for a while



Pragmatism and Data

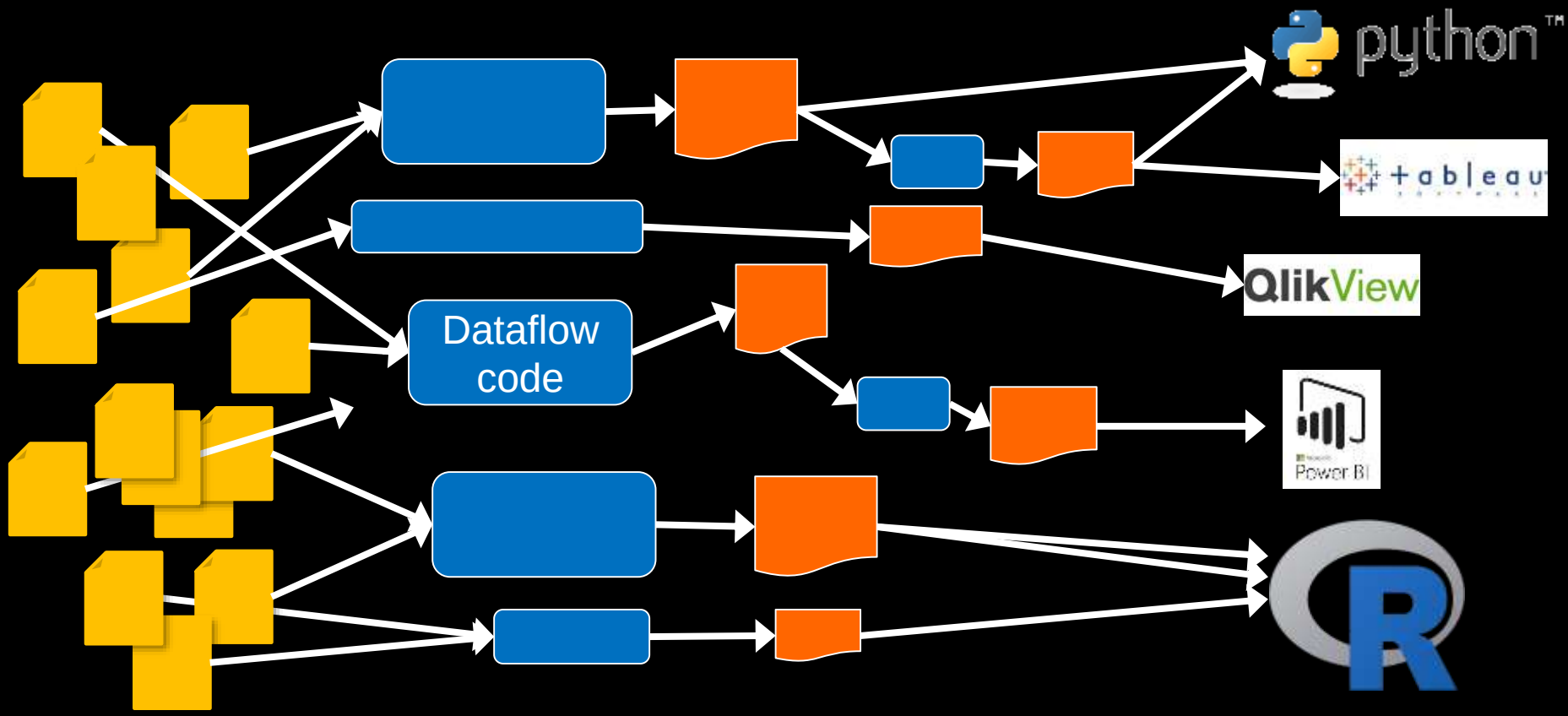
Lessons learned during the ad-hoc SQL era of the BI market:

- When the technology is awkward for the users, the users will stop trying to use it
- Even “simple” schemas weren’t enough for anyone other than analysts and their Brio…

Led to the evolution of metadata-driven SQL-generating BI tools, ETL tools.

Today's model: Lake + data engineers, looks familiar…

The Lake with data pipelines to files or Hive tables
is exactly the same pattern as the COBOL batch



We already know that people don't scale. Don't do this

Evolution: 3 stages of maturing data practice

1. Data lake: store all the raw data. A data lake is not *entirely* worthless, just *mostly* worthless
   - This was the big data fad, because data in one place is easier than data from source, and the DW has (largely org / process) problems
2. Feature repository: finalized data for use in models
   - Next stop, because we all want to reinvent data marts
   - There is no difference between “feature repo” and “data mart”
3. Standardized data: not *conformed* like a DW, *standardized*
   - Data is the primary element of reuse, not code
   - Final stop because eventually you realize a DW was the right conceptual model all along, just misapplied

What do the experts say?

TIDY DATA: Hadley Wickham makes the case for Tidy data sets, that have specific structure, are easy to work with, that free analysts from mundane data manipulation chores – there's no need to start from scratch and reinvent new methods for data cleaning

Source: Tidy Data by Hadley Wickham, Journal of Statistical Software, Vol 59, issue 10 (2014)

Third Nature

What about AI? GIGO!

"If your boss asks you, tell them that I said build a unified data warehouse"

Andrew Ng
Leading AI Researcher

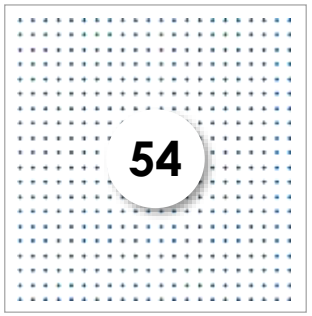
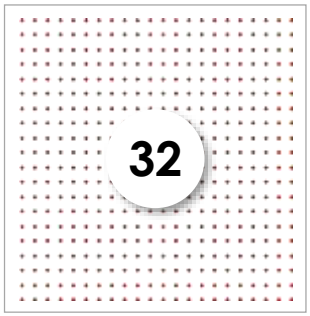
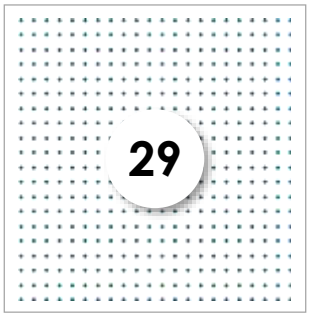
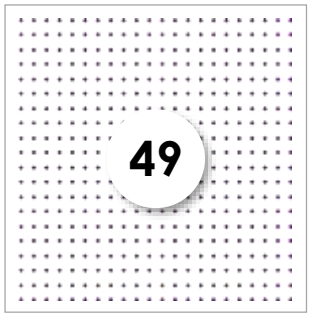
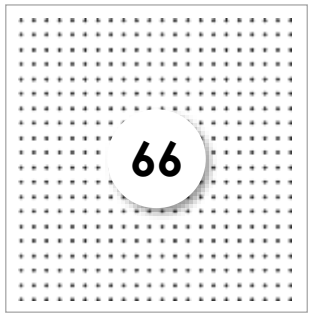
Everyone wants shortcuts. There's aren't any shortcuts

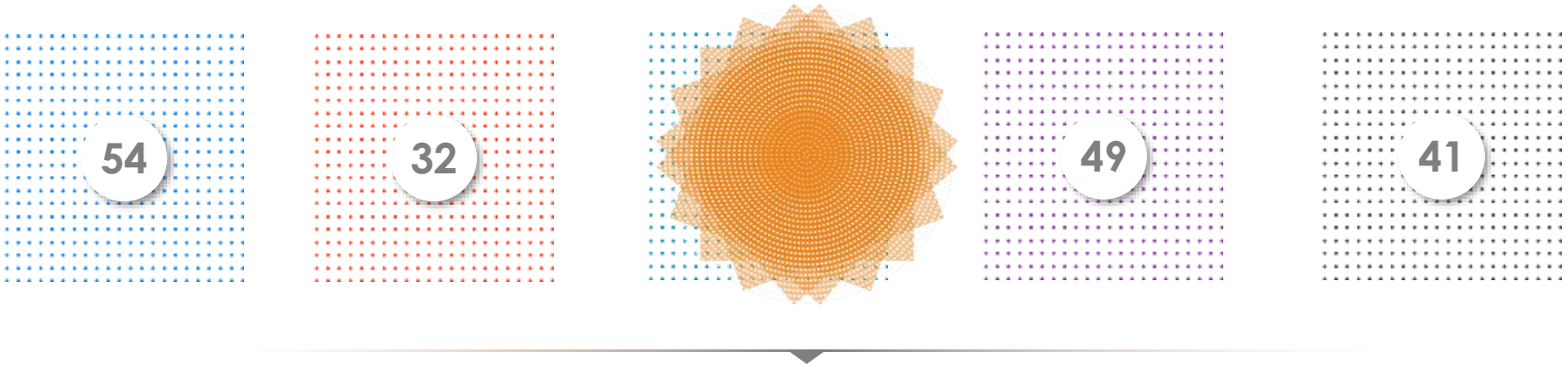
How did we get to this state with analytics?

There’s a difference between having no past and actively rejecting it.

Third Nature

We started with silos, and they were useful

How many batteries are in inventory by plant?	What is the trend of warranty costs?	How many people made a warranty claim last week?	How many sales have been made quarter to date?	Which customers should get a communication on extended warranties?
				
OPERATIONS Inventory Returns Manufacturing Supply Chain	**FINANCE** Revenue Expenses Customers	**CUSTOMER CARE** Customer Products Orders Case History	**SALES** Orders Customers Products	**MARKETING** Customers Orders Campaign History


54
32
49
41

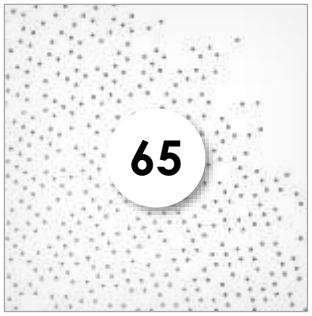
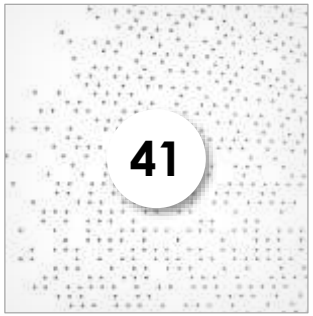
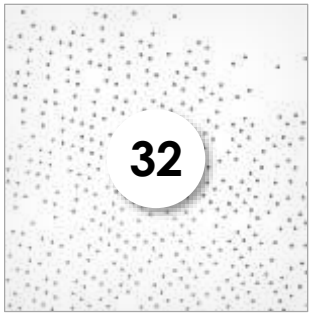
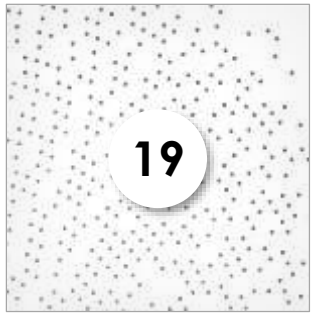
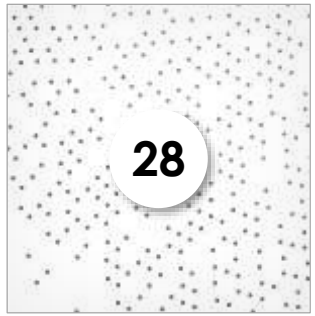
Given the rise in **warranty costs**, isolate the problem to be a **plant**, then to a **battery lot**.

Communicate with **affected customers**, who have not made a warranty claim on batteries, through **Marketing** and **Customer Service** channels to recall cars with affected batteries.

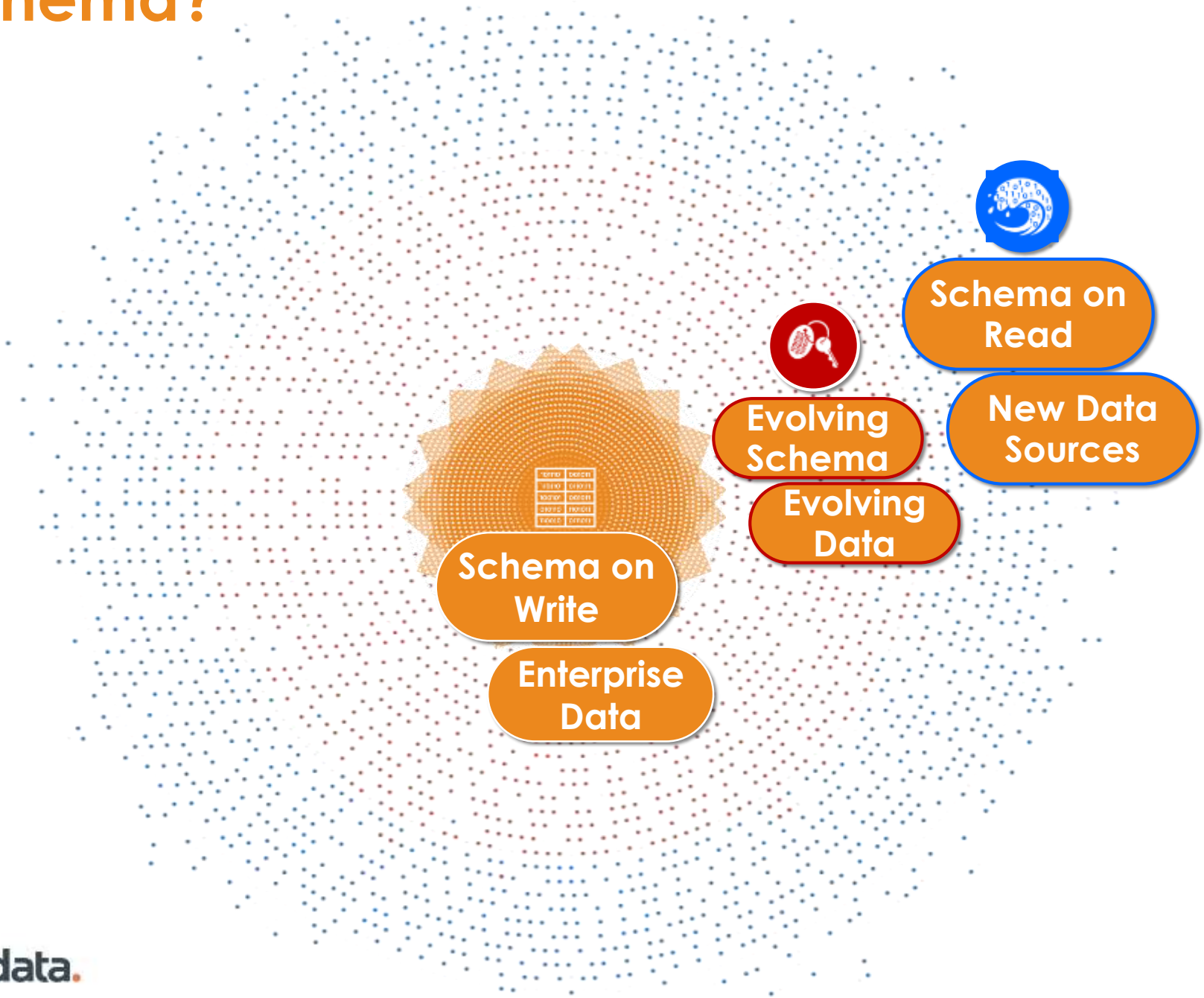
Enterprise Data

teradata.

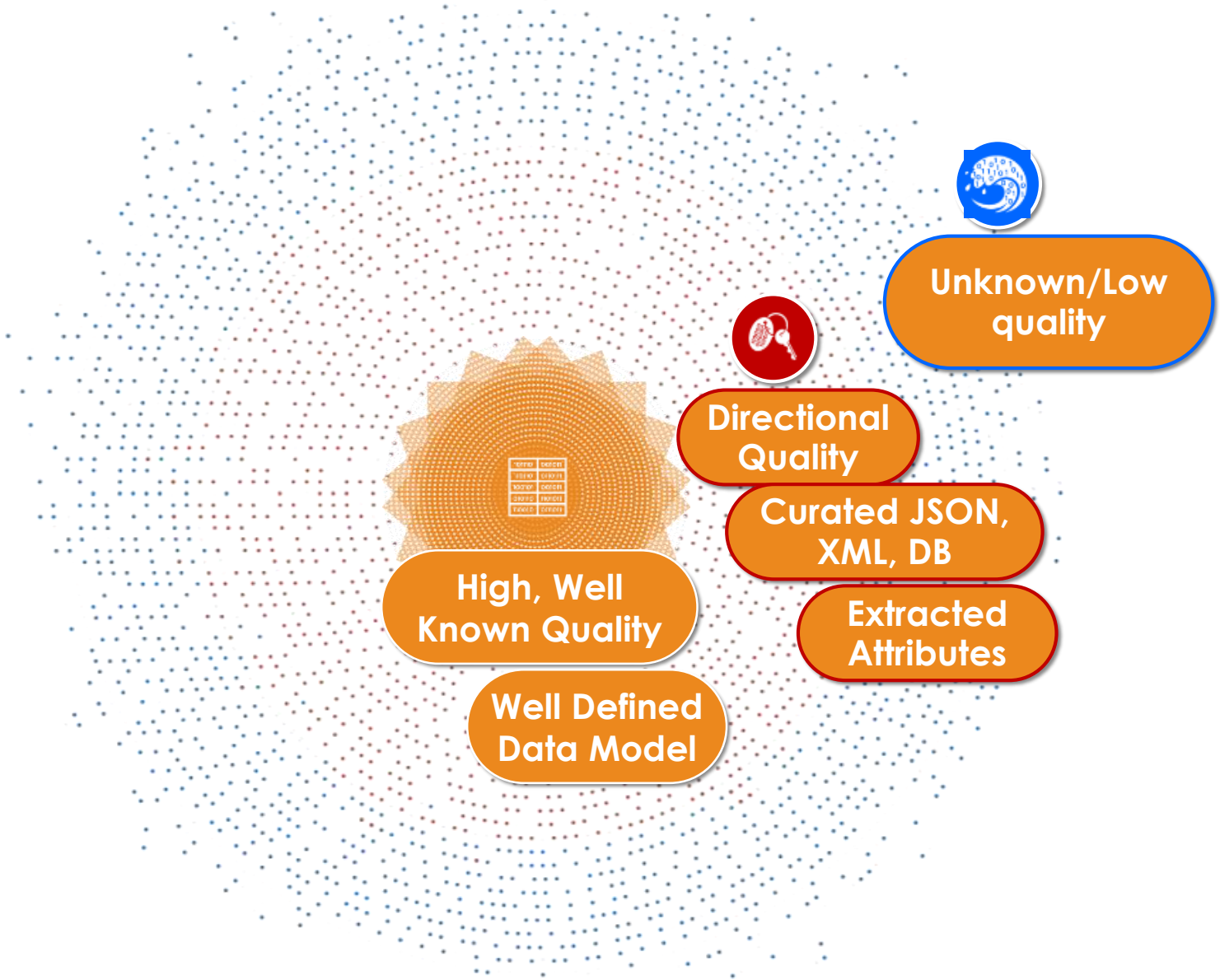

Along came
BIG
DATA

How many visitors did we have to our hybrid cars microsite yesterday?	What are the temperature readings for batteries by Manufacturer?	What is the sentiment towards line of hybrid vehicles?	Which customers likely expressed anger with customer care?	Which ad creative generated the most clicks?
				
CLICKSTREAM	PRODUCT SENSOR	SOCIAL MEDIA	CUSTOMER CARE AUDIO RECORDINGS	DIGITAL ADVERTISING

Schema?

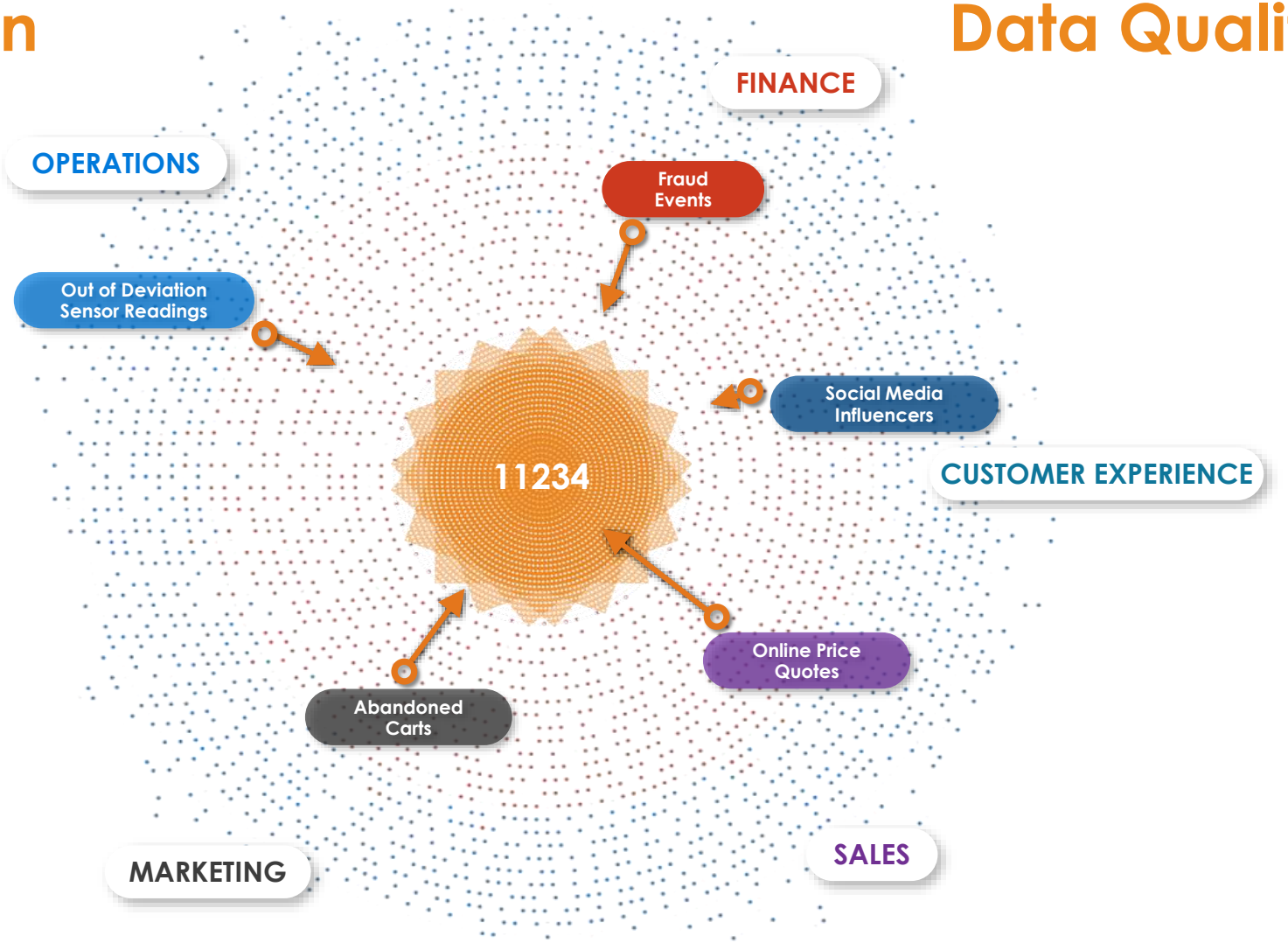

Schema on Read
New Data Sources
Evolving Schema
Evolving Data
Schema on Write
Enterprise Data

Curation Required

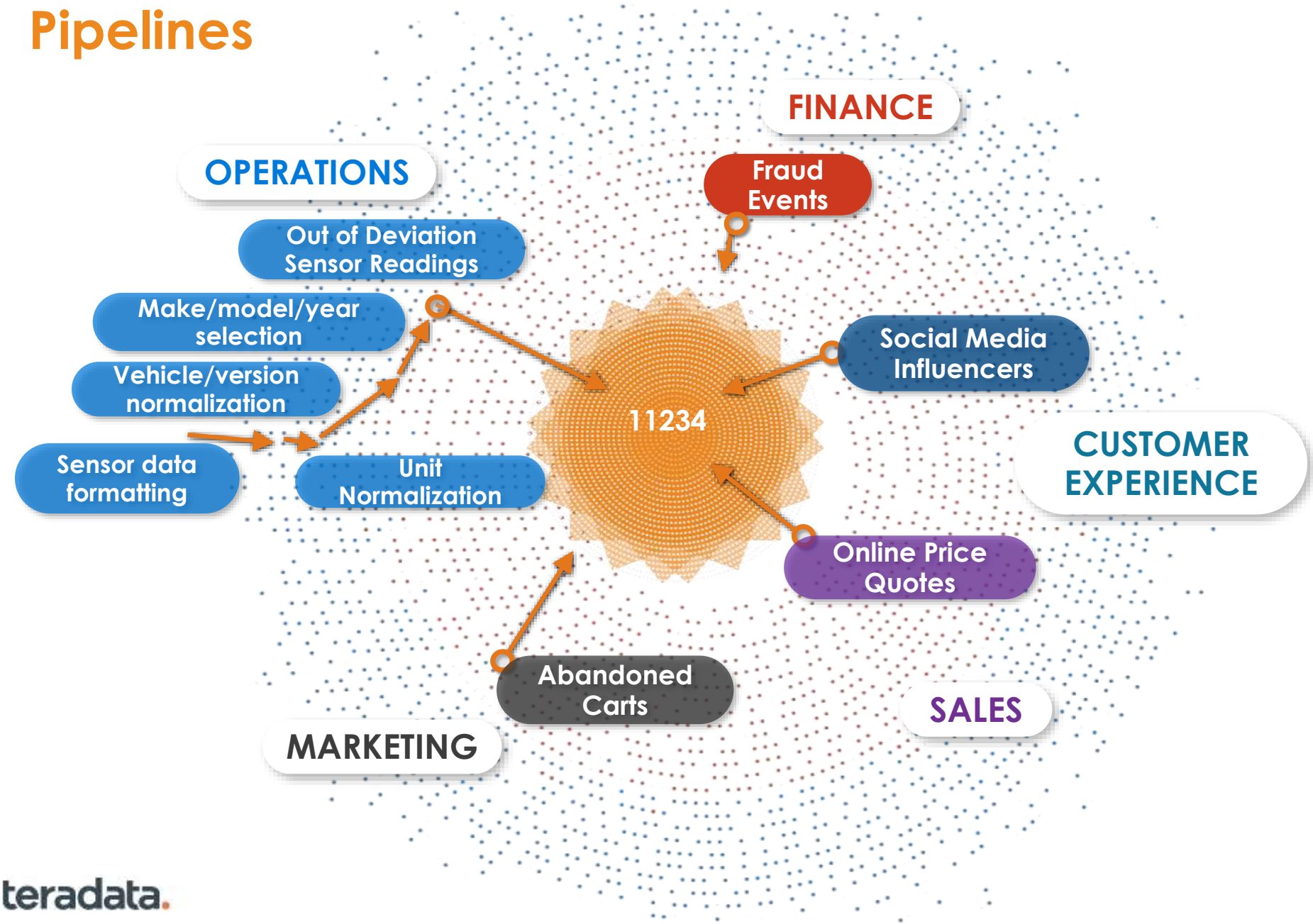


Minimum Viable Curation

Minimum Viable Data Quality

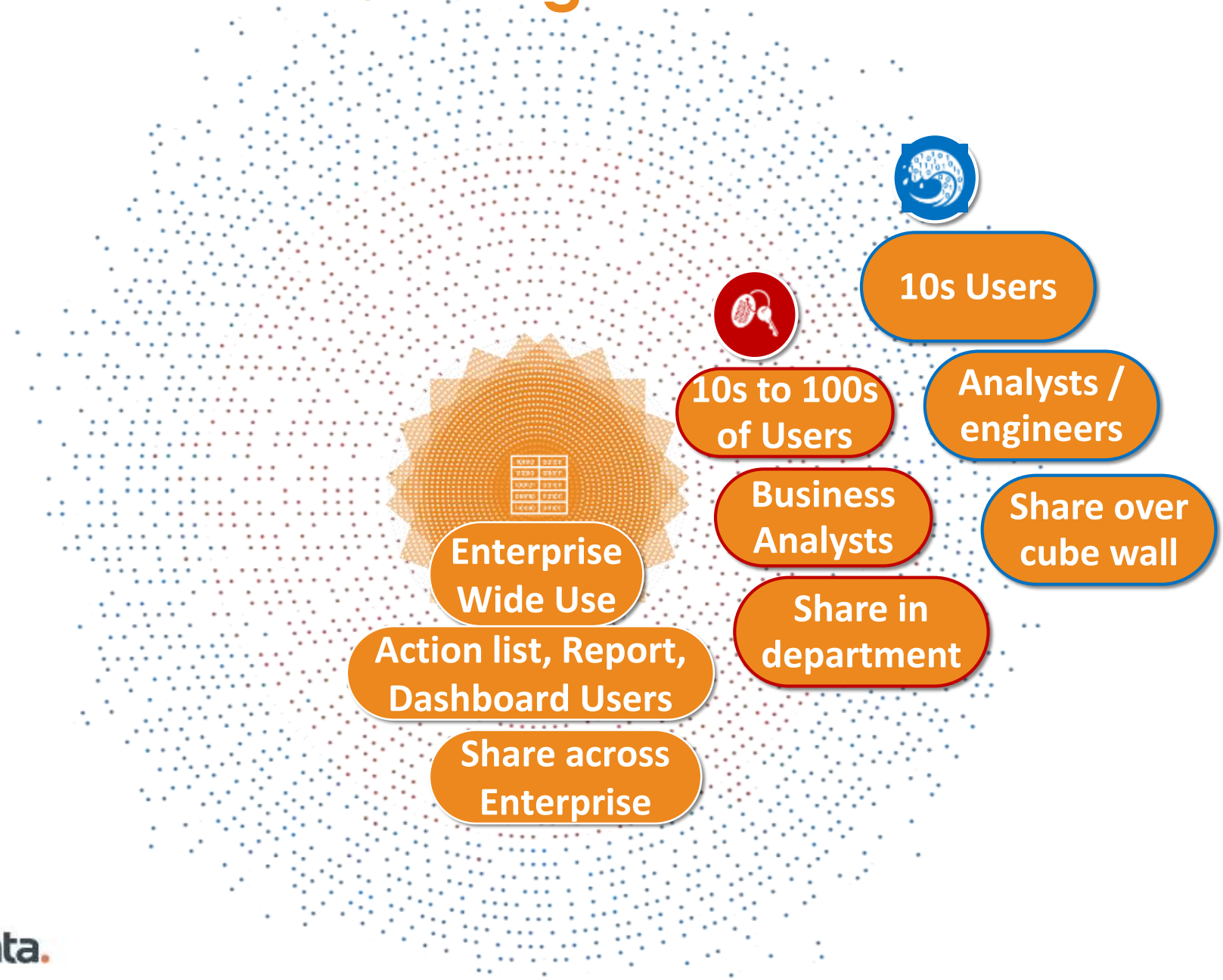


Data Comprehension, Pipelines

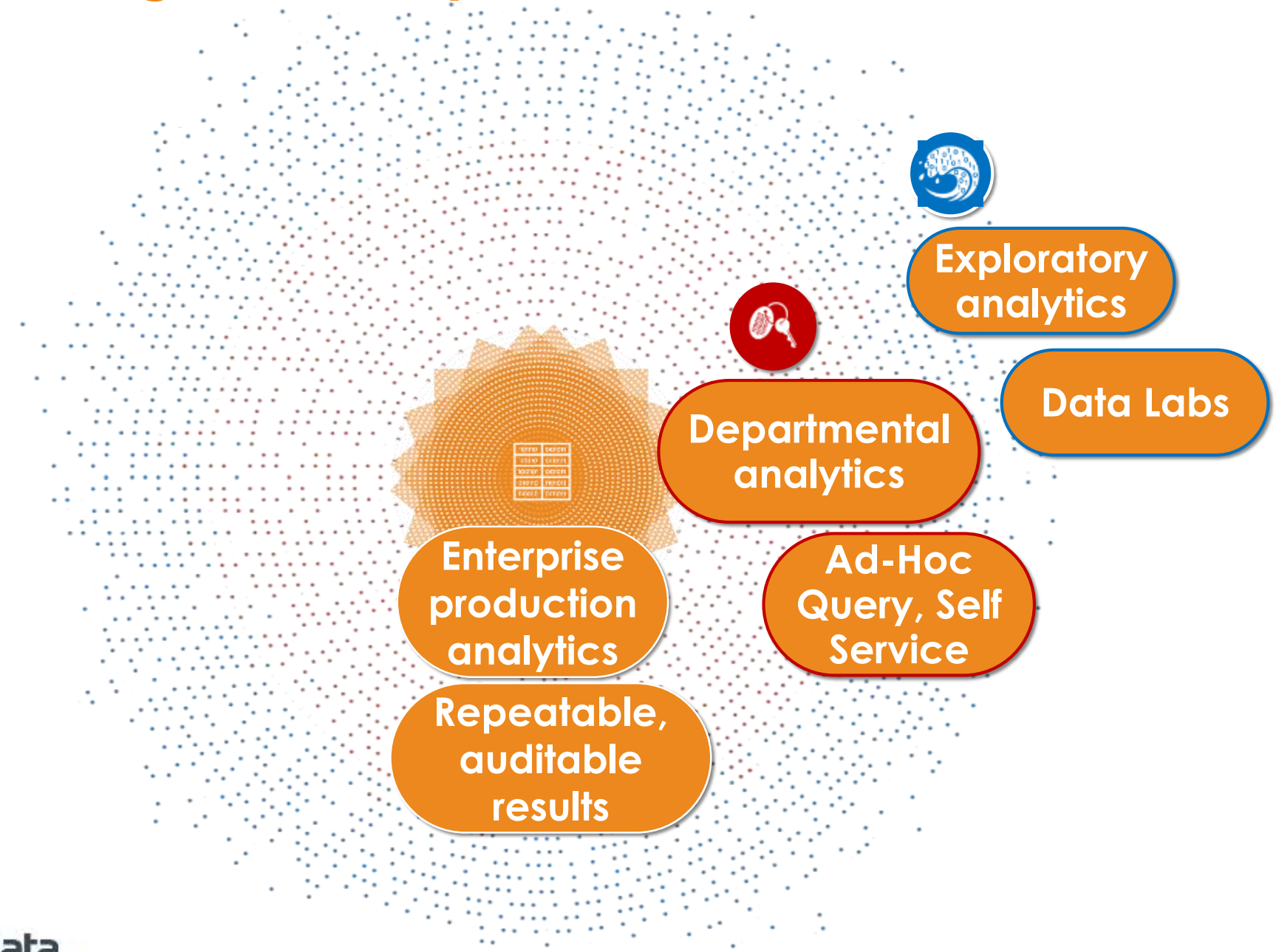


teradata.

User Base and Sharing



Evolving Consumption

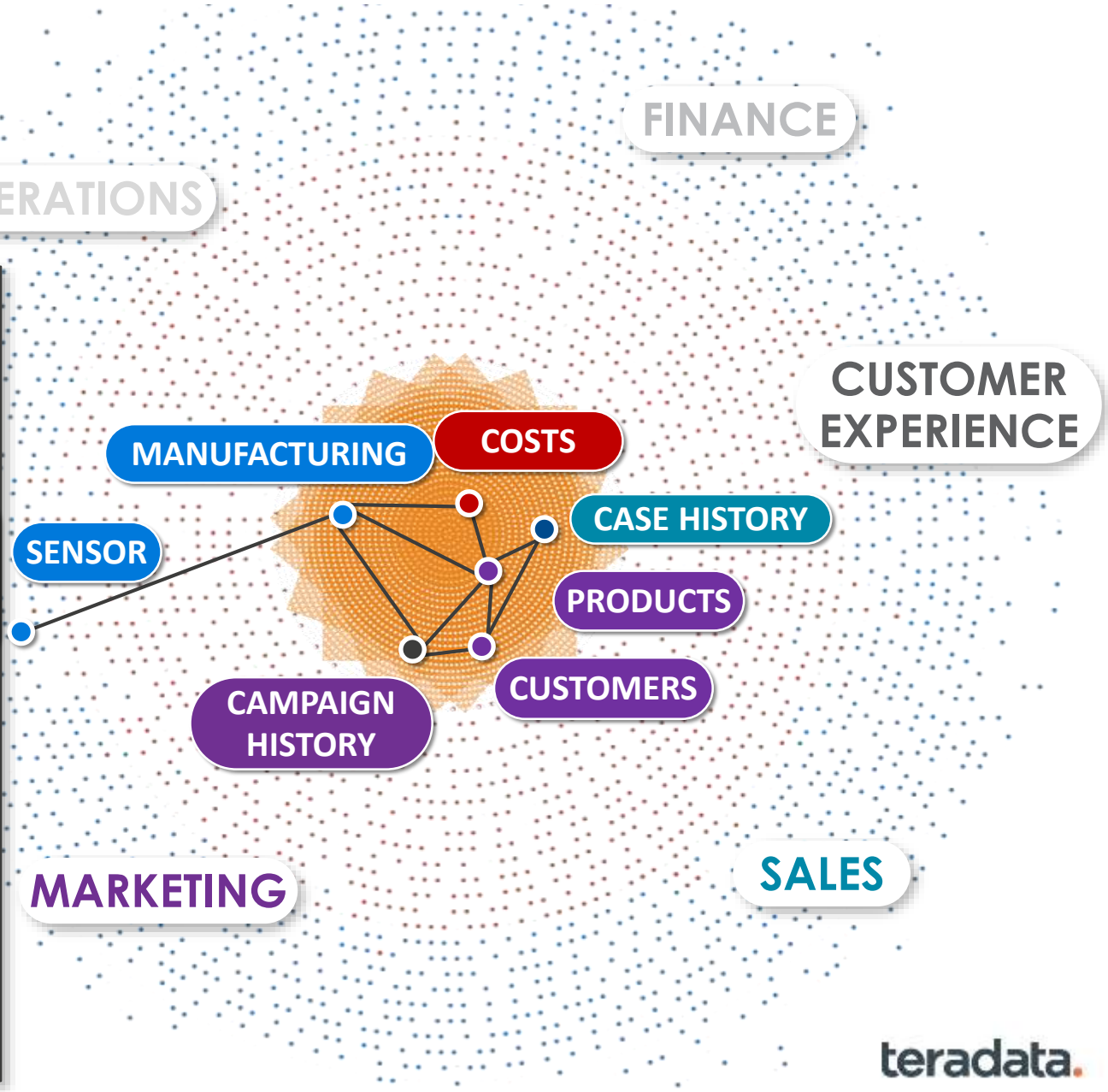


Access Wide Variety of Data to Answer a Question

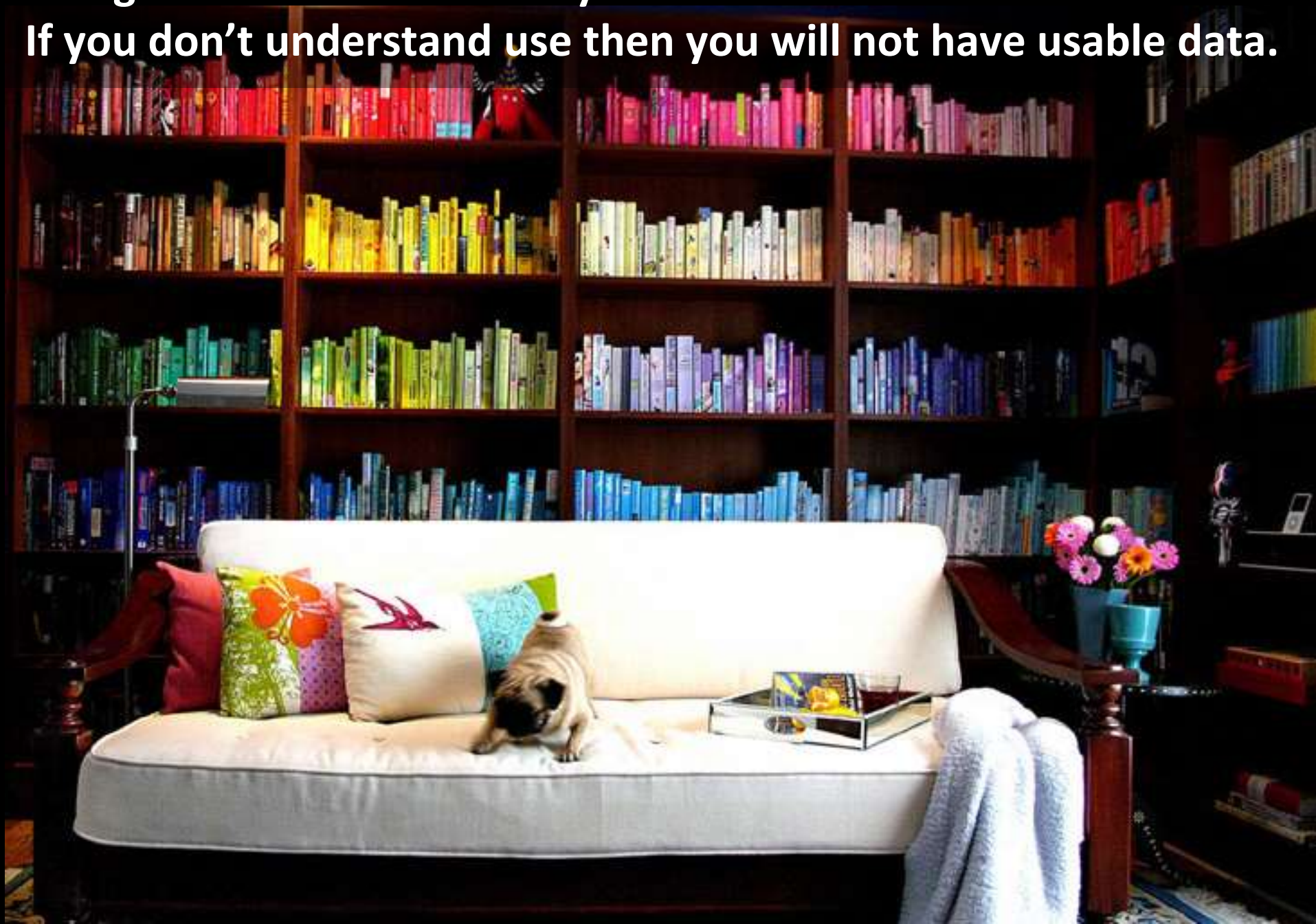
Given the rise in warranty costs, isolate the problem to be a plant and the specific lot.

Exclude 2/3rd of the batteries from the lot that are fine.

Communicate with affected customers, who have not made a warranty claim, through Marketing and Customer Service channels to recall cars with affected batteries.



To organize and curate data you must understand how it is used.
If you don't understand use then you will not have usable data.

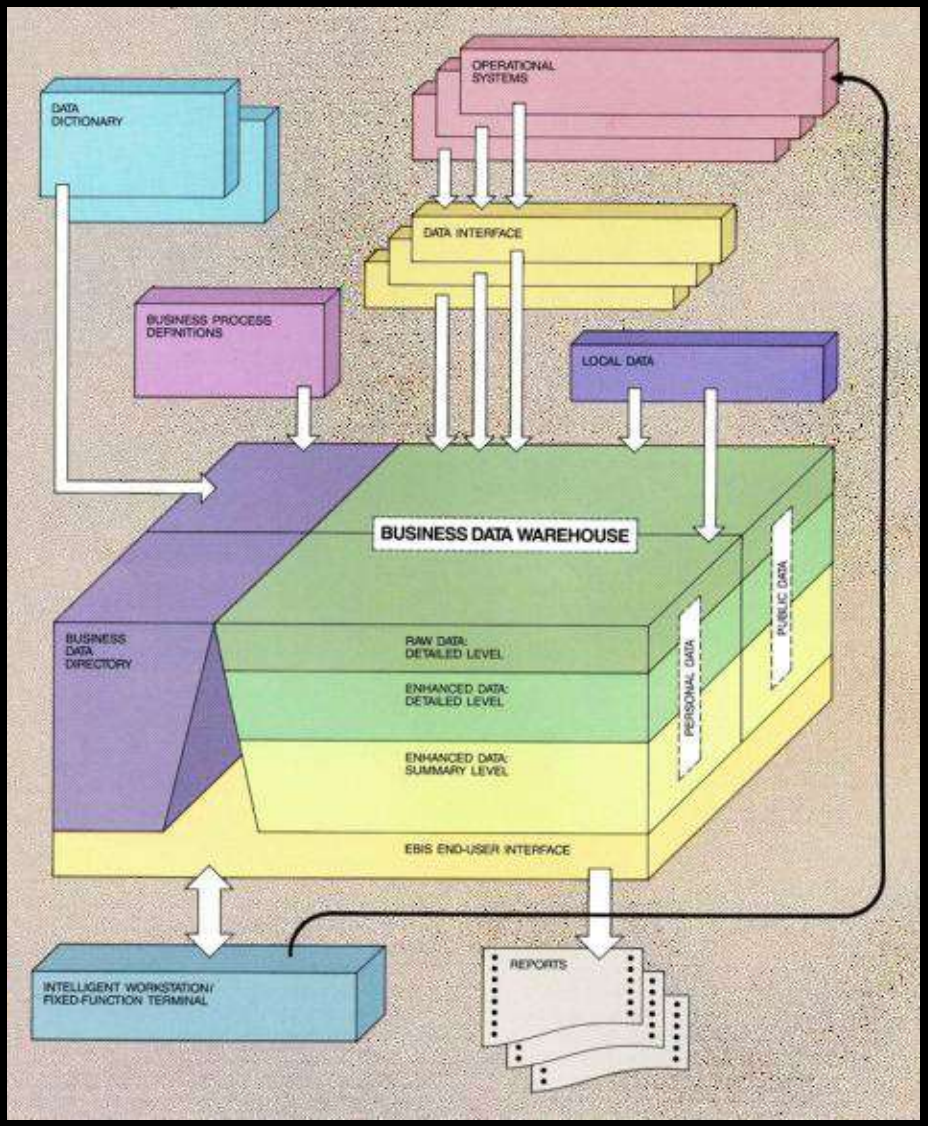


We’re so focused on the light switch that we’re not talking about the light

DATA ARCHITECTURE

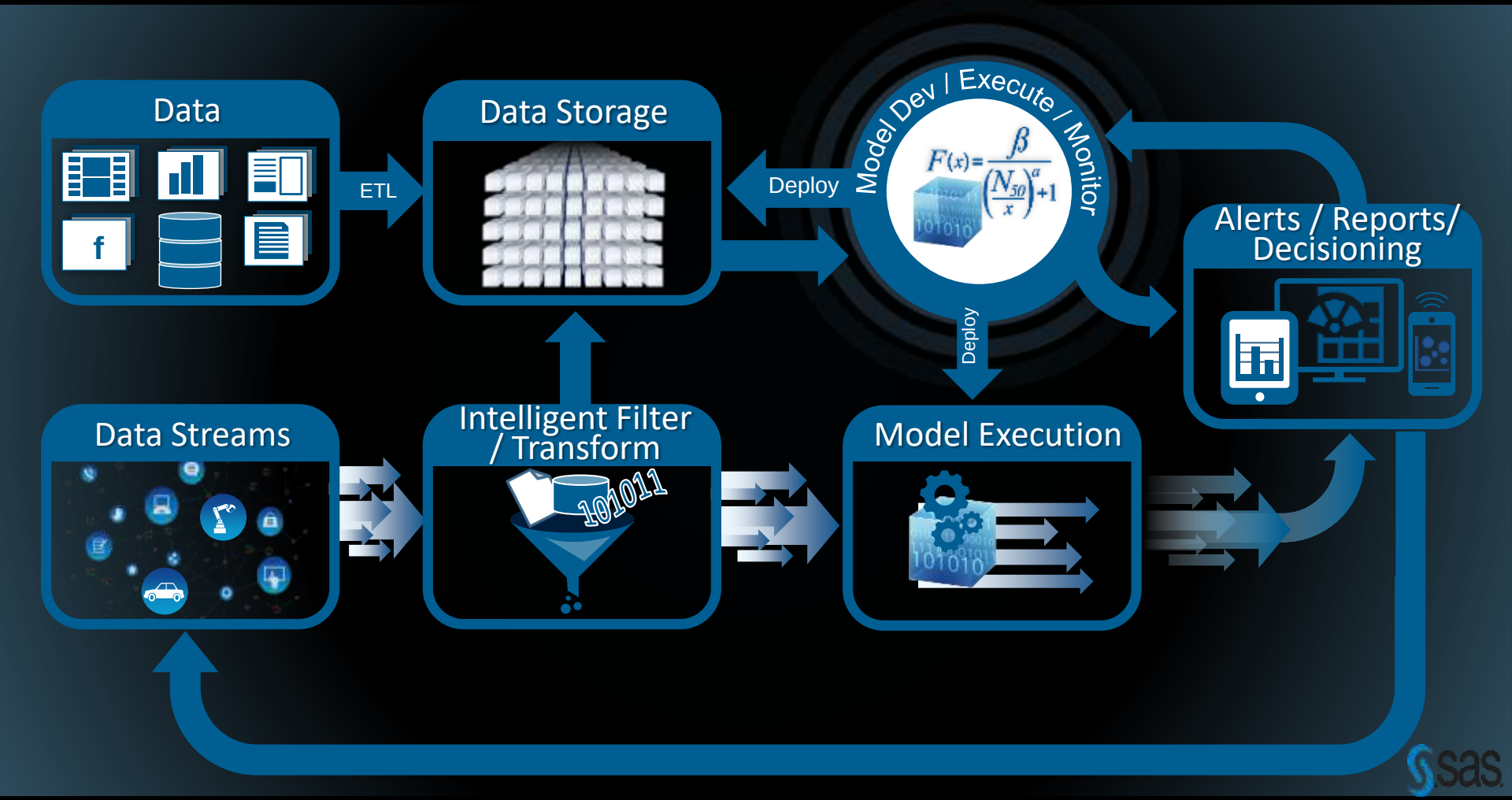
The architecture from 1988 we SHOULD HAVE BEEN USING

The general concept of a separate architecture for BI has been around longer, but this paper by Devlin and Murphy is the first formal data warehouse architecture and definition published.



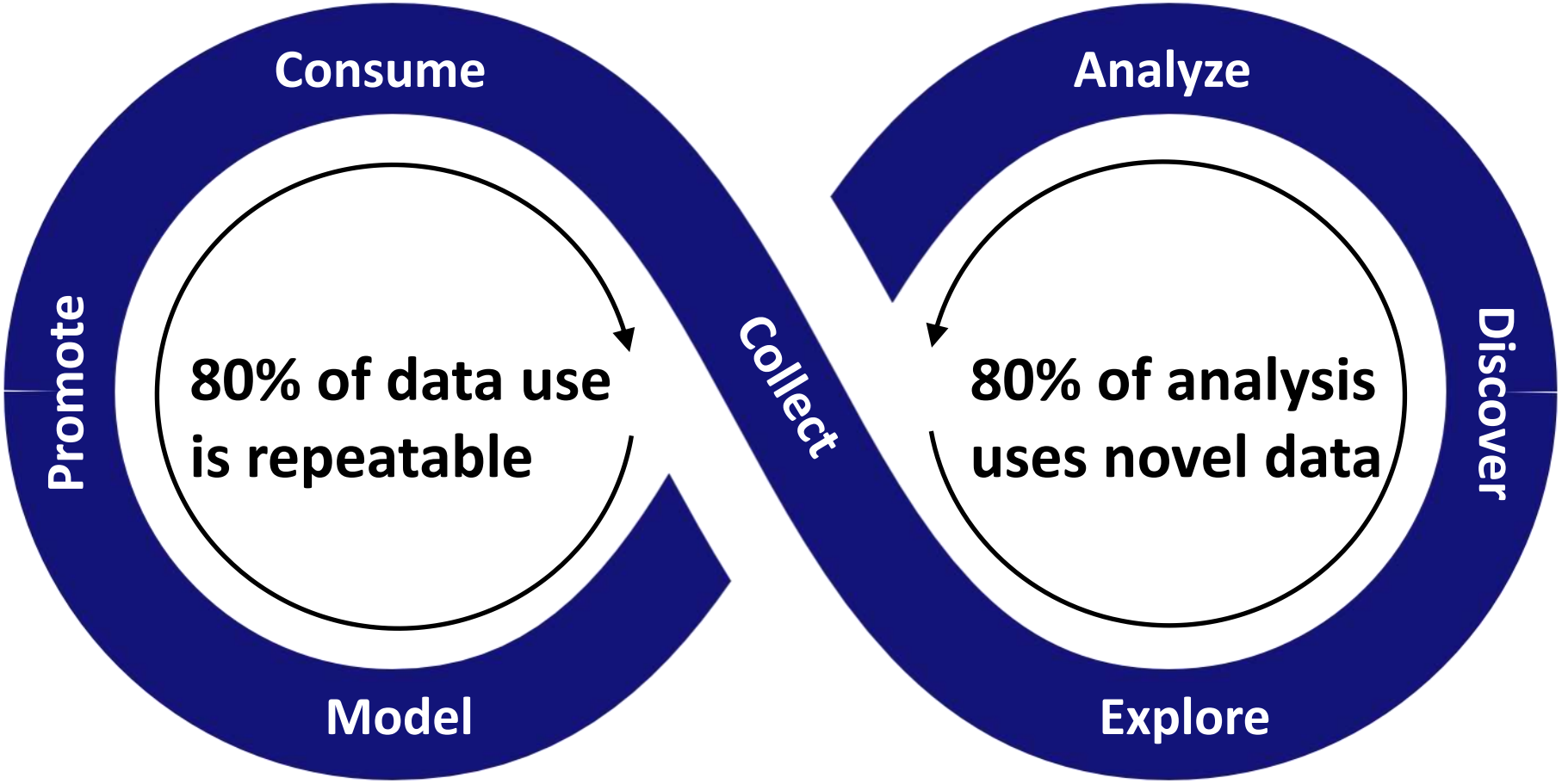
"An architecture for a business and information system", B. A. Devlin, P. T. Murphy, IBM Systems Journal, Vol.27, No. 1, (1988)

But 30 years ago we did not expect so many different models of deployment, execution and use.



Analytics for eyeballs and analytics for machines are different

We Need to Support Repeatability *and* Discoverability



Focus is on repeatability

Application cycle time

90% of users *just want answers*

Focus is on discoverability

Analyst cycle time

9% analysts, 1% data scientists

The current needs are beyond lakes and warehouses

We need a new data architecture that is not limiting:

- Deals with change more easily and at scale
- Does not enforce requirements and models up front
- Does not limit the format or structure of data
- Assumes the range of data latencies in and out, from streaming to one-time bulk
- Allows both reading and writing of data
- Makes data linkable, and provides governance
- *Does not give up the gains of the last 25 years*

Break down the monolithic architecture – not one building, multiple buildings in a block

Divide the platform architecture to address 3 different goals

Collection

Creation, collection, storage of new data

Distribution

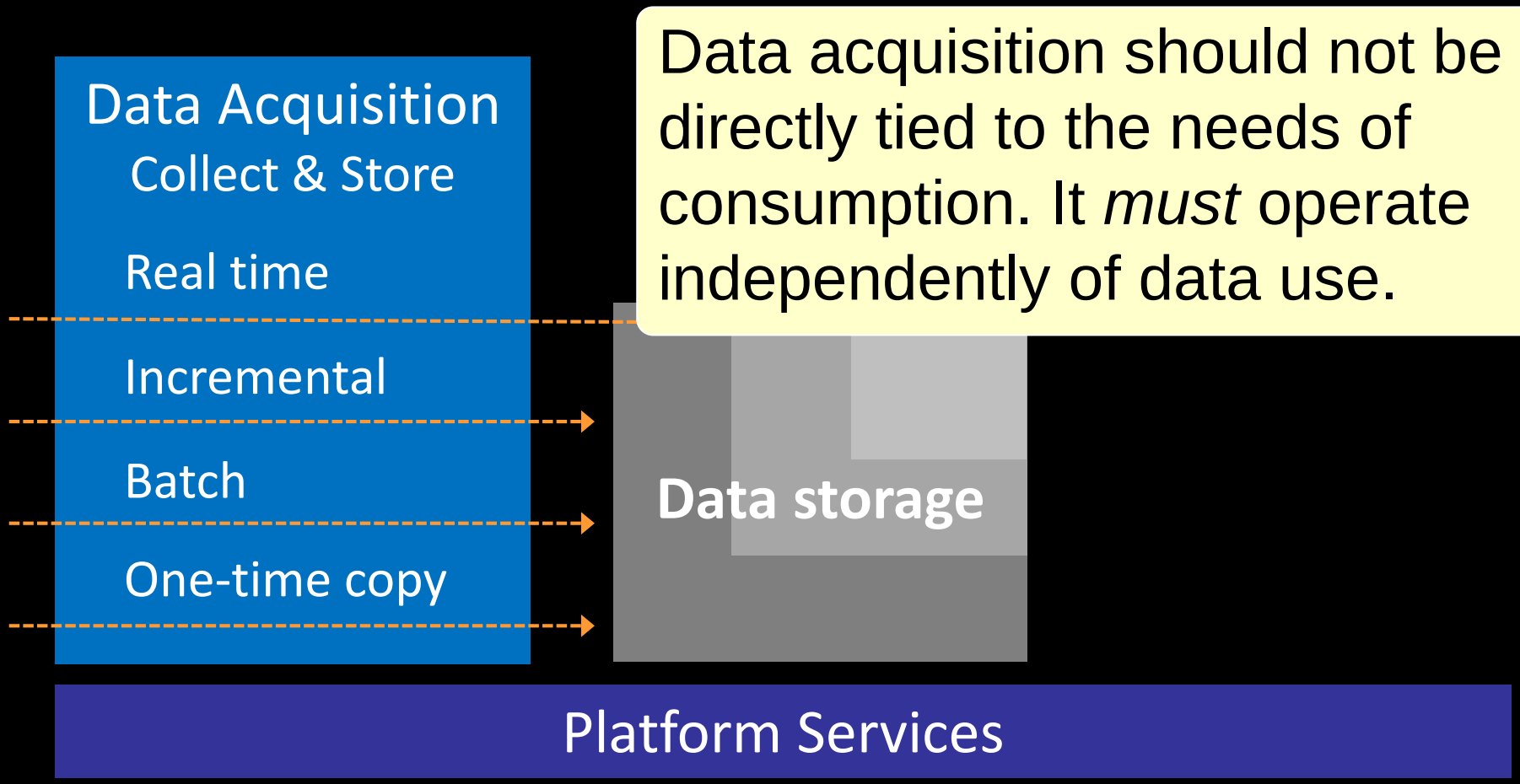
Organization and provisioning of data to multiple points of use

Consumption

Direct support of data use

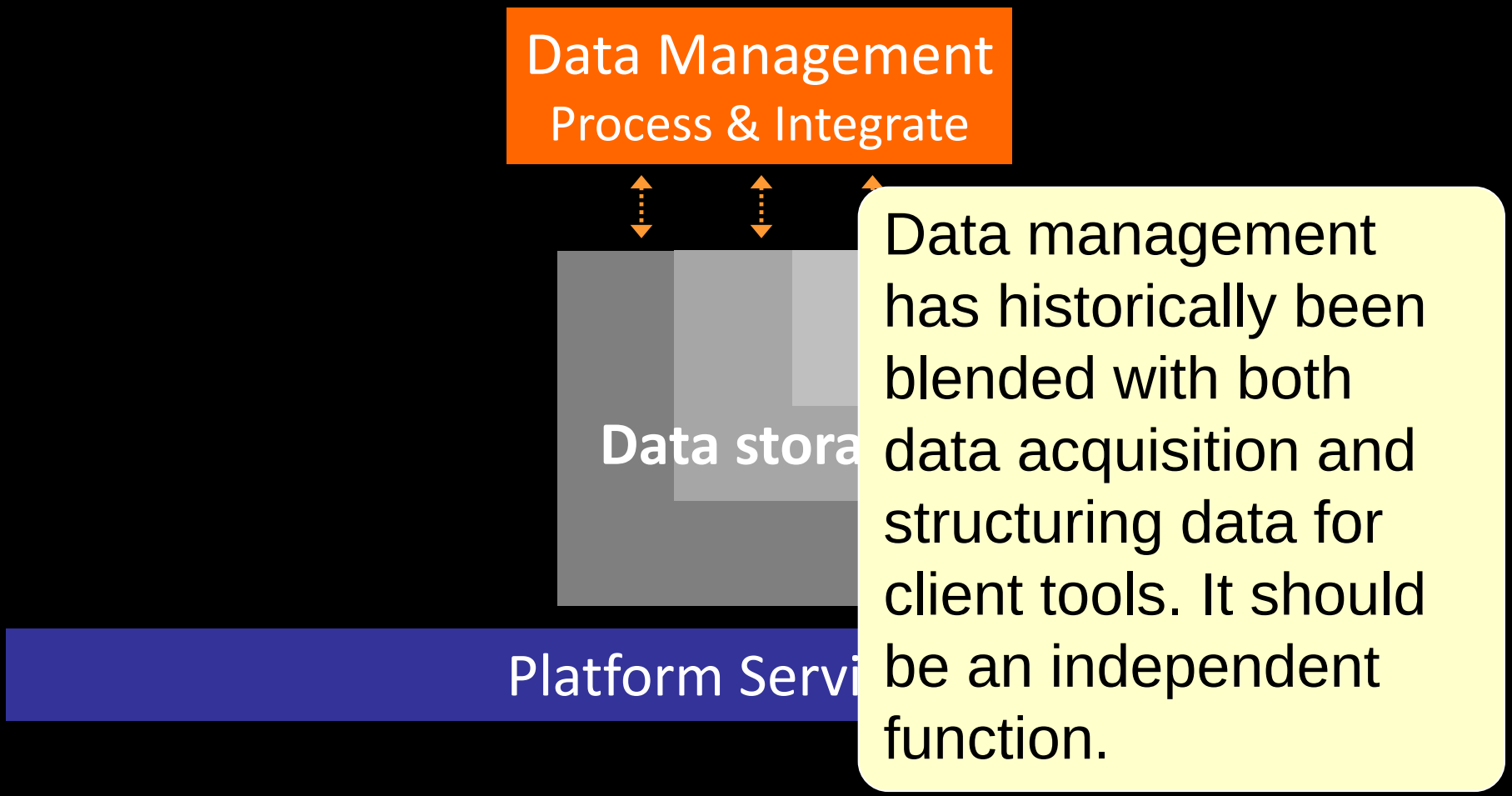
Separation of concerns, coordination of process

The goal is to decouple: solve the application and infrastructure problems separately, independently



Data arrives in many latencies, from real-time to one-time. Acquisition can't be limited by the management or consumption layers.

The goal is to decouple: solve the application and infrastructure problems separately, independently

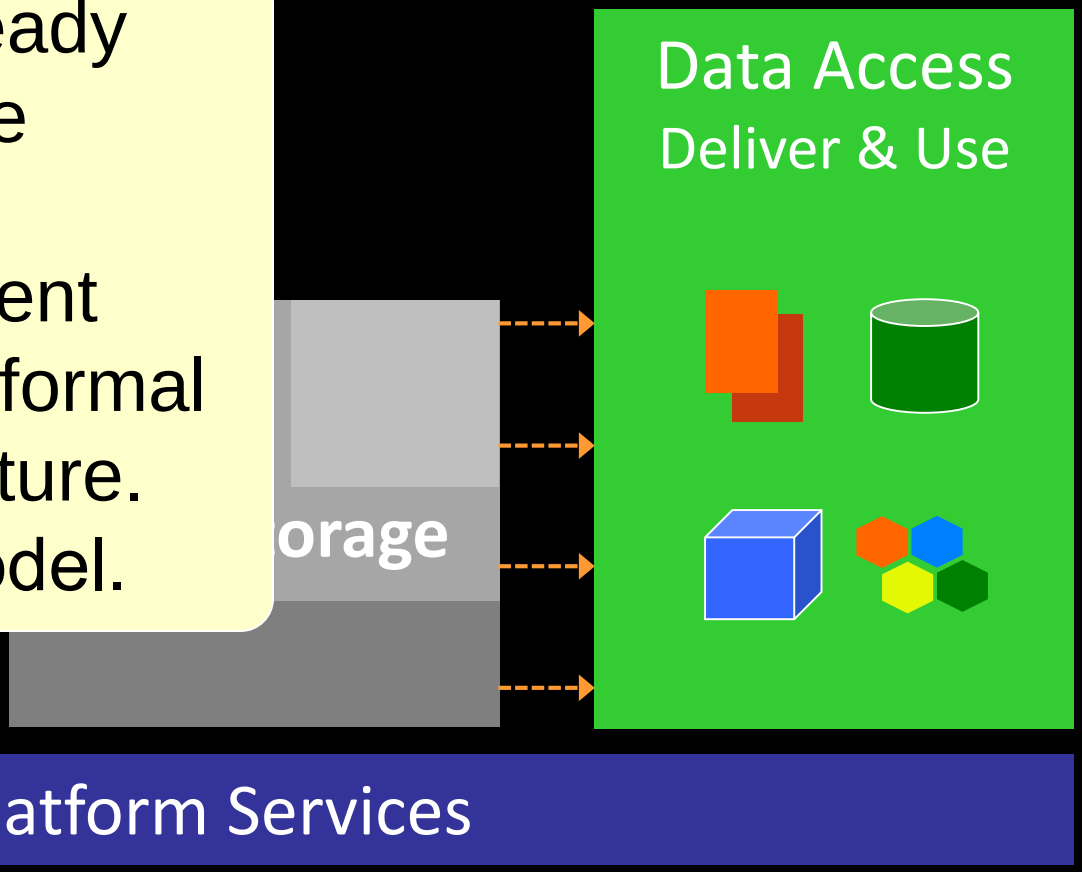


Data management has historically been blended with both data acquisition and structuring data for client tools. It should be an independent function.

Data management should not be subject to the constraints of a single use

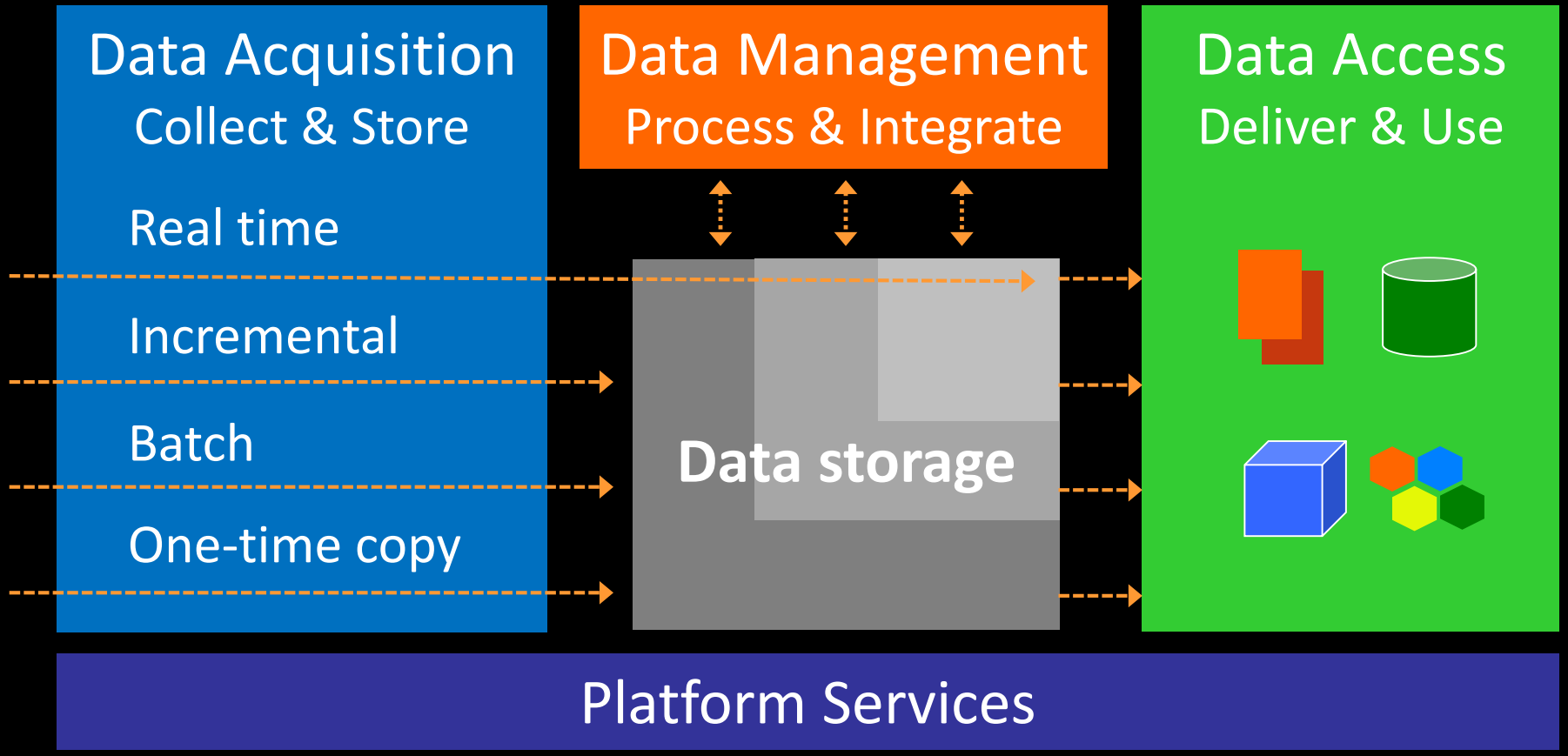
The goal is to decouple: solve the application and infrastructure problems separately, independently

Data access is already somewhat separate today. Make the separation of different access methods a formal part of the architecture. Don't force one model.



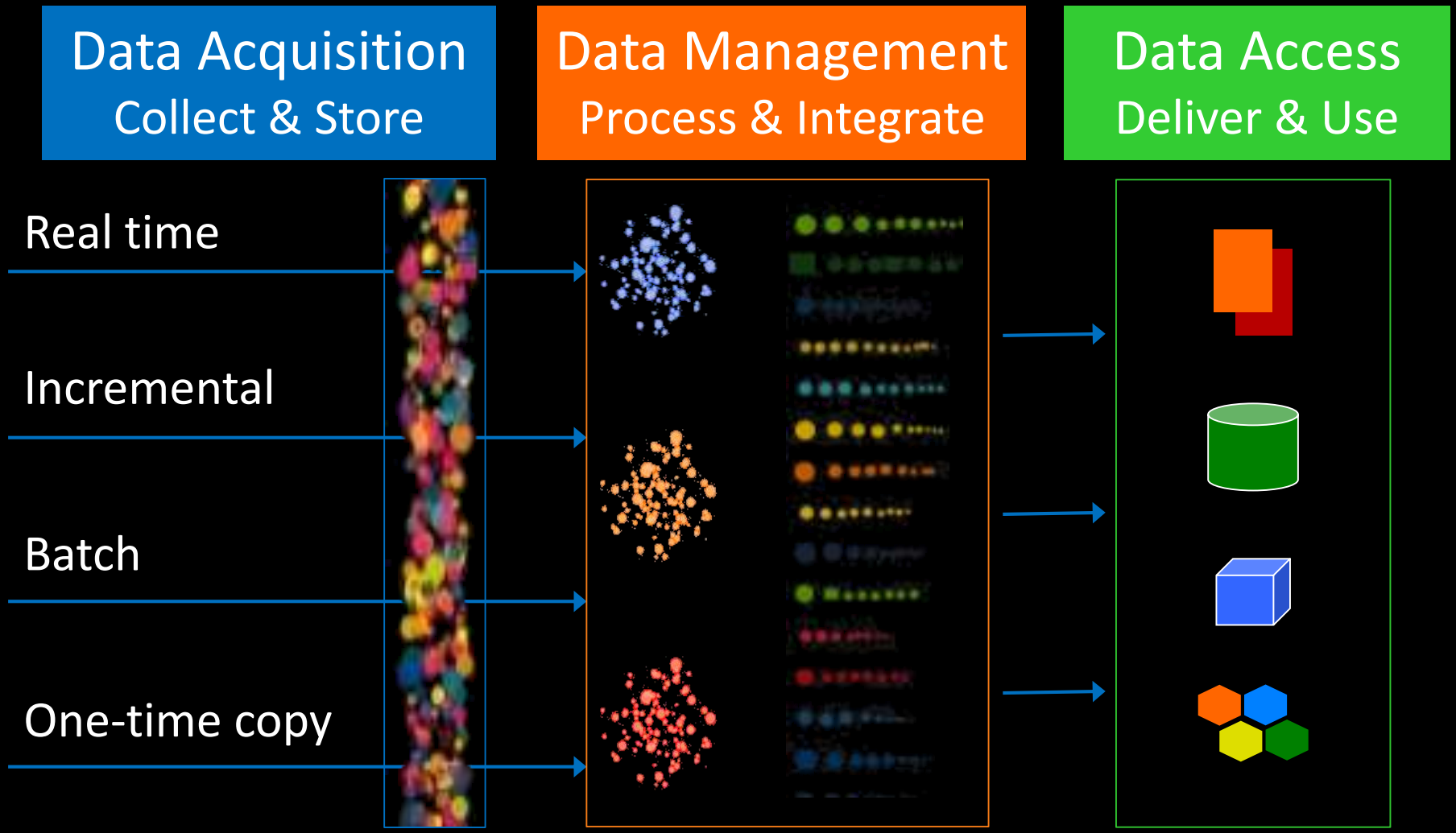
This separates uses of data from each other, allowing each type of use to structure the data specific to its own requirements.

The full analytic environment subsumes all the functions of a data lake and a data warehouse, and extends them



The platform has to do more than serve queries; it has to be read-write.

The data architecture must align with system components because each of them addresses different data needs



Separating concerns is part of the mechanism for change isolation

The design focus is different in each area

Ingredients

Goal: available

User needs a recipe in order to make use of the data.

Pre-mixed

Goal: discoverable and integrateable

User needs a menu to choose from the data available

Meals

Goal: usable

User needs utensils but is given a finished meal

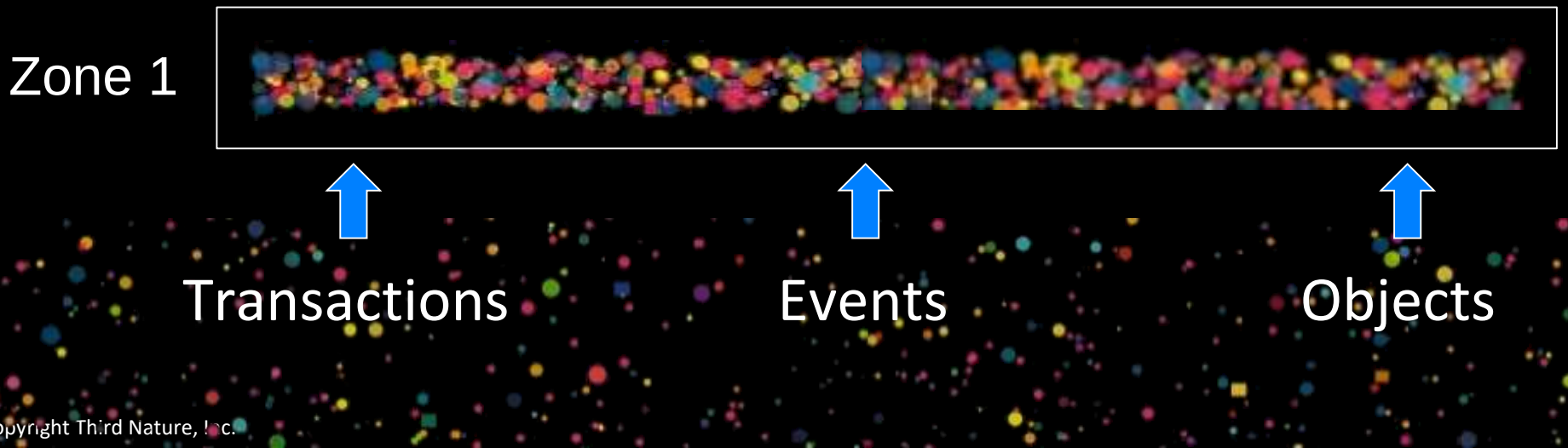
Food supply chain: an analogy for analytic data

Multiple contexts of use, differing quality levels

You need to keep the original because just like baking, you can't unmake dough once it's mixed.

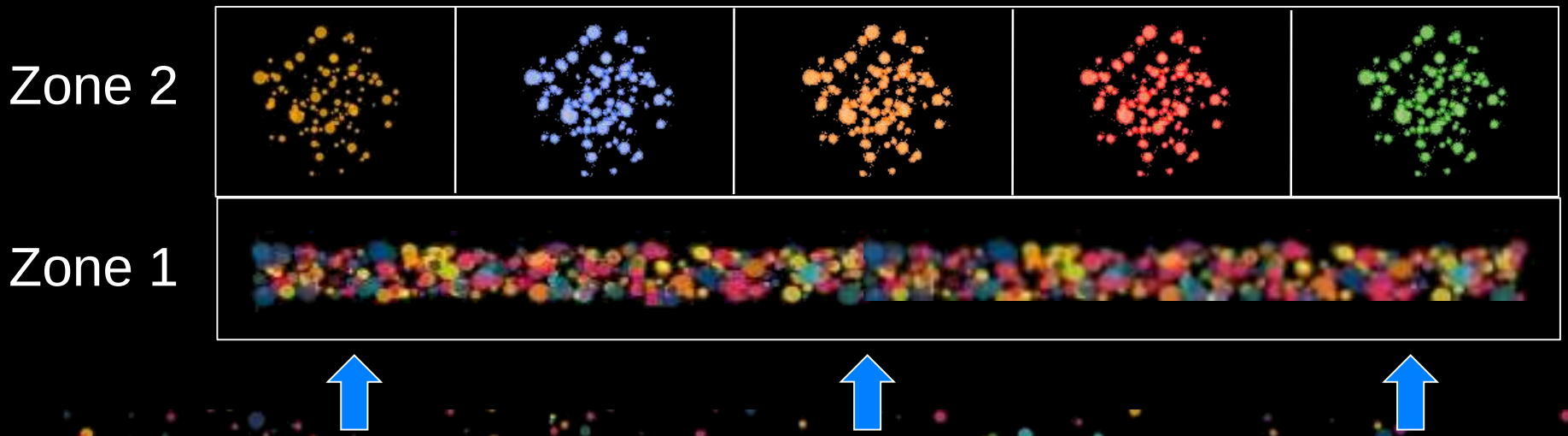
Zone 1: Acquistion

- Focus is only on collecting and tracking data
- Direct recording of data from sources
- Each dataset has as much schema as the source provides, could be explicit or implicit or none
- Foundation layer for all subsequent use



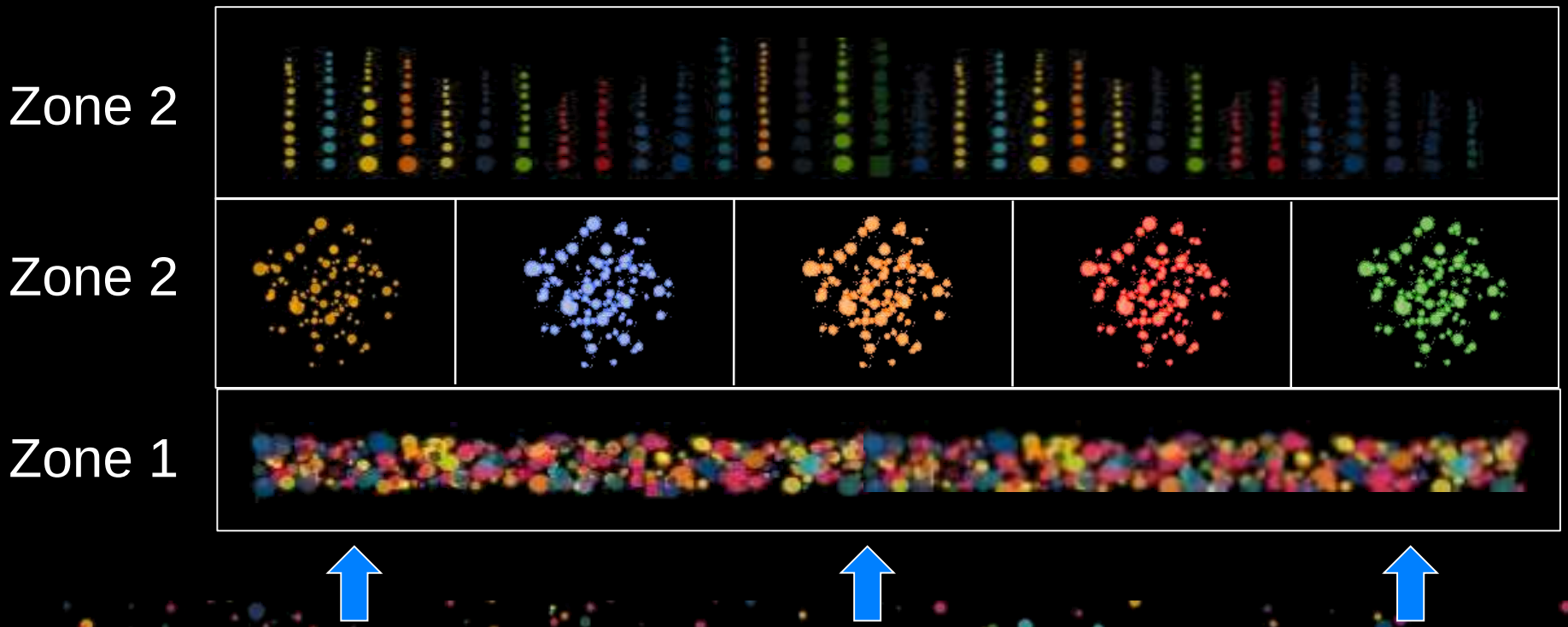
Zone 2: Integration - Standardized

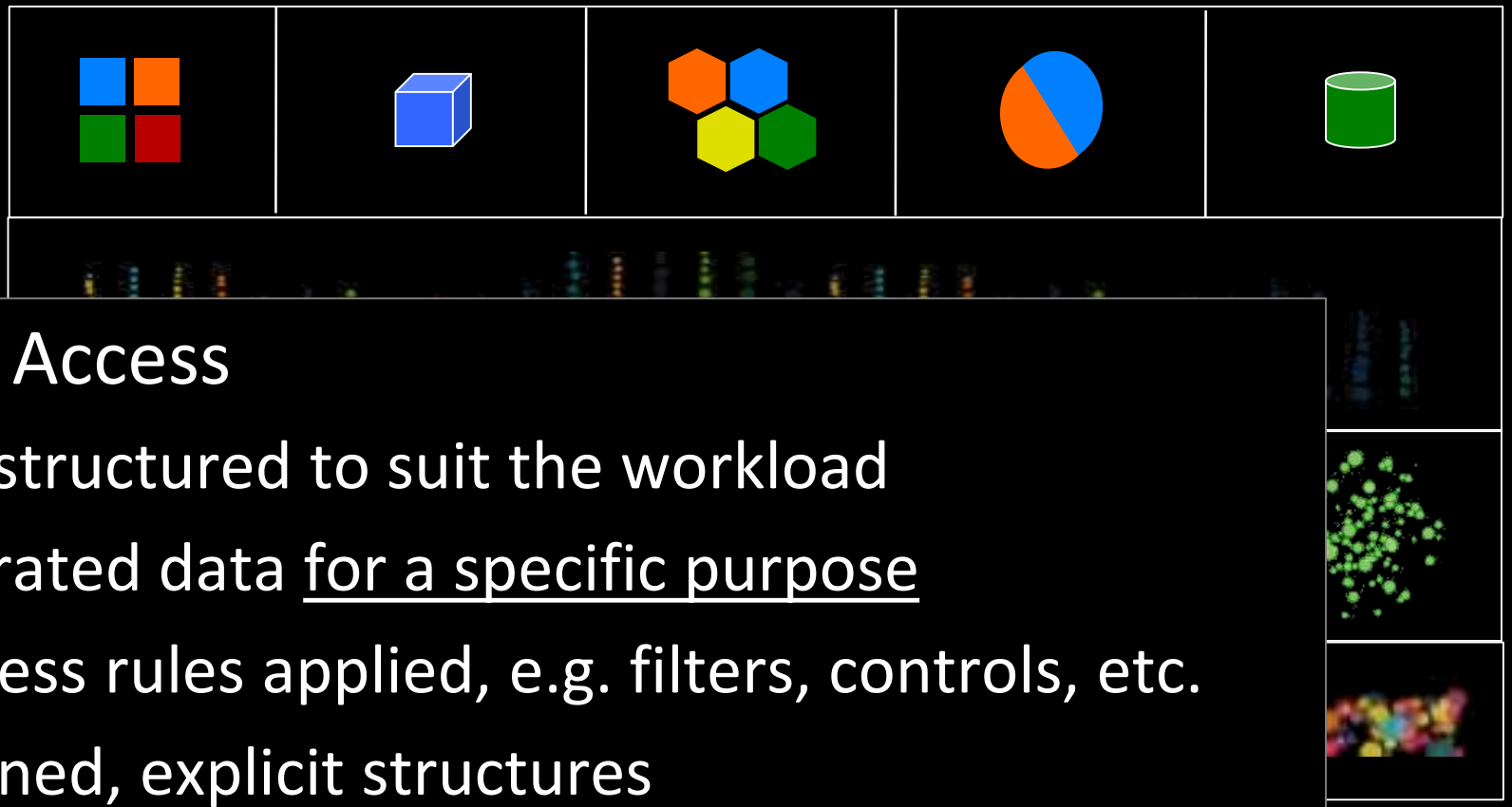
- Parsed and cataloged – all structure and form are made explicit so data can be accessed
- Namespace (e.g. keys) managed
- Common elements are standardized
- Datasets are profiled, indexed, available



Zone 2: Integration - Enhanced

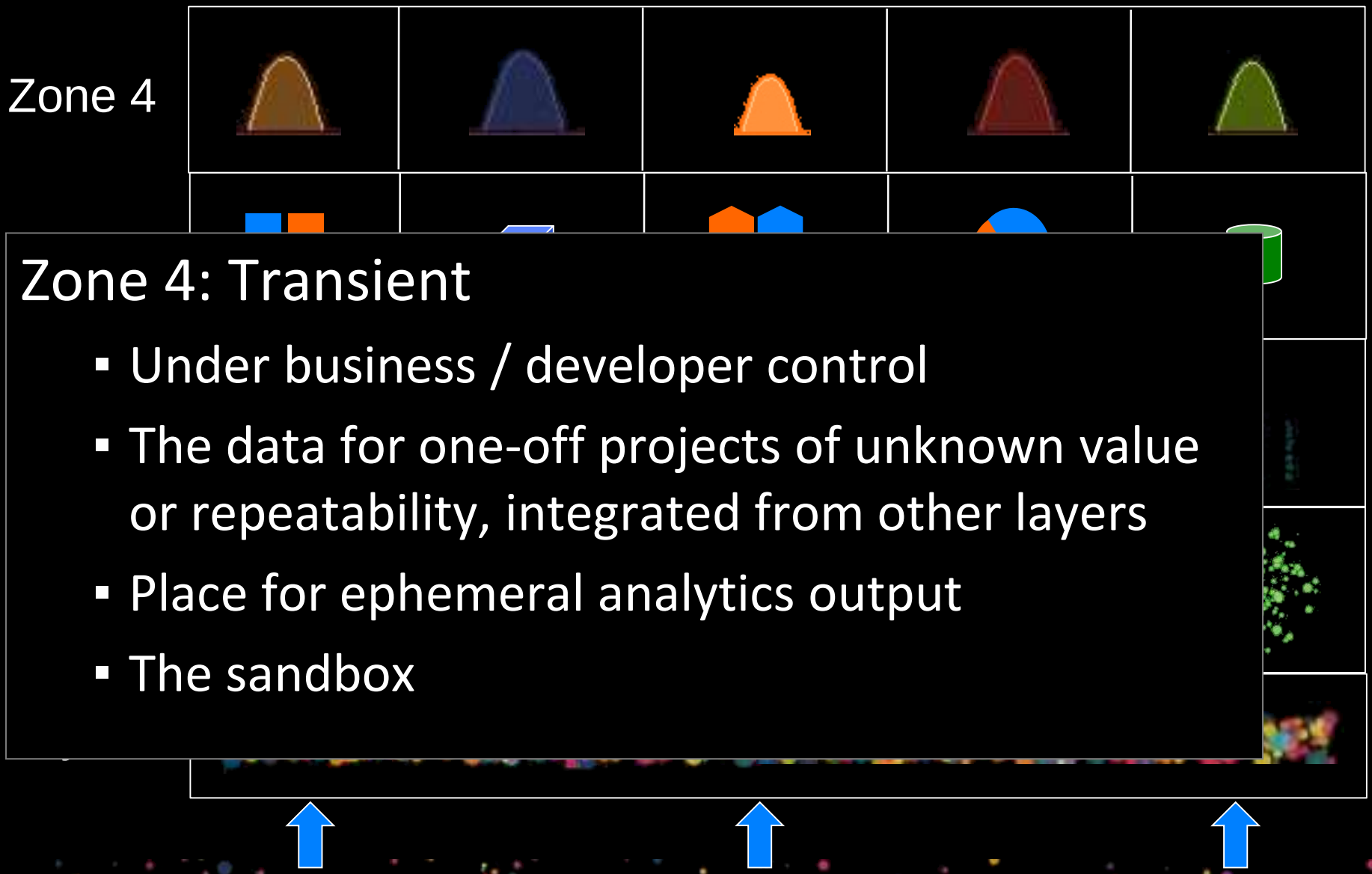
- Common shared KPIs, master datasets
- Extracted and derived data available, e.g. NEE output
- Data is linkable, labeled, possibly cleaned





Zone 3: Access

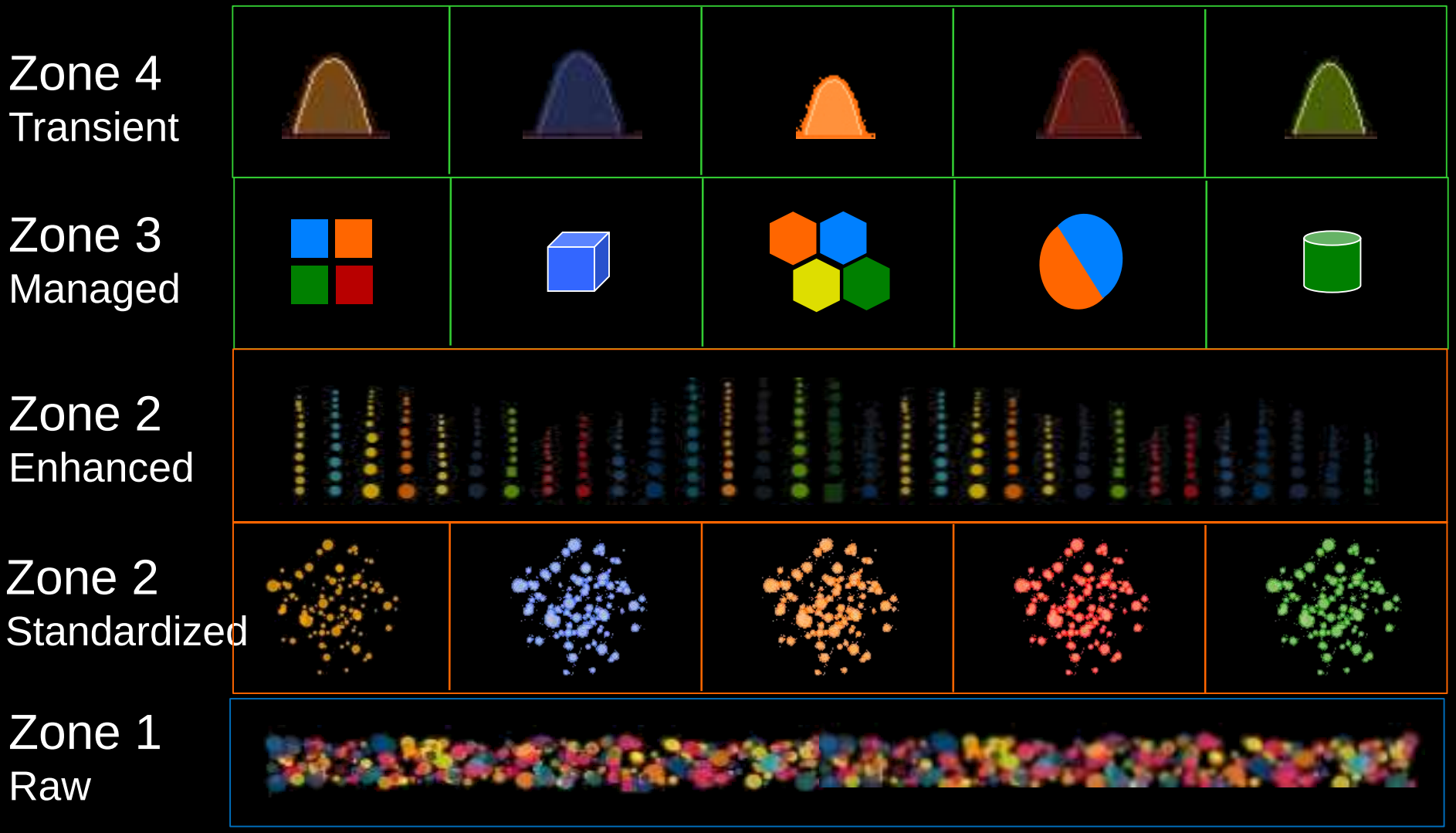
- Data structured to suit the workload
- Integrated data for a specific purpose
- Business rules applied, e.g. filters, controls, etc.
- Designed, explicit structures
- Generally repeatable use



Zone 4: Transient

- Under business / developer control
- The data for one-off projects of unknown value or repeatability, integrated from other layers
- Place for ephemeral analytics output
- The sandbox

Decoupled data architecture

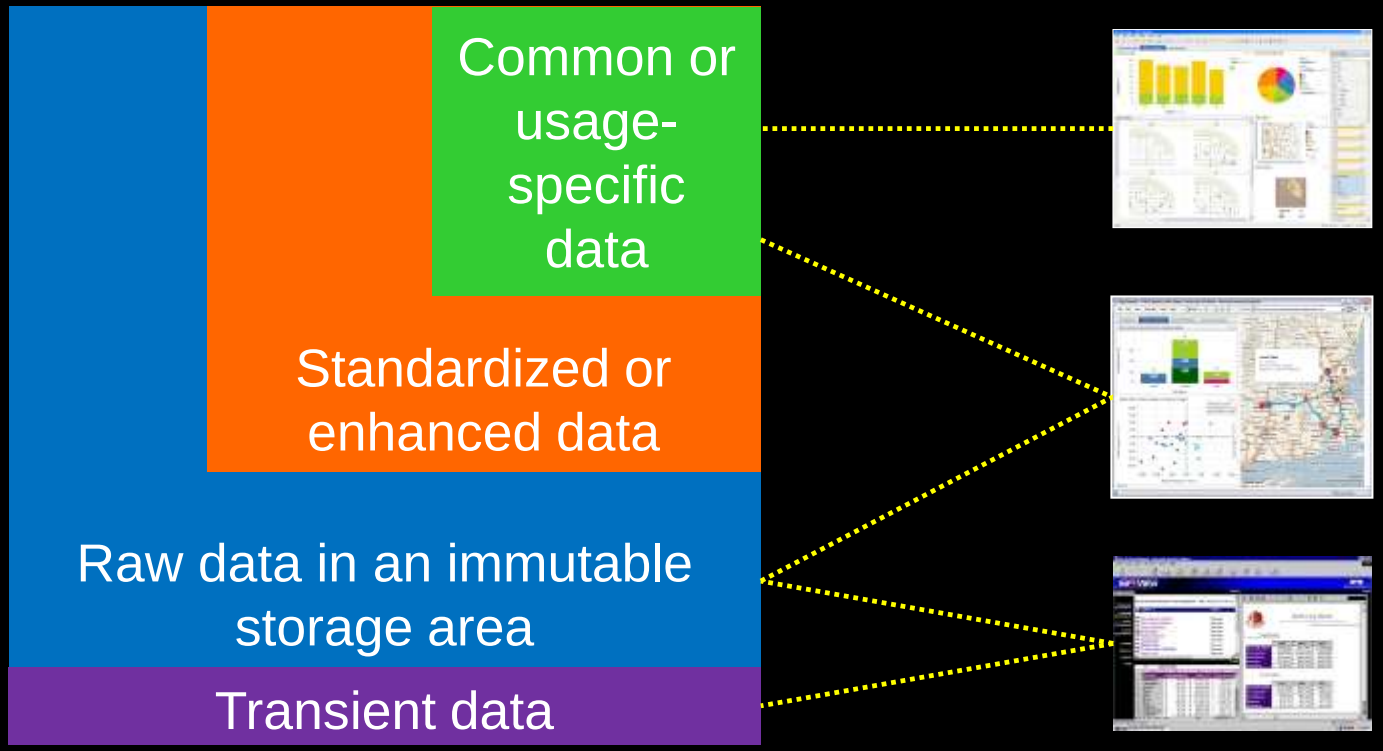


The data is in zones of management, *not* isolating layers

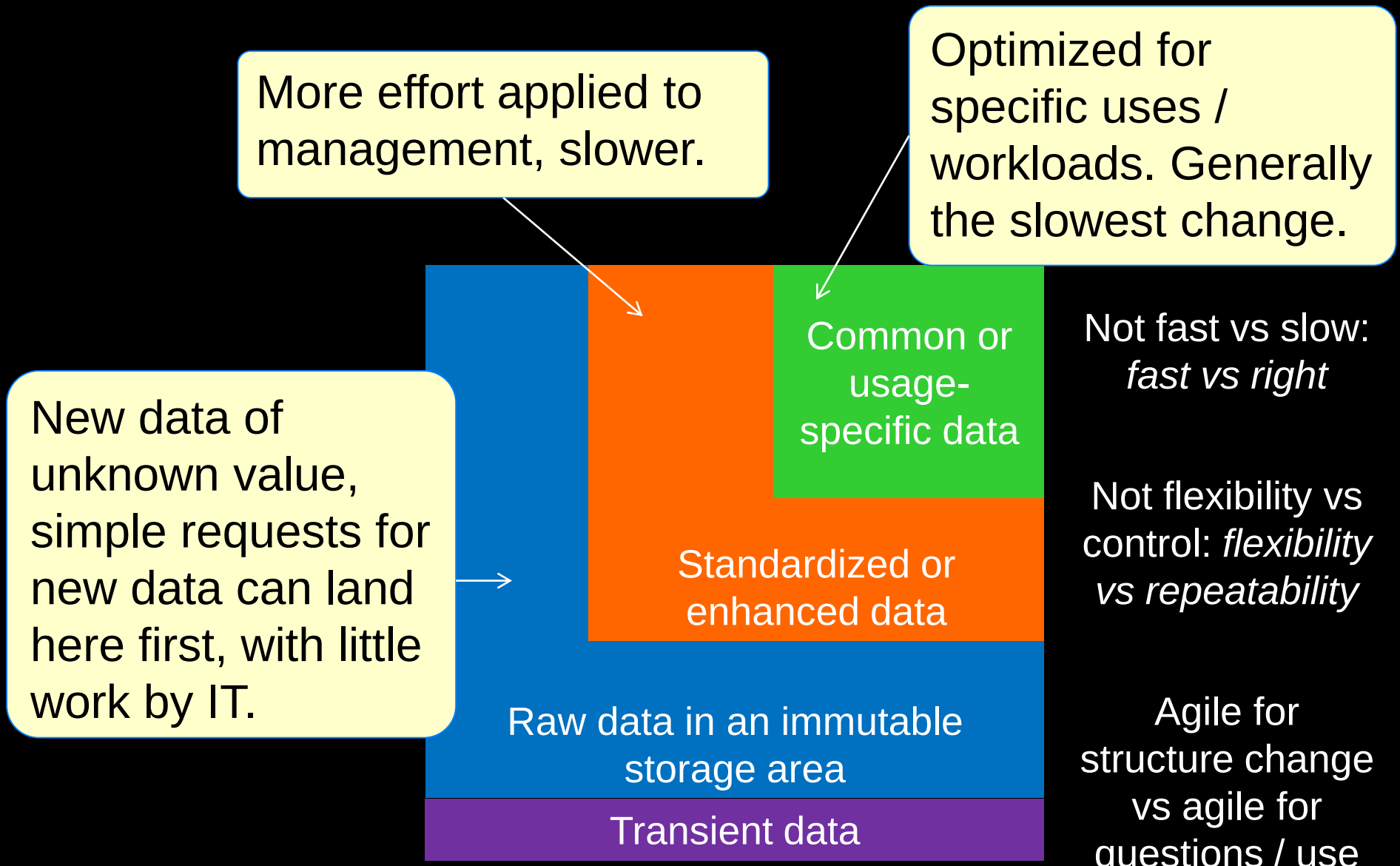
Relax control to enable self-service while avoiding a mess.

Do not constrain access to one zone or to a single tool.

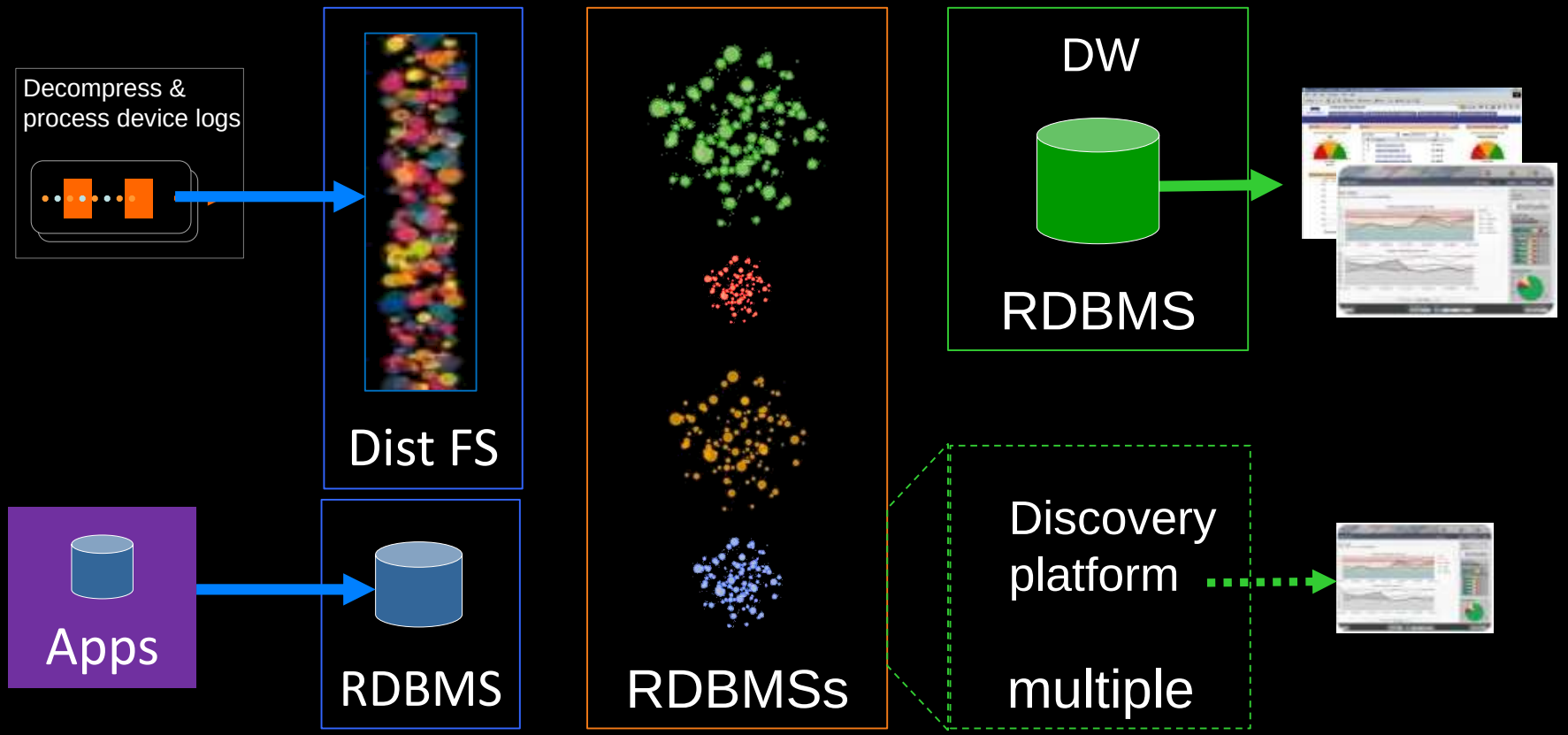
Focus on visibility of data use, not control of data.



This data architecture resolves rate of change problems



The concept of a zone is not a physical system. It's data architecture

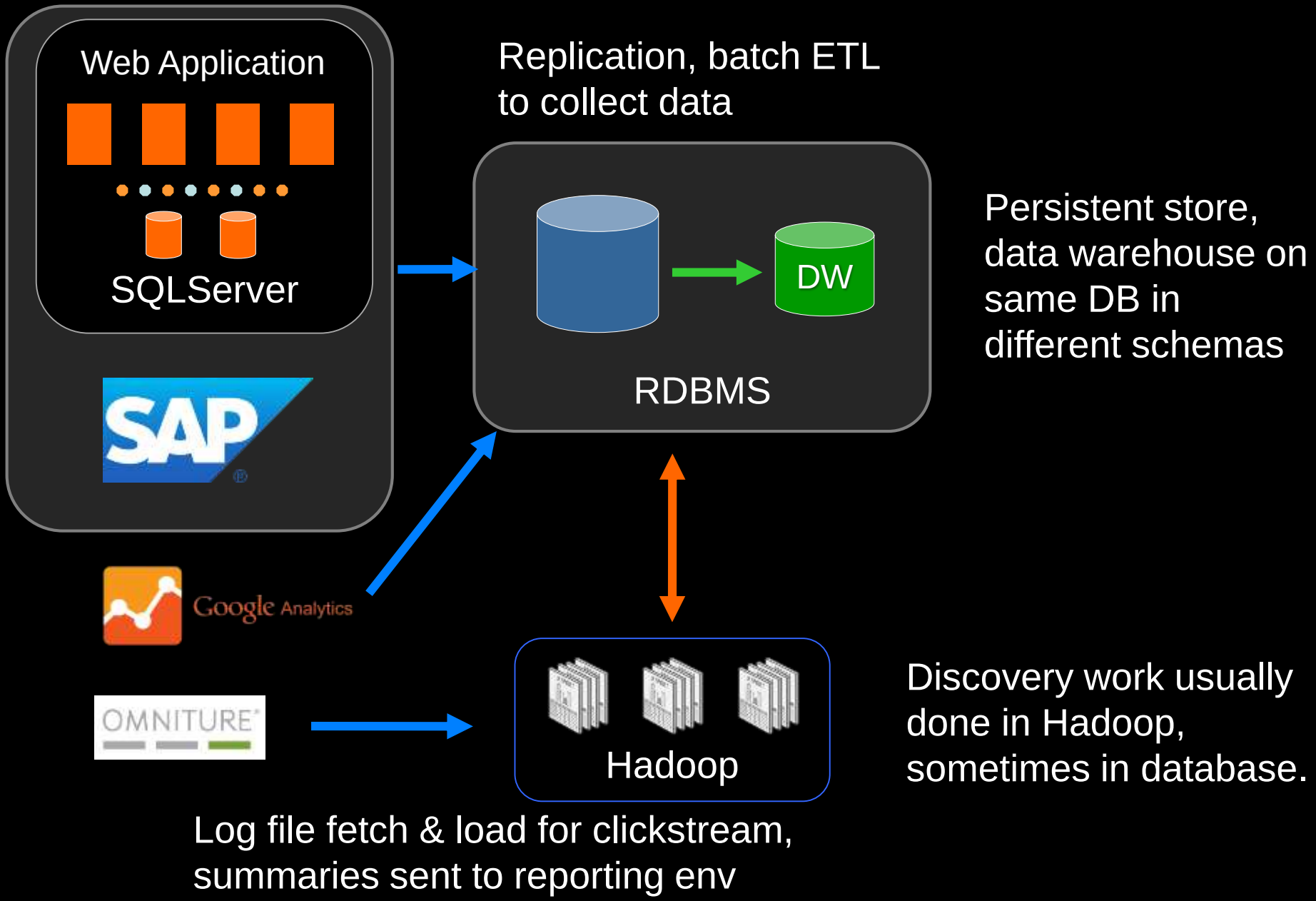


The biggest decision is to separate all data collection from the data integration from consumption.

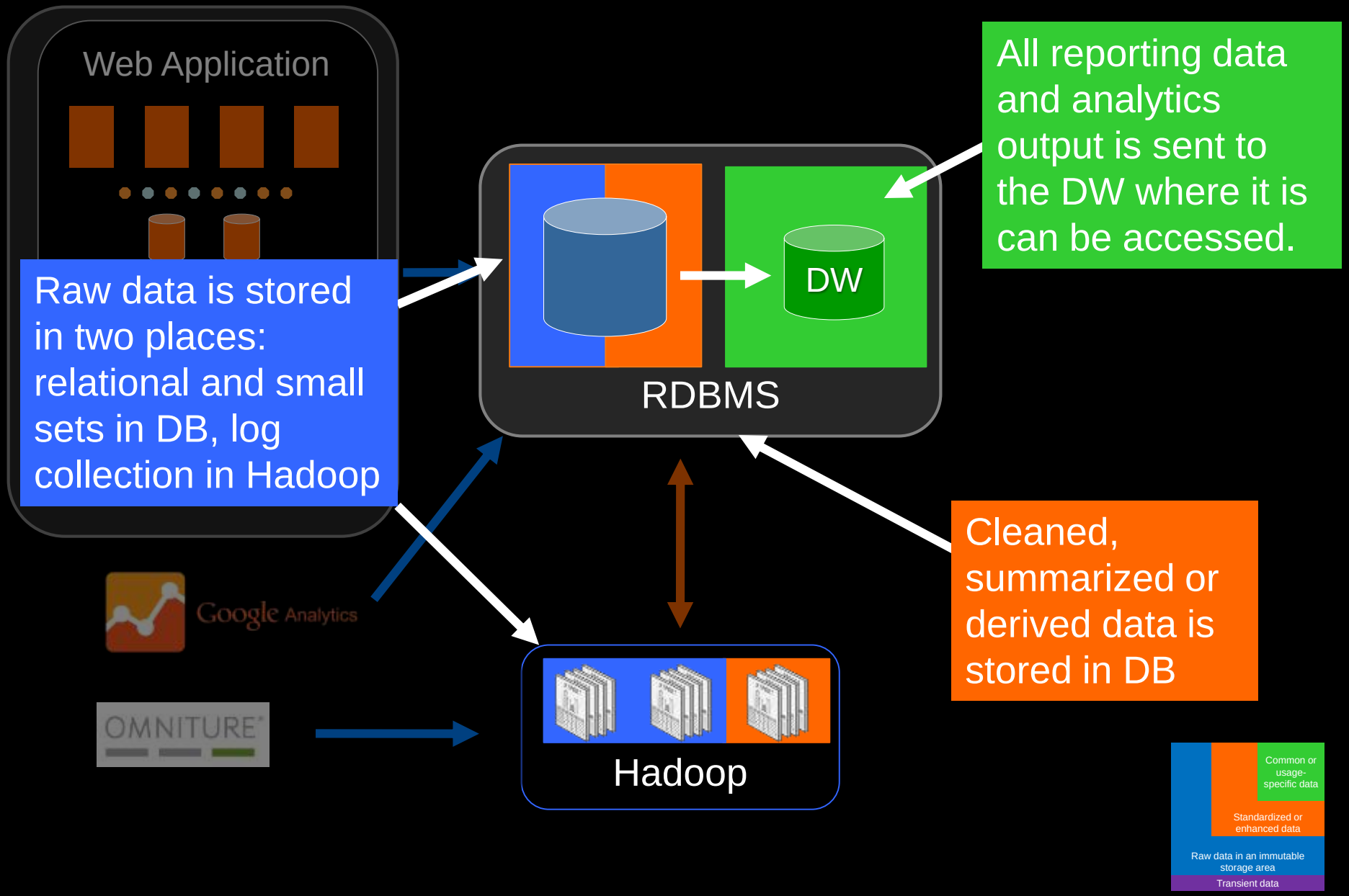
Physical system/technology overlays are separate, depend on the specific use cases and needs of the organization.

Third Nature

Example: data environment, mid-size retailer

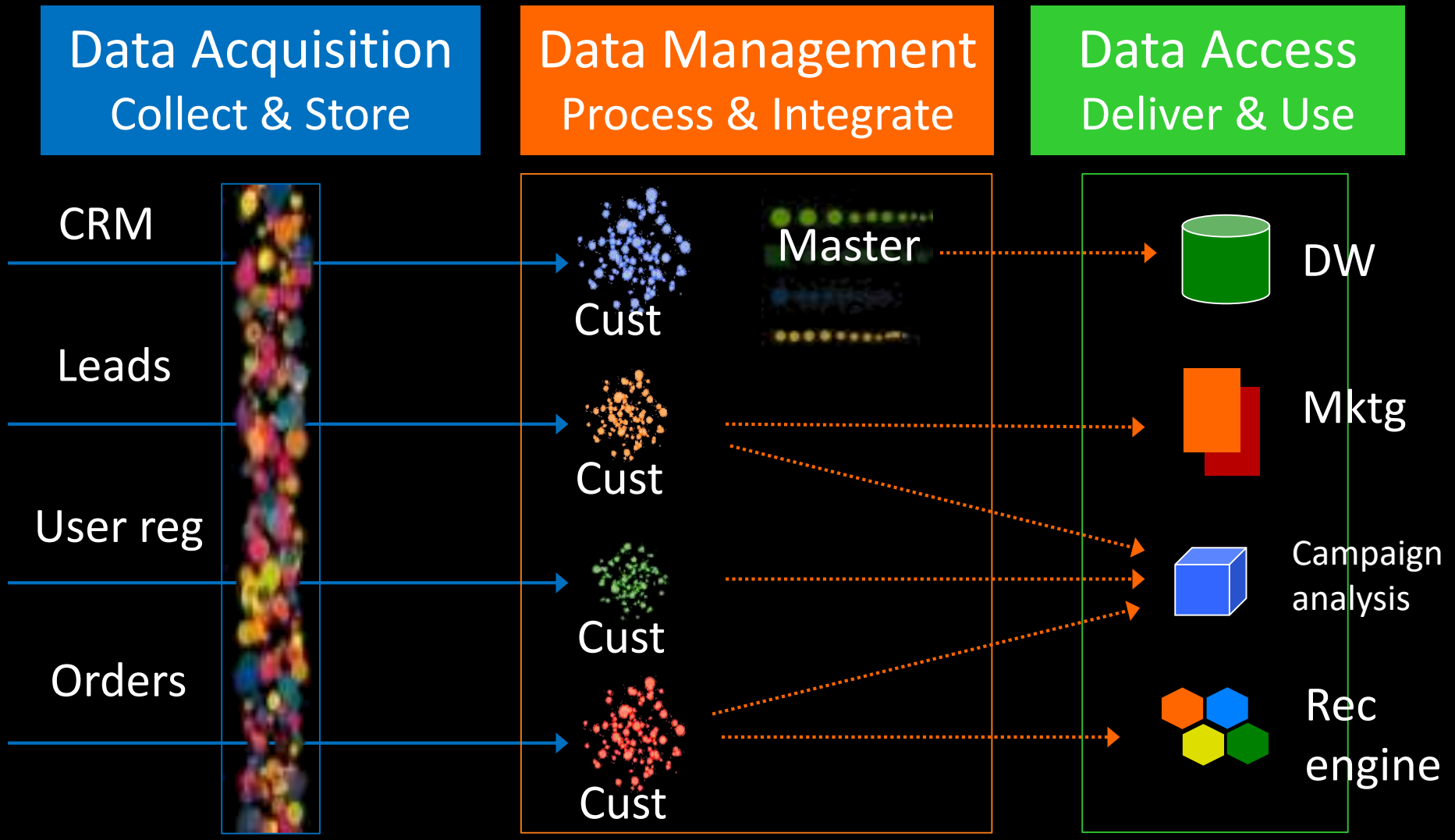


This data architecture uses the 3 zone pattern



Data has to be moved, standardized, tracked

There is a lot of data policy and governance to think about

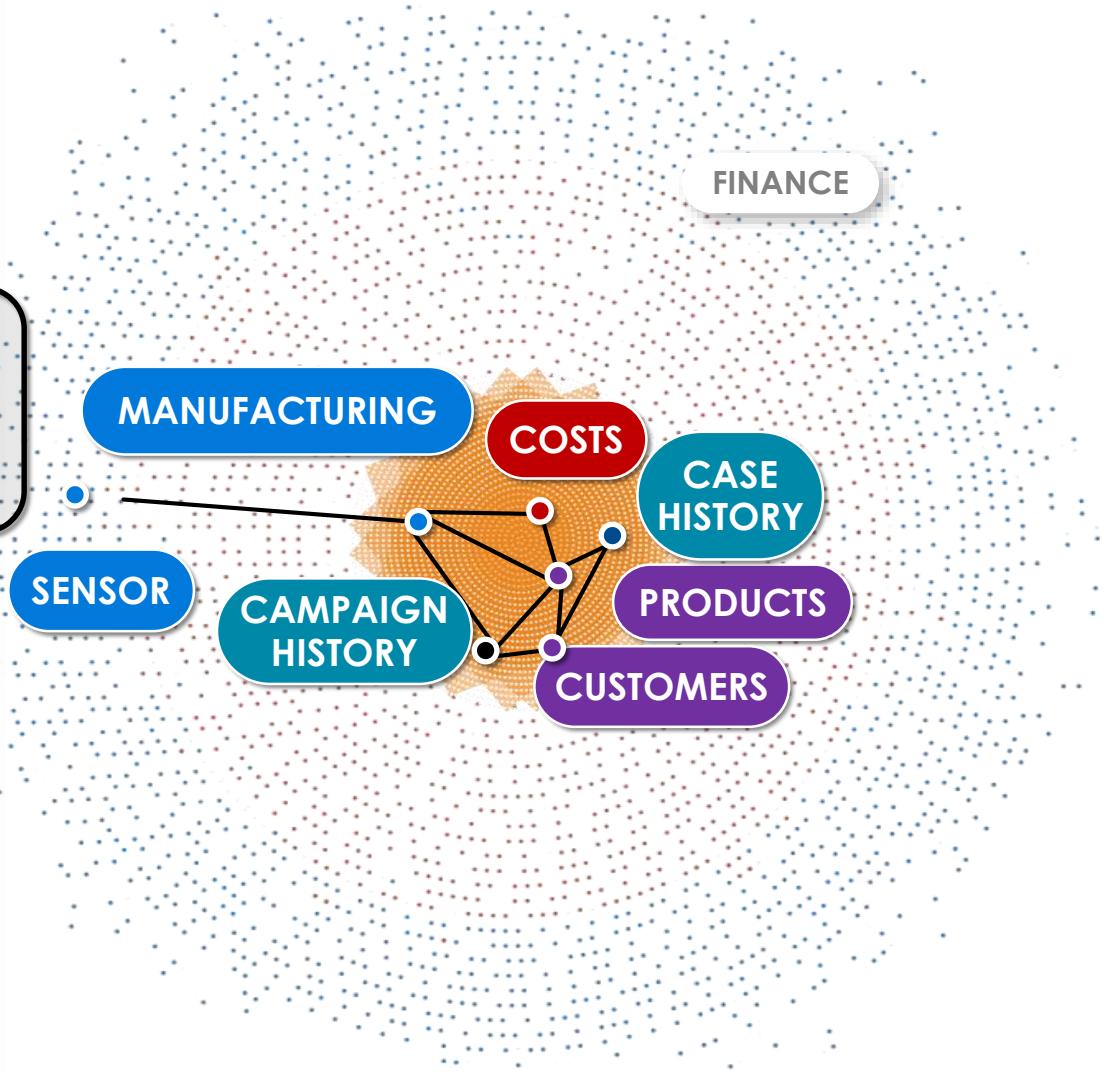


Linking data across zones of curation and storage *is required*

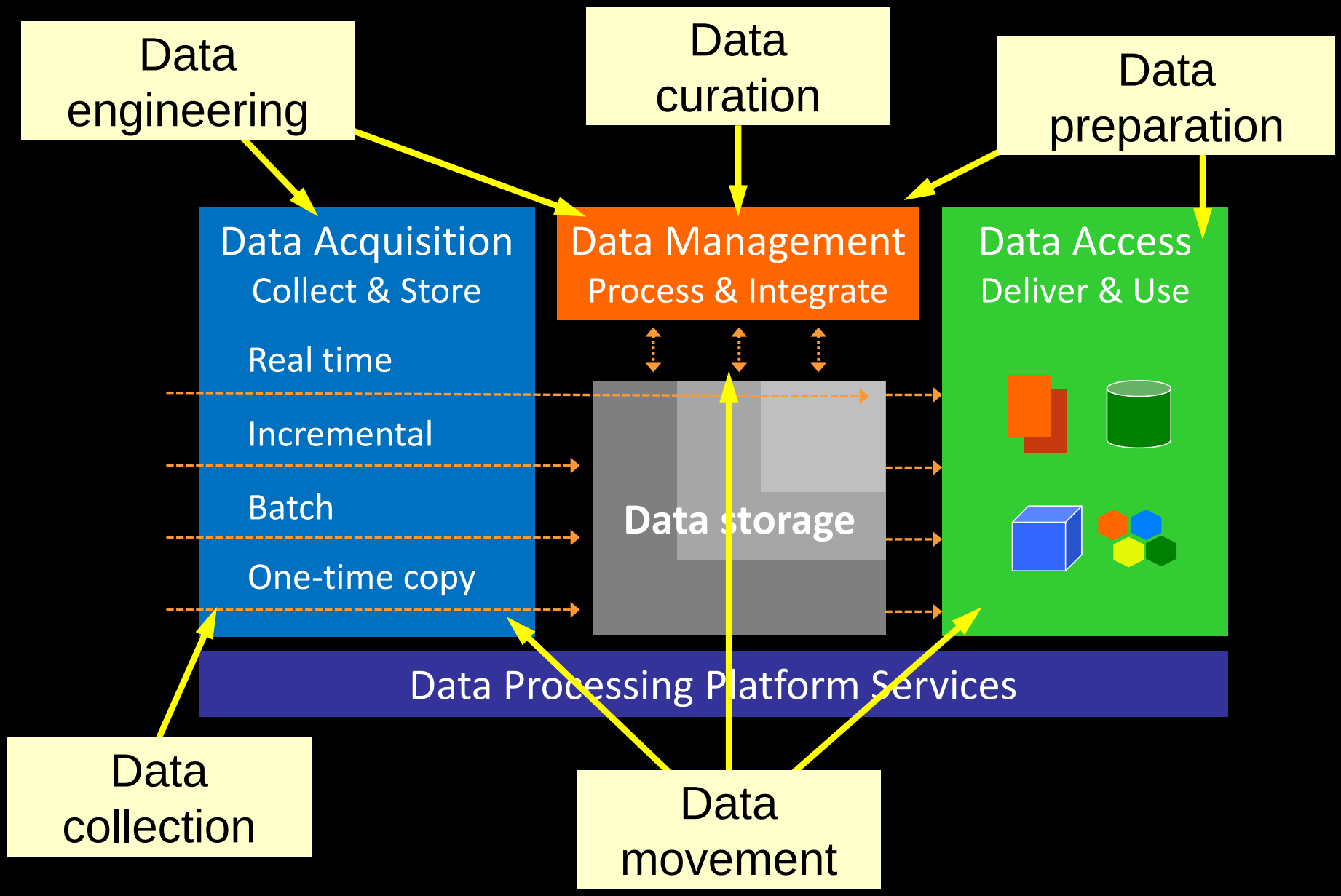
Given the rise in warranty costs, isolate the problem to be a plant and the specific lot.

Exclude 2/3rd of the batteries from the lot that have no problem.

Communicate with affected customers, who have not made a warranty claim, through Marketing and Customer Service channels to recall cars with affected batteries.



Data integration is a portfolio in the new environment



New terminology for our bad-with-words market

Data engineering (technical) – the heavy lifting of integrating data, many to many table mappings, cleaning

Data preparation (technical/nontechnical) –working with and across datasets to make them usable or consumable by oneself or others

Data blending (nontechnical) – “preparation lite”, joining, simple transformation, single output

Data curation (nontechnical) – managing data at the dataset level, we don’t do this at all because we always assumed one data model/schema

Data movement (technical) – data isn’t just accessed via SQL, it can be in many different forms.

The missing ingredient from most data projects

The problem of “too many” forces new ways to organize

As early as 1255: Since the multitude of books, the shortness of time and the slipperiness of memory do not allow all things which are written to be equally retained in the mind, I decided to reduce in one volume in a compendium and in summary order some flowers selected according to my talents from all the authors I was able to read.

A data warehouse is less like a library than it is like an encyclopedia

Today's market solution:

the Data Lake to replace the Data Warehouse

Data hoarding is not a data management strategy

Third Nature

The market solution to the ensuing mess?

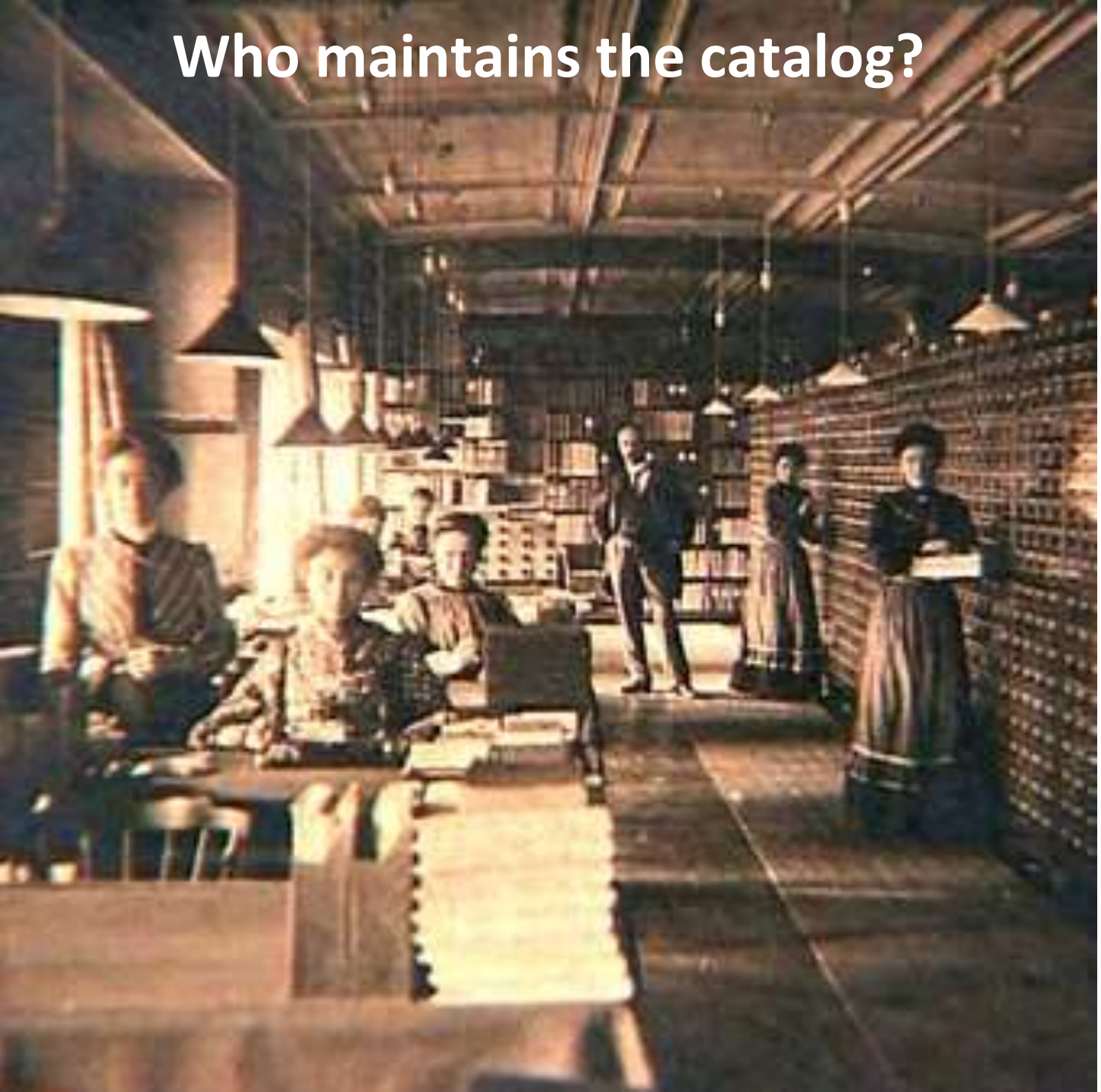
Buy a catalog!

Just add more technology to solve your non-technical problem.

You know what's there - how do you find it? How do you get it?

Third Nature

Who maintains the catalog?



IT is already viewed as a bottleneck.

Many organizations do not have full-time data administrators, and the DW team is already overtaxed.

Third Nature

Let the users manage the catalog!

- Data is already too complex for them to understand their BI tool's single semantic layer.
- Can end users can solve data usability problems by themselves?
- They can probably *access* the data, but beyond that it becomes a free-for-all of confused meanings and redundant, conflicting integration.
- Unconstrained tags entered by users are not an answer, just create future work.

Practices need to catch up to technologies

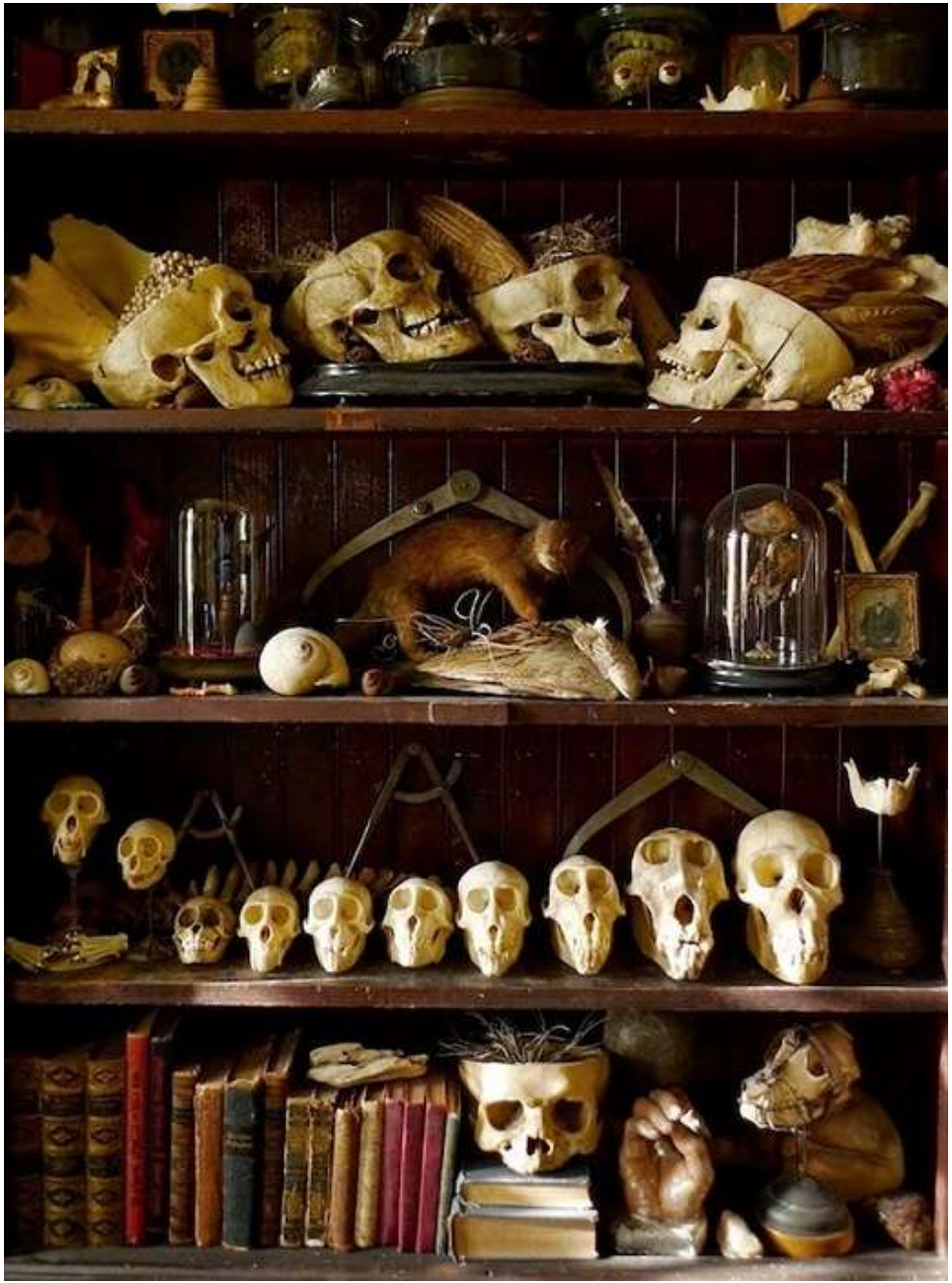
A catalog is a useful, necessary component.

It is useless without organizing principles and practices.

AKA data curation and data architecture

Third Nature

Data curation is not data modeling



The problem with so many sources, types, formats and latencies of data is that it is now impossible to create in advance one model for all of it.

Data modeling is about the *inside* of a dataset. **Curation is about the entire dataset**.

It's about: creating, labeling, organizing, finding, navigating, retiring.

Data curation, rather than data modeling, is becoming the most important data management practice.

Third Nature

Data and technology architecture needs process

Collection

Capture metadata (including request)
Record the structure
Apply keys
PII masking, restrict
Start lineage

Distribution

Common structures
RDM and MDM
Subject models
Make data findable and linkable
Data provisioning

Consumption

Model for target use
Quality rules
Track provenance
Apply SLAs
As few engines as possible – not fewer

Decide on policies for when to place data in which area

Once again we have to look at the context of what we are building

"Always design a thing by considering it in its next larger context - a chair in a room, a room in a house, a house in an environment, an environment in a city plan." – *Eliel Saarinen*

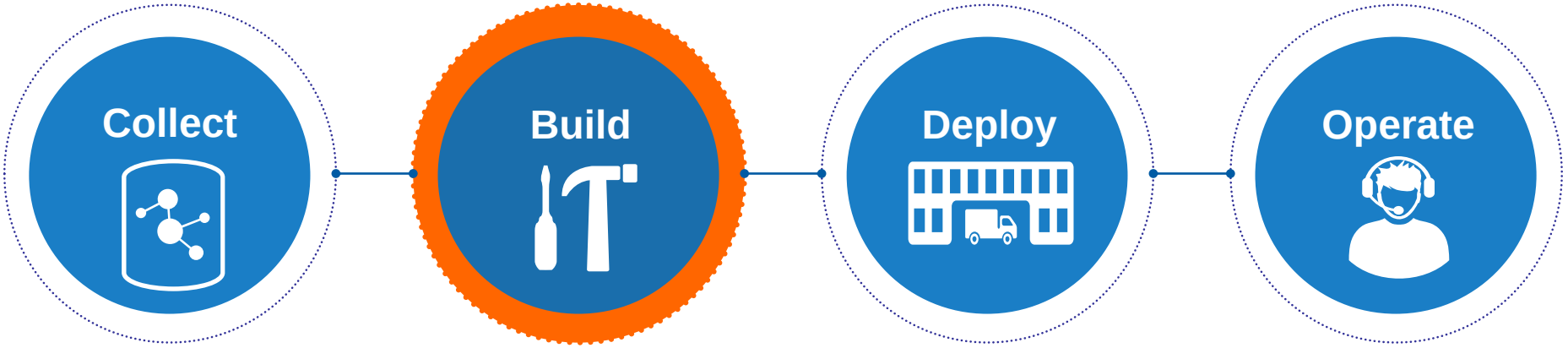
Don’t design for development, design for operation

The design point of many things we see is making it easy to build:

- Building models
- Building pipelines
- Building applications

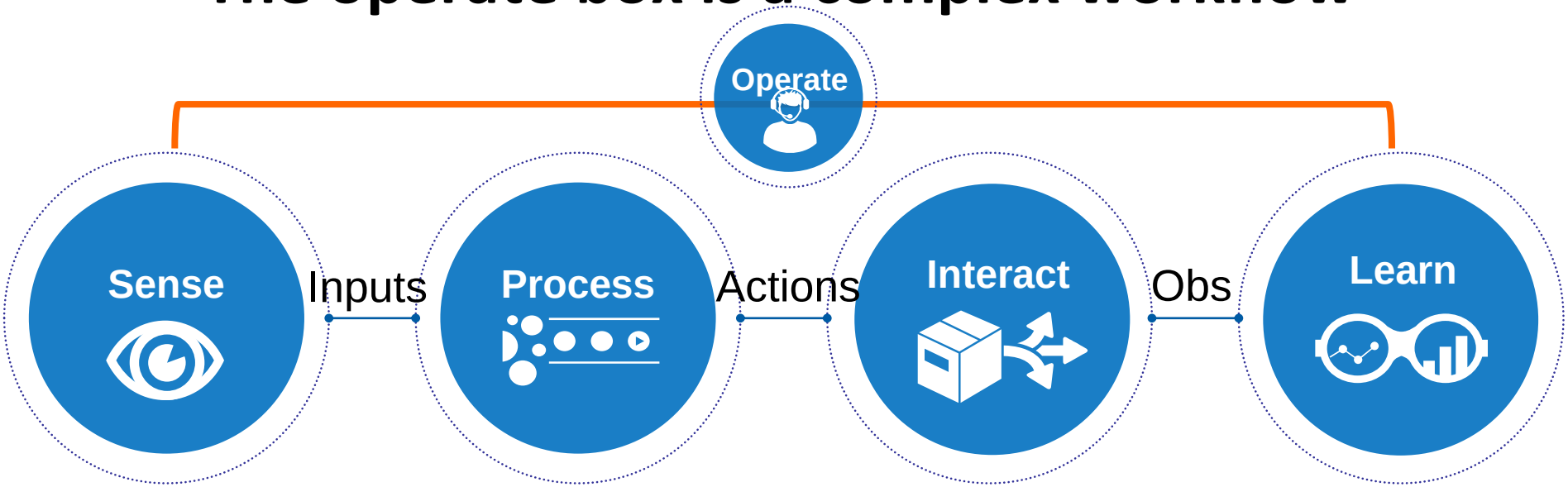
But value comes only after deployment, and must be sustained

Expanding the perspective beyond the initial bit



- There are upstream parts to the development process: collecting and managing data, both for dev and in prod.
- There are downstream parts, in deployment and then in production operation.
- Data and artifacts are exchanged as part of the workflows

The operate box is a complex workflow



Collect inputs
AKA clean data

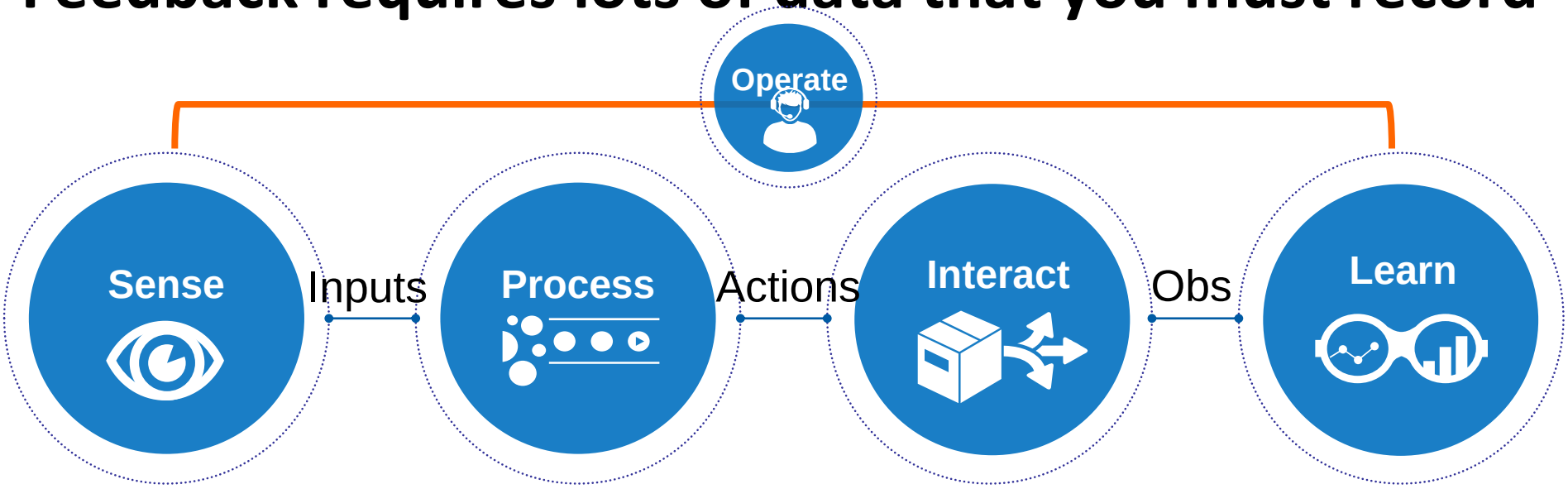
"reasoning"
Execute model to select and post actions

"acting"
Perform the desired actions

Measure, compare, adjust

Learning: could be human methods (manual adjustment) or machine methods (e.g. reinforcement learning), which change the sensing and processing.

Feedback requires lots of data that you must record



Record the inputs

Record the action, the expected outcome (tracking metrics and OEC

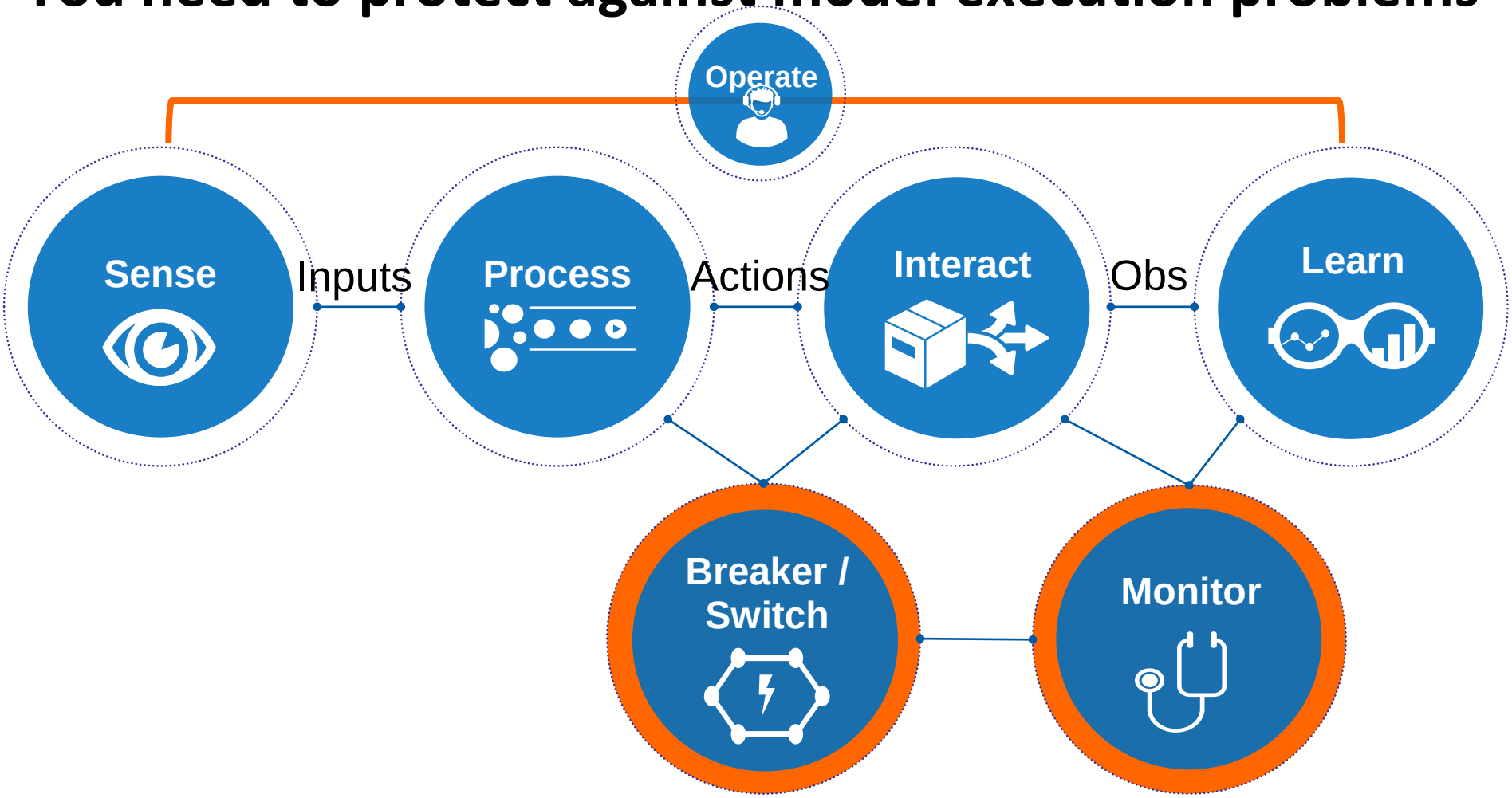
Record the execution. Record the metric deltas

Record the changes

Data volumes explode with all the telemetry:

1 execution = raw data in, inputs, the action, each metric used (expected values), execution log, metric data (actuals), deltas, model changes, technical resource information

You need to protect against model execution problems



You have to track the actions / executions and their results, including the OEC, in real time, to protect against failures.

This adds monitors and circuit breakers.

“A production ML system is never all green”

Much of the time, the ML app is a distributed system.

Distributed systems are hard.

Monolithic architectures are great if you can use them.

ML is not like code: Monitoring in production

Unlike BI, ML has different metrics for “correct”

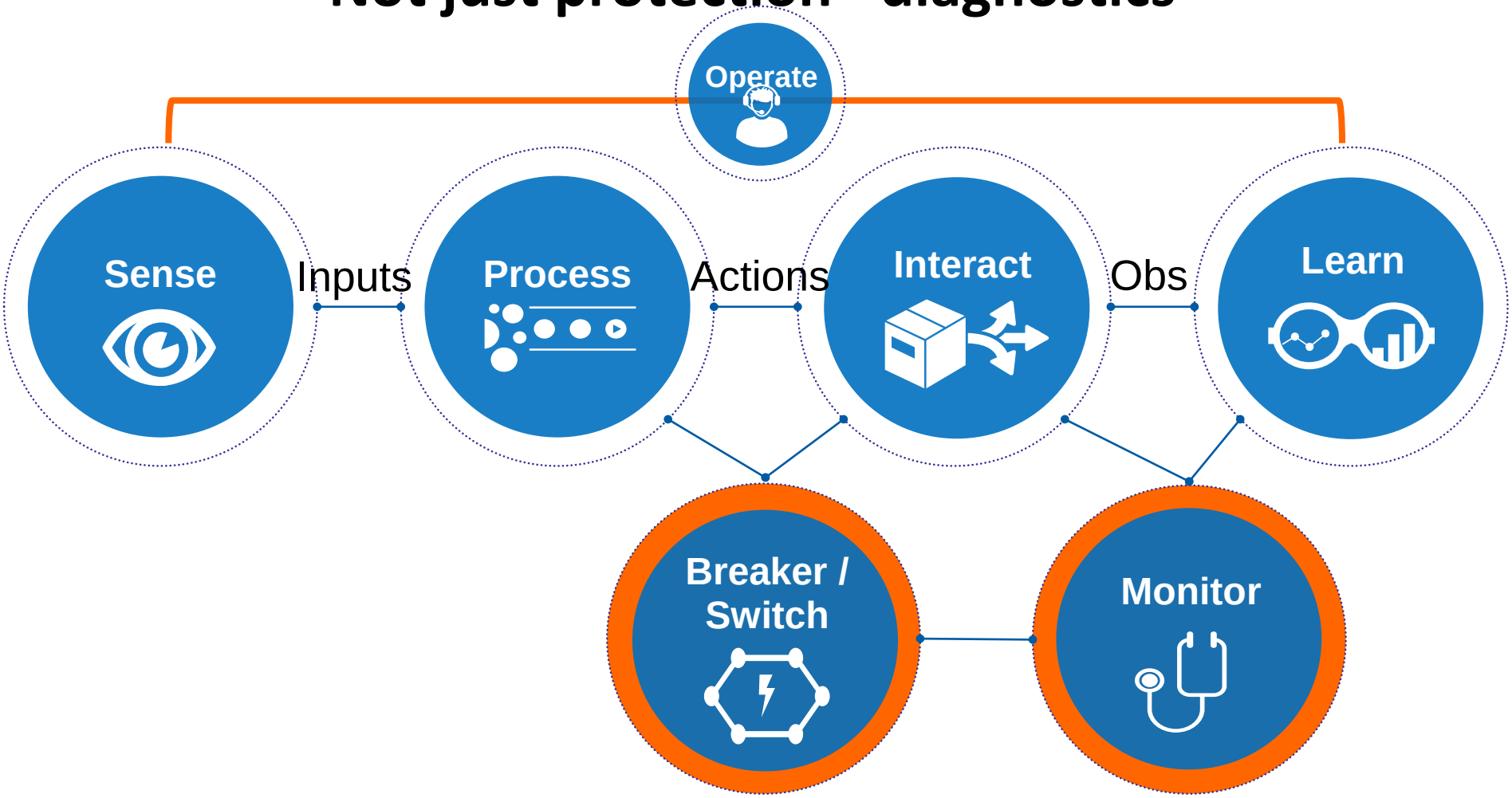
The metrics are relative and can change over time

You must monitor performance closely, which is like doing BI on your AI.

“observability”, because a problem *may not be the model but the data, or the infrastructure.*

- **Reduce the time to diagnose, rather than emphasizing the prevention of coding errors**

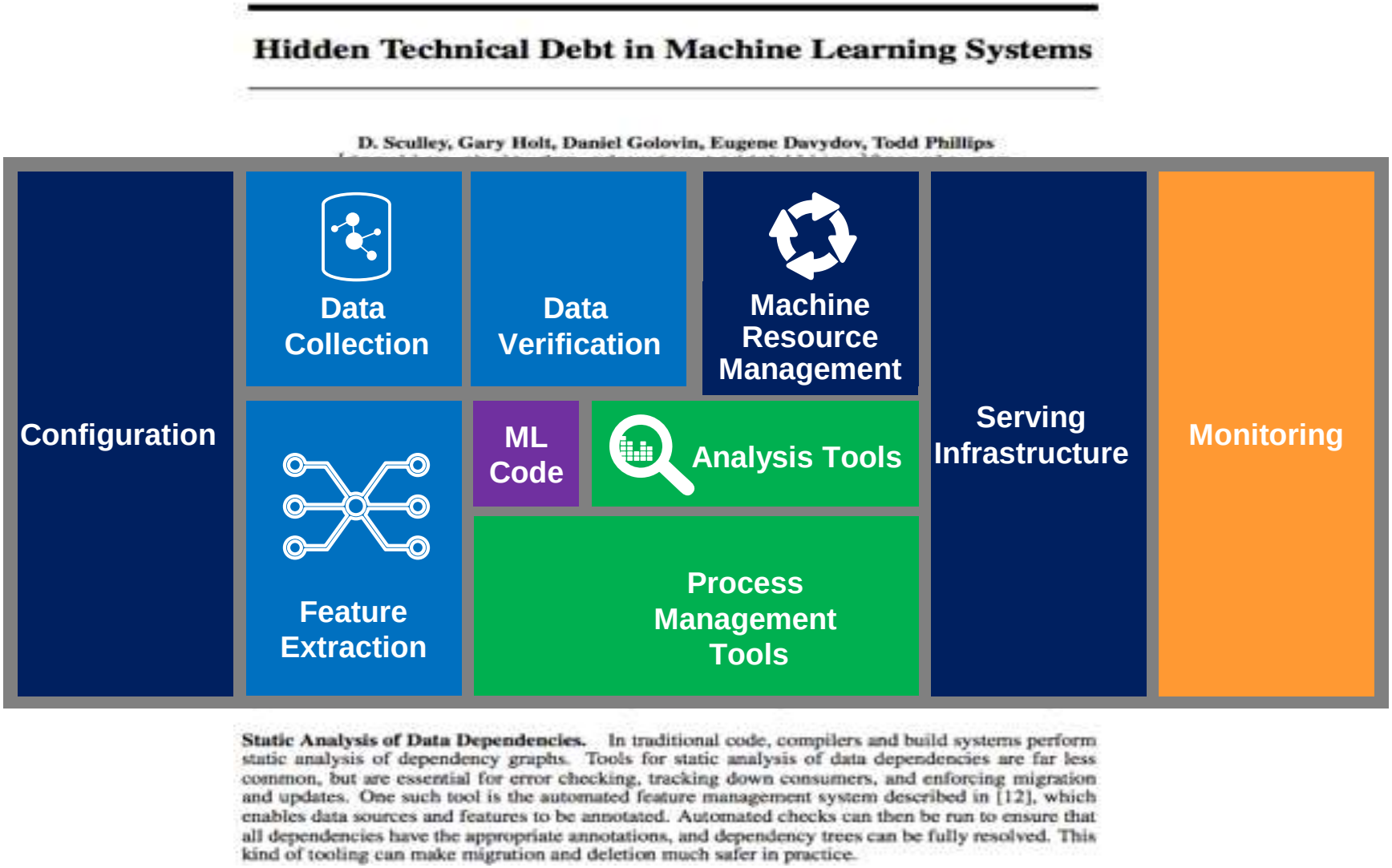
Not just protection - diagnostics



You need telemetry about the entire environment for monitoring, but you also need it for *diagnostics*.

This means you need to think about *observability.*

Machine learning is the smallest part of the environment



https://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems

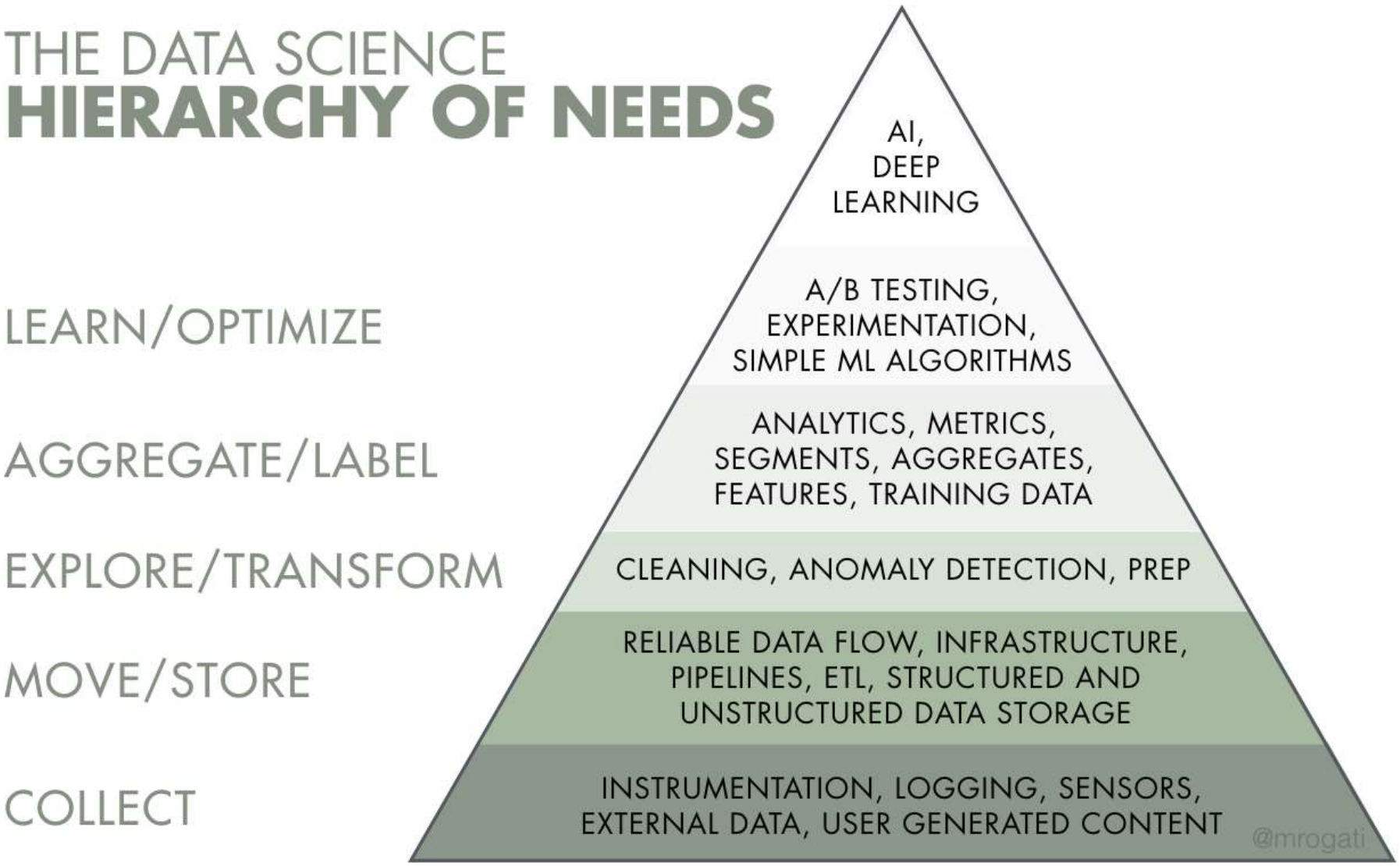
We need a system of record for analytics

There is an extensive list of requirements to support

Primary requirements needed by constituents	S	D	E
Data catalog and ability to search it for datasets		X	X
Self-service access to curated data		X	
Self-service access to uncurated (unknown, new) data		X	X
Temporary storage for working with data		X	
Data integration, cleaning, transformation, preparation tools and environment		X	X
Persistent storage for source data used by production models		X	X
Persistent storage for training, testing, production data used by models		X	X
Storage and management of models		X	X
Deployment, monitoring, decommissioning models			X
Lineage, traceability of changes made for data used by models		X	X
Lineage, traceability for model changes	X	X	X
Managing baseline data / metrics for comparing model performance	X	X	X
Managing ongoing data / metrics for tracking ongoing model performance	X	X	X

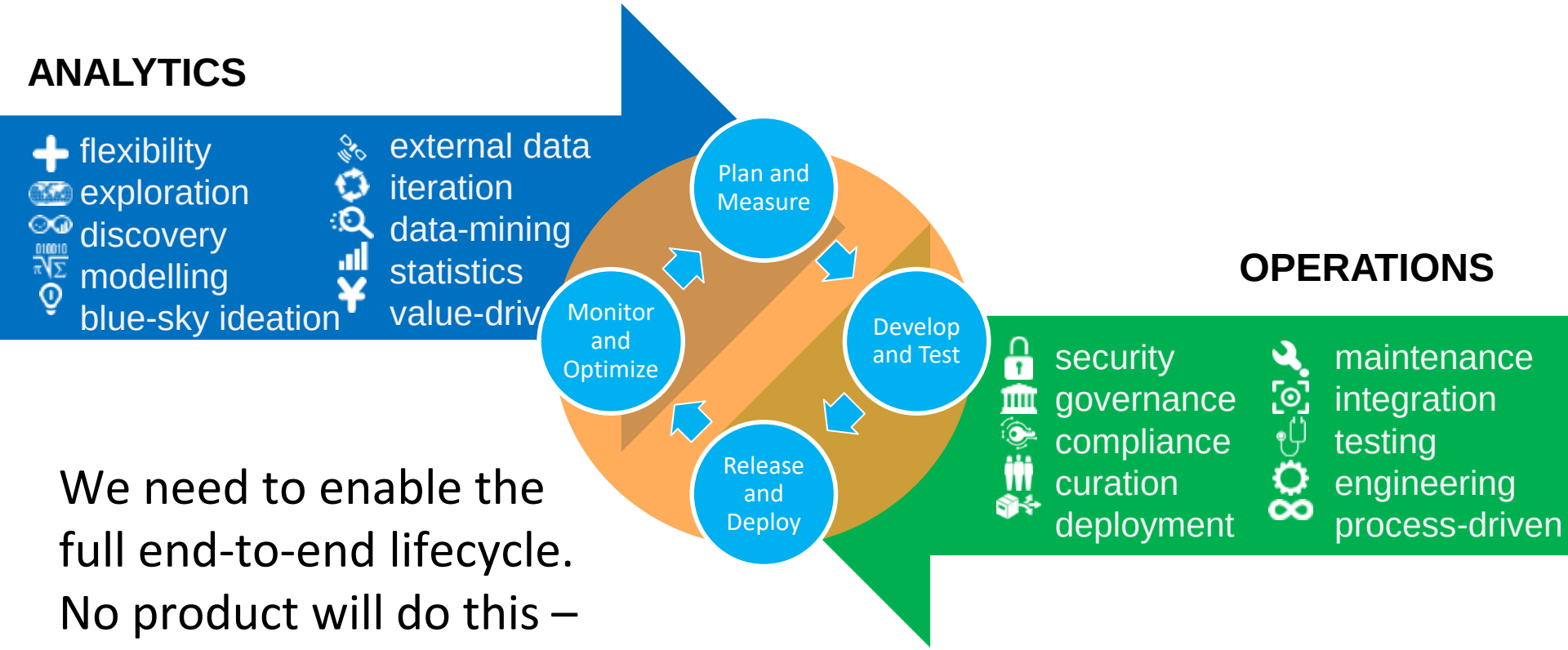
S = stakeholder, user, D = data scientist, analyst, E = engineer, developer

ML and AI have a lot of requirements: no shortcuts



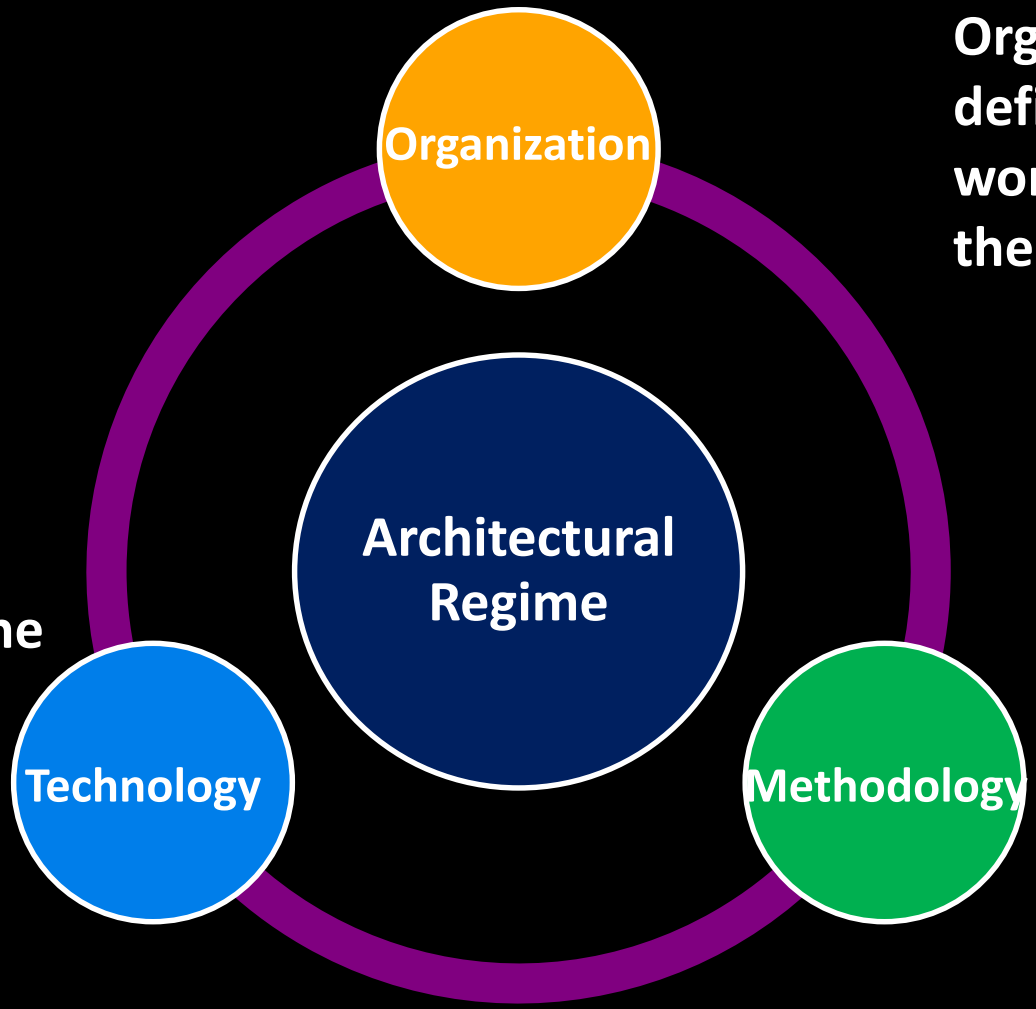
https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007

We need a discipline of AnalyticOps



We need to enable the full end-to-end lifecycle. No product will do this – it's a workflow, process, and architecture problem.

Reinforcing relationships resist change, despite radical technology and practice shifts



Organization defines where the work is done and the roles.

Technology defines what work can be done in a given area.

Methodology defines how work is done and what that work is.

Note how only one third is tech

Third Nature

What about the technology? Do I need an <X>?

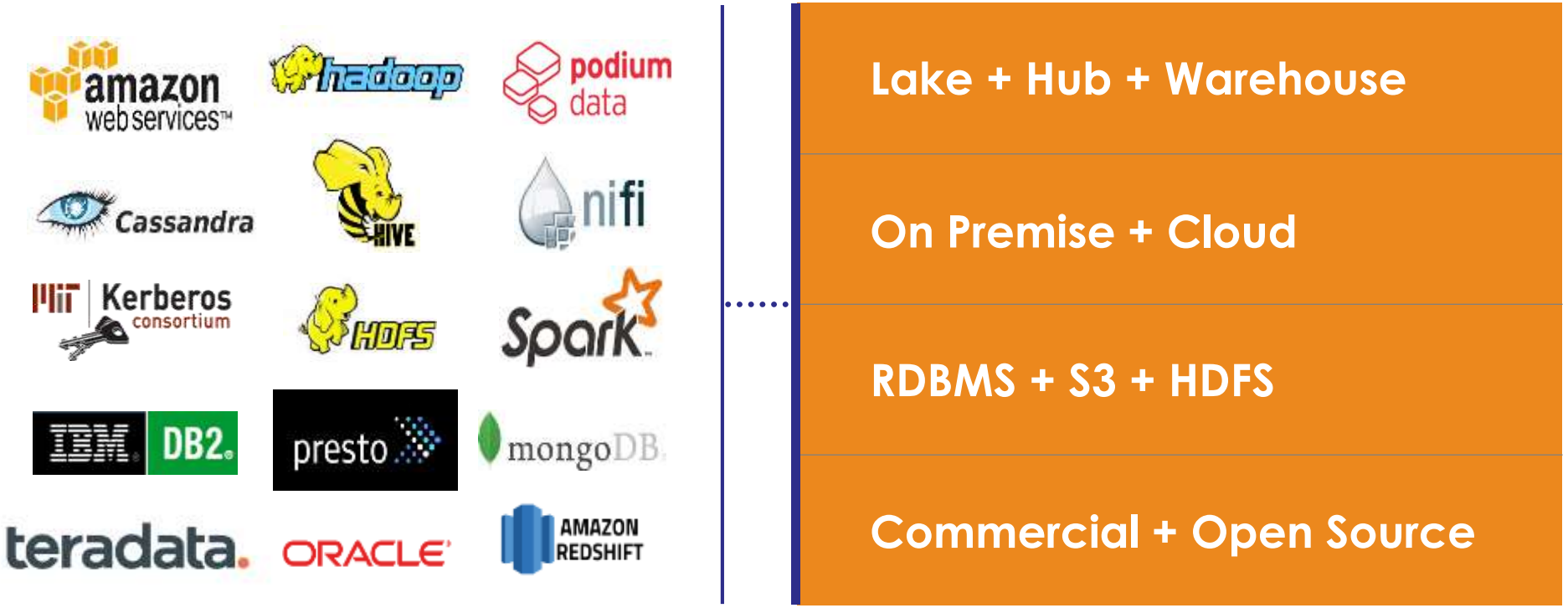
Third Nature

TANSTAAFL

When replacing the old with the new (or ignoring the new over the old) you always make tradeoffs, and usually you won't see them for a long time.

Technologies are not perfect replacements for one another. Often not better, only different.

Blended Architectures Are a Requirement, Not an Option



You can't just buy one thing platform from one vendor. We aren't building a death star.

Each of the zones is likely to have products specific to that zone's usage. The uses differ, the people using them differ, shouldn't the tools should differ too?

In piena foresta indiana, un uomo aspetta il treno vicino alla linea ferroviaria. Improvvisamente un boa assale il malcapitato, stringendolo nelle proprie spire potenti. Ma ecco una tigre slanciarsi a sua volta contro l'enorme rettile il quale avvolge, allora, anche la belva nella stretta mortale. Sul mostruoso groviglio sopraggiunge, frattanto, il treno.. Il viluppo è spezzato sanguinosamente dalle ruote del convoglio. (Disegno di A. Beltrame)

Manage your data (or it will manage you)

Data management is where developers are weakest.

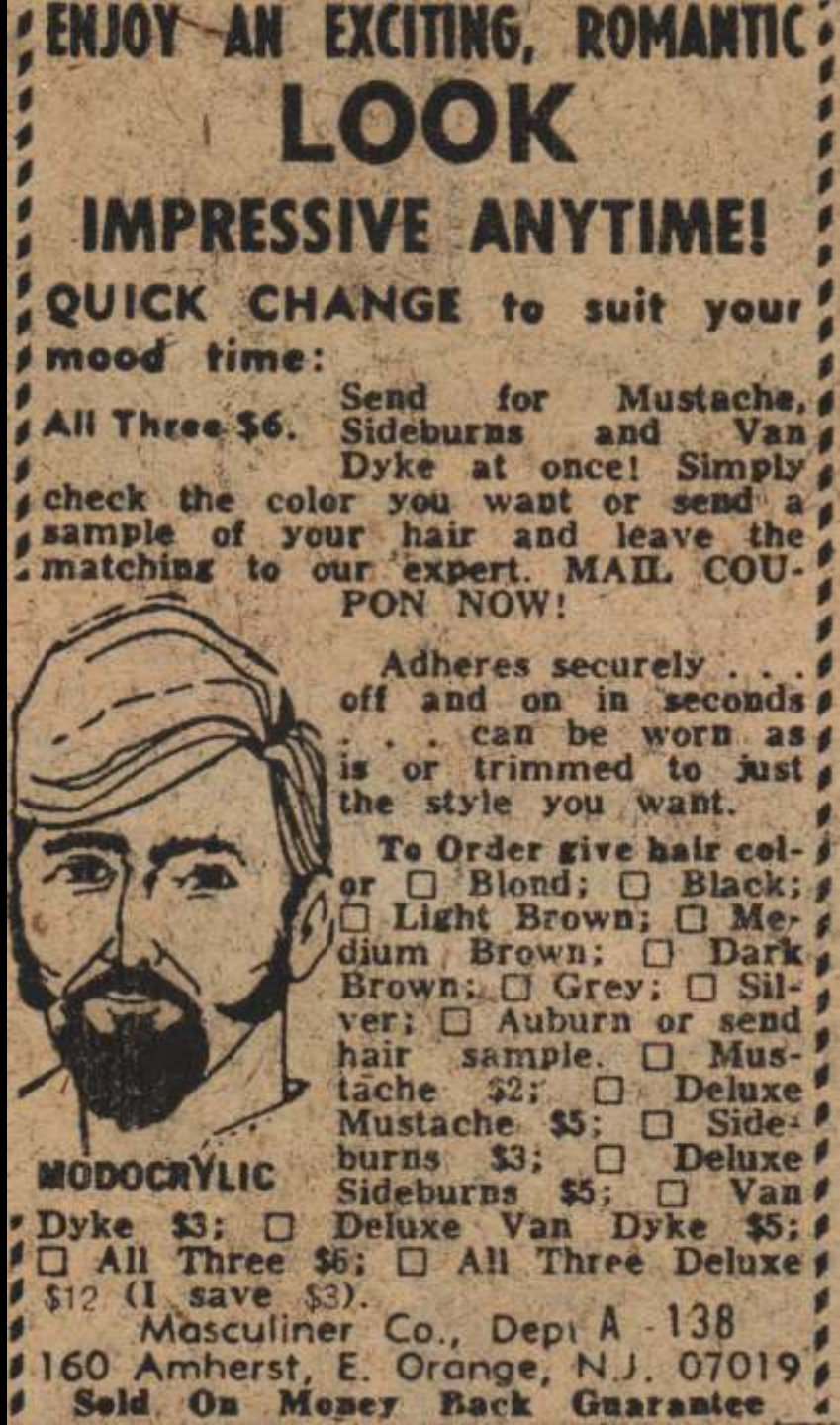
Modern engineering practices are where data management is weakest.

You need to bridge these groups and practices in the organization if you want to do meaningful work with data. Remember Conway's Law when you build.

Third Nature

A good design is not the one that correctly predicts the future, it's one that makes adapting to the future affordable.

— Venkat Subramaniam



Summary

1. It’s not about storing data, it’s about using data
2. Use drives architecture. Understand the uses, what you are designing for, to drive decisions.
3. Put data at the center, not technology. Don’t let the tech define what you can do or how you do it.
4. The death star is not the answer. The data model is not a flat earth. You are not building a monolith.
5. Know your history. Avoiding wheel reinvention saves time, money, careers.

About the Presenter

Mark Madsen is a Fellow at Teradata in the Technology & Innovation Office. Prior to that he was president of Third Nature, a research and consulting firm focused on analytics, data integration and data management. Mark is an award-winning author, architect and CTO whose work has been featured in numerous industry publications. Over the past ten years Mark received awards for his work from the American Productivity & Quality Center, TDWI, and the Smithsonian Institute. He is an international speaker, chairs several conferences, and is on the O'Reilly Strata program committee. For more information or to contact Mark, follow @markmadsen on Twitter.

Todd Walter
CEO - Archimedata

- Focused on off the grid island living, grandchildren and adventure travel.
- Delivers occasional strategy consulting and speaking engagements. A pragmatic visionary, Walter helps business leaders, analysts and technologists better understand all of the astonishing possibilities of big data and analytics.
- Retired from Teradata after a 31 year career working with organizations of all sizes and levels of experience at the leading edge of adopting big data, data warehouse and analytics technologies. Roles included a decade as CTO of Teradata Labs and a decade as Chief Technologist. He holds more than a dozen Teradata patents and was named Teradata Fellow in recognition of his long record of technical innovation and contribution to the company.