



# STARDOG

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Transform your Data into an Asset  
with a Knowledge Graph

# Our Presenter



Mike Grove

Founder & VP of Engineering, Stardog

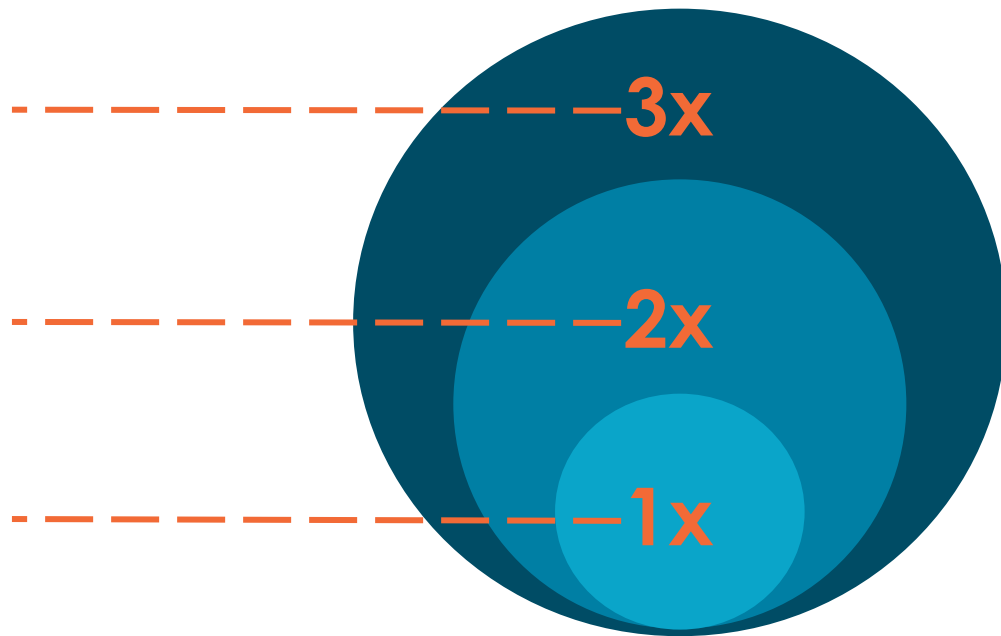
# The market acknowledges companies that have successfully leveraged their data

## Market vs tangible asset value ("Tobin's q" ratio)

Companies who directly monetize their data whether through ads, derived data products, etc

Companies recognized as "information-savvy" by leveraging their data successfully

All others; companies with direct 1:1 market-to-book value



# Data goals may appear disparate...



**Operational efficiencies:** supply chain optimization, predictive maintenance



**Knowledge management:** internal smart search, scientific research applications



**Product improvement:** recommendation engine, customer 360



**Risk reduction & compliance:** fraud detection, GDPR, SR-14



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# But they boil down to the same core goals



# Is enterprise data really an asset?

THE MAZE



It's only an asset  
if you can access it.



But accessing enterprise  
data is HARD.

# Common barriers

What's preventing you from leveraging your data as an asset?

Data unavailable;  
access limited (by  
social or structural  
issues)

Data is collected  
centrally but you  
don't know what  
data you need

Analysis is hampered  
by data quality or  
data preparation  
time required

Machine learning is  
in use but lack of  
model explainability  
results in resistance  
to adoption

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- Lines of business manage their own datasets and do not yield access, have incompatible data formats to other LOBs, or both
- Data is in a format that is unreadable by current systems (frequently unstructured data)



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# Company spotlight:



## Knowledge Management



*Stardog enables us to see all the data and all the relationships. It's a 10-to-1 savings."*

Andrew Schain,  
Program Data Integration Manager,  
Exploration Systems Division, NASA

## Problem

NASA's Space Launch System is the foundation for human exploration beyond Earth's orbit. Successful mission planning and execution requires navigating largely disconnected and siloed datasets across complex systems. To determine the impact a slight change in acceptable vibration had on humans, NASA engineers needed 6-8 weeks to pull the relevant data manually from each dataset, analyze and qualify it, and then create a report.

## Solution

NASA implemented Stardog's knowledge graph to manage, query, and analyze their data. To date, the team has unified 24 data sources with 40 specific record types. This unified view is crucial for knowledge management, quality control, and decision support.

## Benefits

NASA has saved countless hours assembling the answers they need from interconnected data. What took weeks to compile now takes seconds. Engineers can now focus on exploring their data, asking new questions, and examining the impact of potential decisions.

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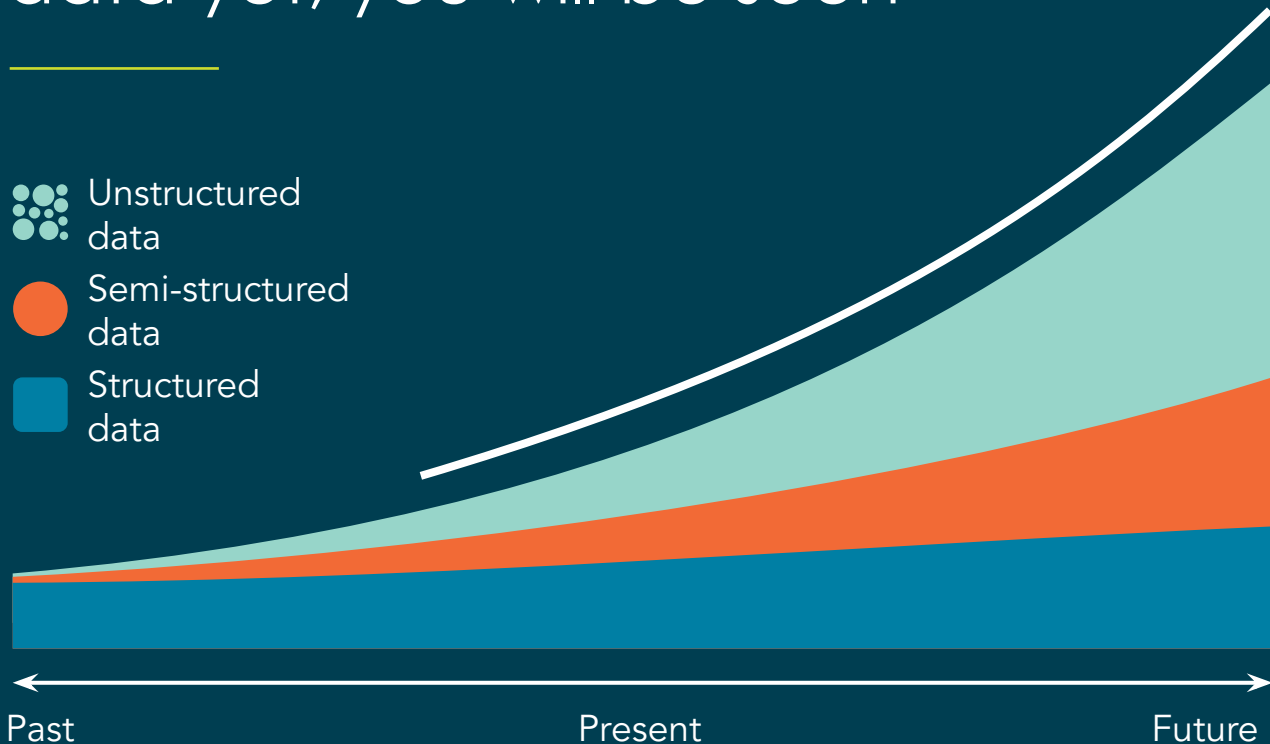
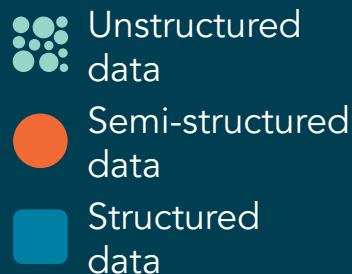
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# If you aren't wrestling with unstructured data yet, you will be soon



30.3%  
CAGR

in non-relational  
analytic data stores

*PREDICTED BY IDC*

800%  
GROWTH

in data volume,  
mostly in  
unstructured

*PREDICTED BY GARTNER*

# Data of all varieties



## Structured

Data with defined length and format, relationships defined by indices

Examples: XLS

Sources: Relational databases, your existing data warehouses



## Semi-structured

Data not organized in fixed fields or records, but has some hierarchies

Examples: JSON, XML

Sources: NoSQL databases



## Unstructured

Data without any organization, often text-heavy; also multimedia formats

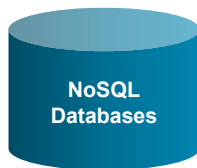
Examples: PDF, social media content

Sources: Often saved in data lake or locked in applications eg Sharepoint, JIRA



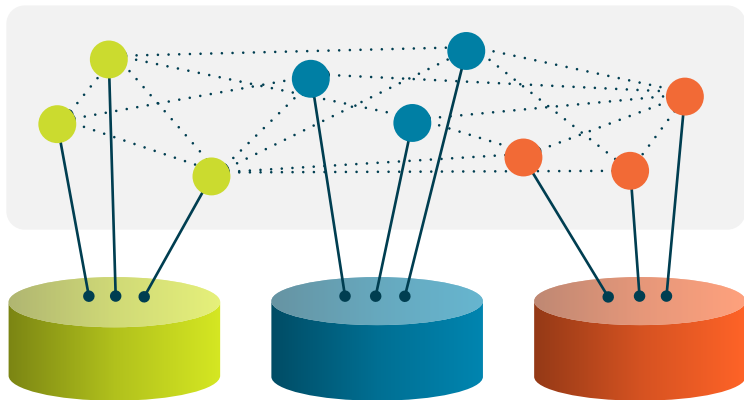
# Data content matters more than data location

Database  
Centric



Most IT organizations have been built to manage data by department and type.

Data  
Centric

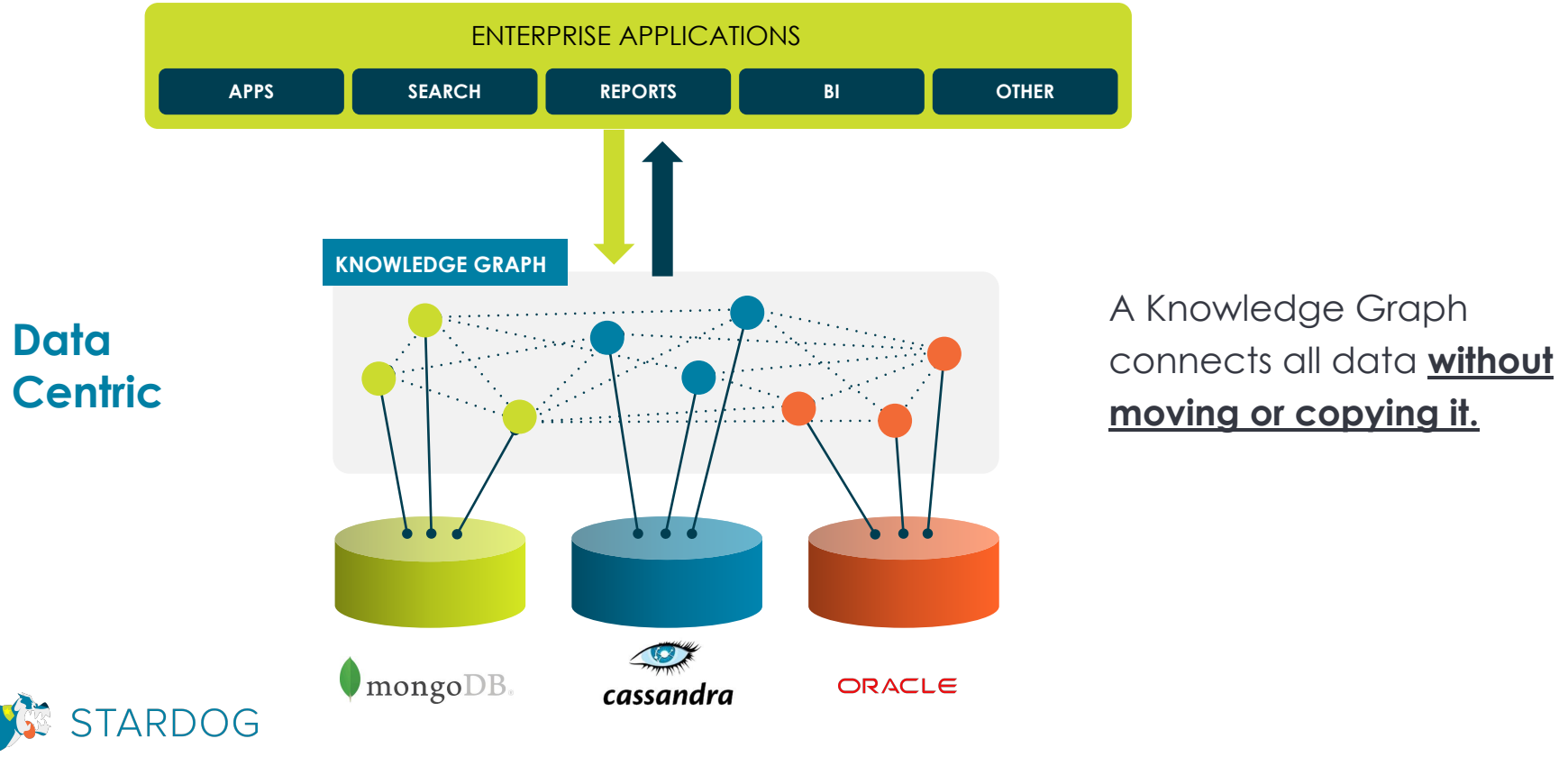


A Knowledge Graph connects all data **without moving or copying it.**



STARDOG

# Data content matters more than data location



# Company spotlight:



## Recommendation Engine

“

*Stardog connects and exposes our global product catalogue – true enterprise scale.”*

Dr. Christian Hütter  
Enterprise Architect, Power Tools

## Problem

Each year, Bosch launches more than 100 new power tools to its global product line, with over 50,000 products in total. Data about these tools is spread across many relational and unstructured sources.

## Solution

- Stardog powers a live Product Recommendation engine on BoschTools.com
- Organized Bosch's content library to create a clean, consistent, customer-facing searchable database -- complete with decades of tools, their optimal usage, associated products, and user manuals

## Benefits

As the online marketplace becomes more competitive for retail goods, Bosch has improved its customer experience with searchable content and product recommendations.

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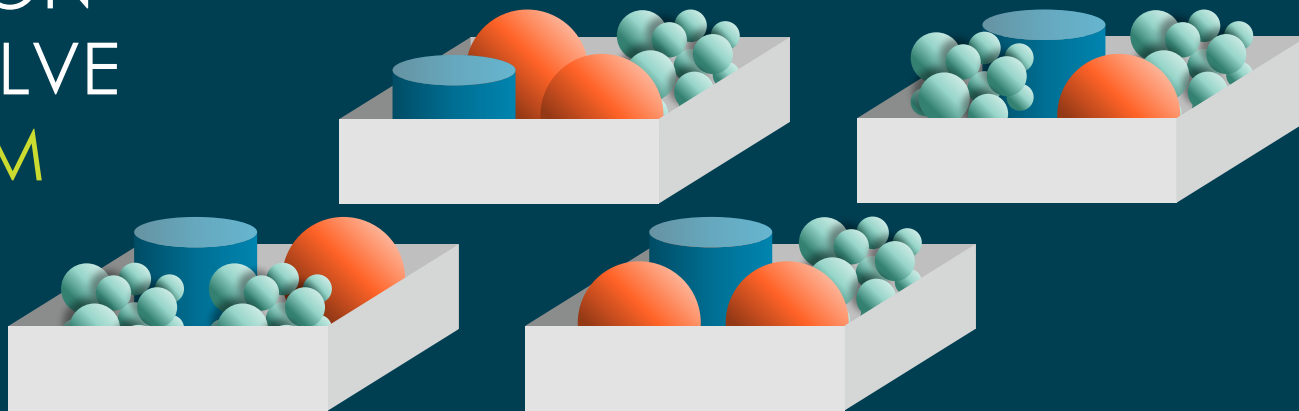
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# CO-LOCATION DOESN'T SOLVE THE PROBLEM

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There is always  
data in another  
location.



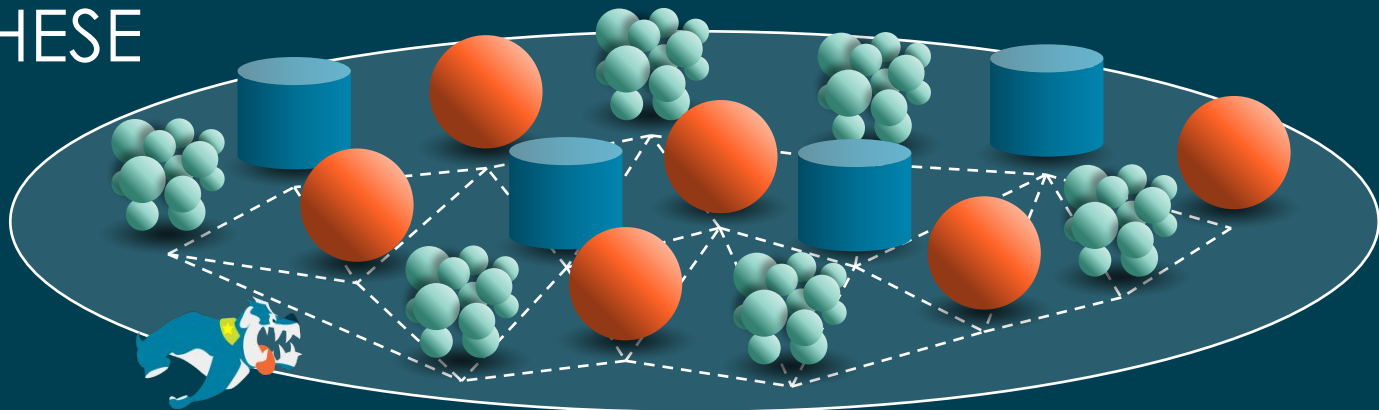
Unstructured  
data is usually left  
out.



Data context is  
critical.

# STARDOG SOLVES EACH OF THESE PROBLEMS

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**Works in a hybrid  
environment**



**Uses graph to  
work across all  
data types**



**Provides valuable  
context to data**

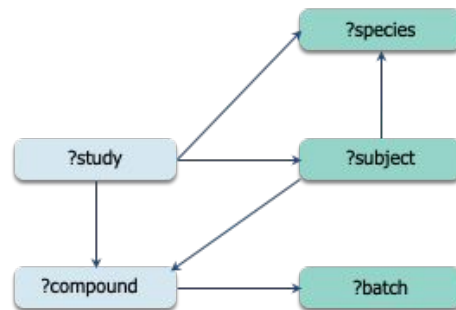
# Relational vs Graph

## Relational Database

	A	B	C	D	E	F	G	H
1	COLUMN_NAME	TYPE_NAME	% NULLABLE	DECIMAL_DIGITS	COLUMN_SIZE	COLUMN_DEF	REMARKS	DATA_TYPE
2	TASK_ID	BIGINT	YES		20			8
3	TASK_NAME	VARCHAR	YES		80			12
4	TASK_DESC	VARCHAR	YES		255			12
5	ACTIVITY_CODE	VARCHAR	YES		255			12
6	ACTIVITY_STATUS	VARCHAR	YES		80			12
7	ACTIVITY_TIME	VARCHAR	YES		80			12
8	ADDITIONAL_CODE	DOUBLE	YES		13			6
9	ADDITIONAL_RESOURCE	DOUBLE	YES		13			6
10	ADD_TARGET	DOUBLE	YES		13			6
11	ANIMAL_PACKING	DOUBLE	YES		13			6
12	ACT_GROUP_TIME	VARCHAR	YES		80			12
13	CLIN_COMPLEXITY	VARCHAR	YES		80			12
14	CLIN_PROTOCOL_COMPLEXITY	VARCHAR	YES		80			12
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- Stores data in rows and columns
- Well-suited for structured data queries with pre-defined relationships
- Rigid structure prevents changes later
- Works well for management of transactional data and simple look-ups

## Knowledge Graph



- Represents data as entities with relationships with an expressive graph model
- Well-suited to query complex and highly connected data
- Flexible design lets you accommodate new use cases and data sources

---

“

Formally transitioning from a relational model to that of linked data was a huge strategic benefit to the bank. We are now able to design and link domain models across organizations and silos.

”

---

Executive Director, Top 5 US Bank



# Company Spotlight:

## Morgan Stanley

### IT Portfolio Management

“

*An hours-long triage of  
outages is a 50ms  
query now.”*

Richard Viana, Executive Director  
Enterprise Infrastructure

### Problem

With nearly 60,000 employees, Morgan Stanley's Enterprise Infrastructure team struggled maintaining a single source of truth across the production, operations, and engineering of all global technology assets.

### Solution

Stardog powers Morgan Stanley's Impact Data program, an IT Portfolio Management platform used to manage global assets and their associations, roles, and entitlements for Morgan Stanley's global employee base.

### Benefits

- Created a single, authoritative view of the entire enterprise and its associated architecture, which enables analytics and reporting
- Platform drives risk management, as well as system & infrastructure cost reporting
- Downstream outage ramifications are now easily identified and quantified

# Common barriers: Analysis

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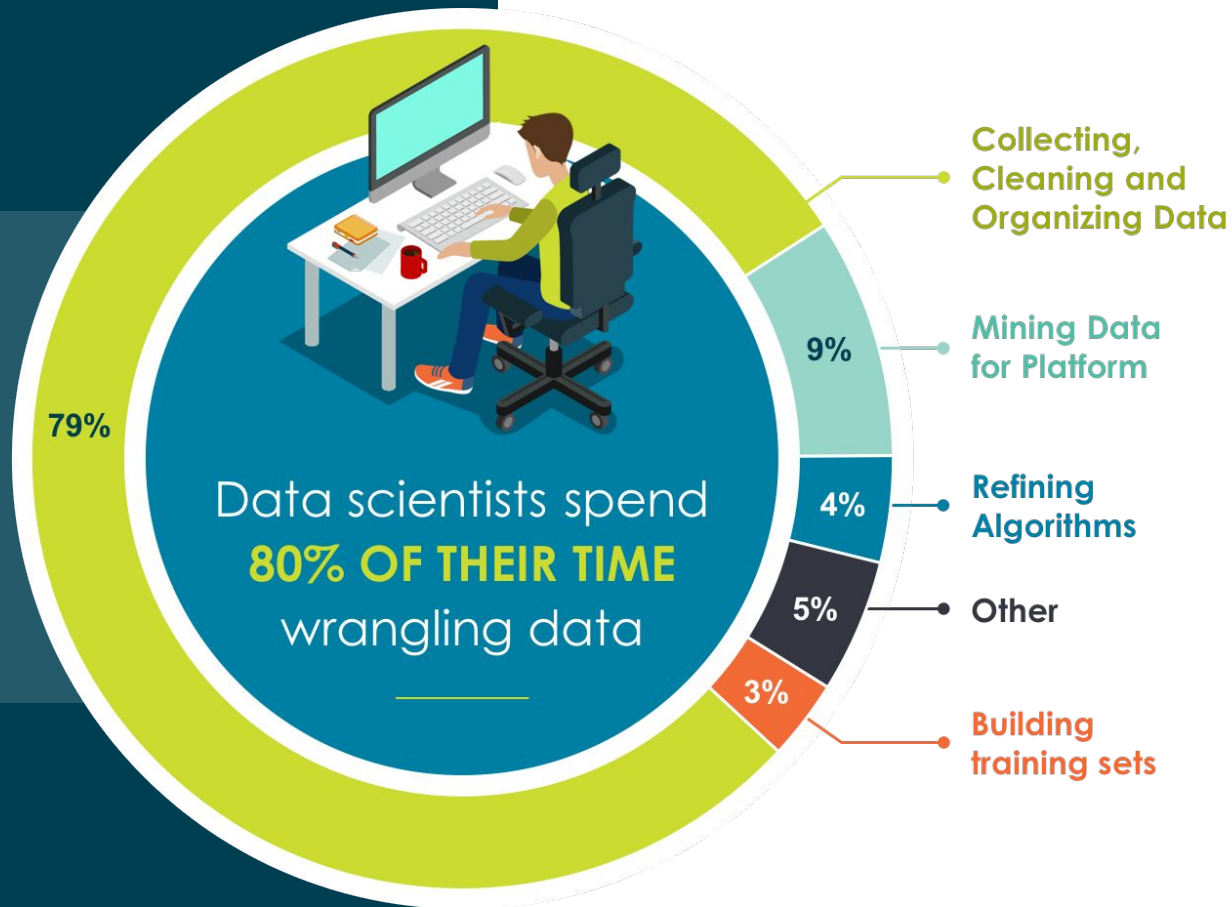
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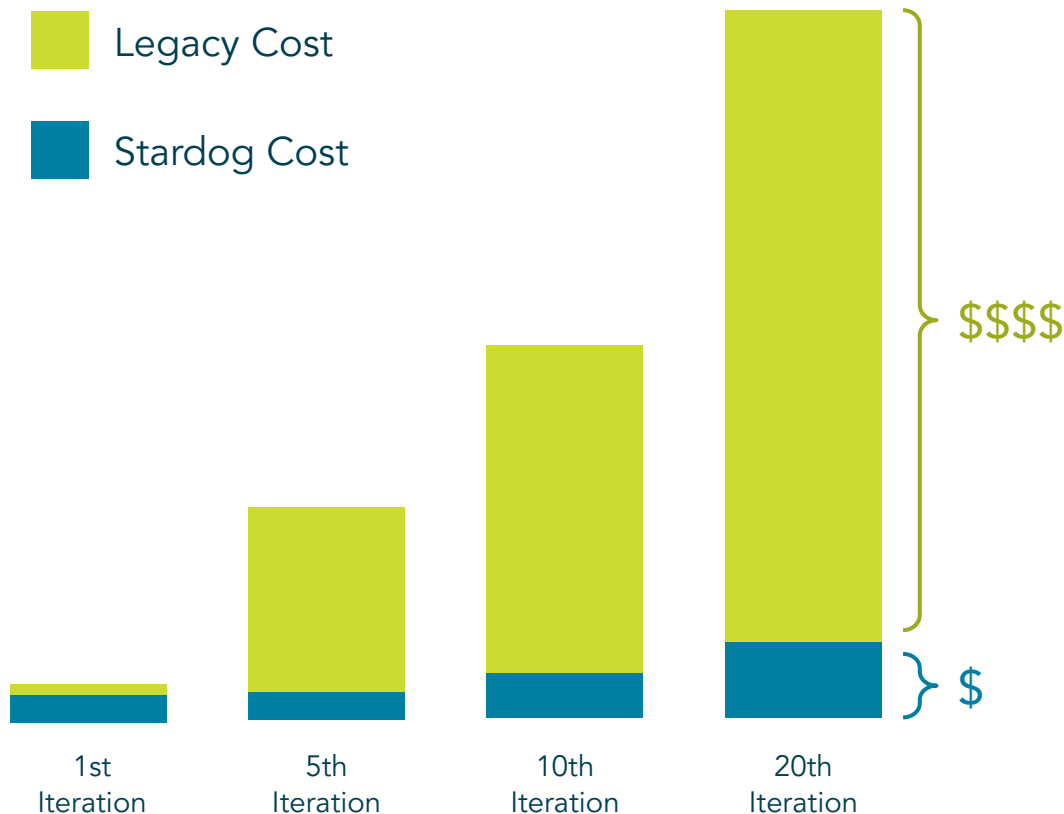
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Every large organization struggles with data analysis



# STARDOG DECIMATES THE COST OF ANALYSIS



Data wrangling is a huge source of inefficiency. Stardog changes the game.

- Logical model works with changing data.
- Simple mapping makes it easy to add new sources.

> Set the logic once and it's done.

---

“

Enterprise “Dark Data” is information collected during the course of business that remains in archives, is not generally accessible, or is not structured sufficiently for analysis. It can include emails, contracts, documents, multimedia, system logs and other overlooked information assets.

Parsing, tagging, linking, or otherwise structuring or extracting usable information from these sources is the greatest immediate opportunity for most businesses among all types of information.

”

---

Gartner: Applied Infonomics

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# Leverage a knowledge graph for gaining buy-in

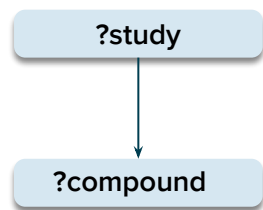
- **Problem:** Machine learning models have high accuracy but low explainability, answers are in a “black box”
- **Solution:** Knowledge graphs allow you to look at the snapshot from the model and ask “What led to this point?” -- bringing context to how the decision was made

“Model interpretation (or explainability) is the ability to explain the decisions of a predictive or prescriptive model to enable accuracy, fairness, reliability, accountability, stability and transparency in algorithmic decision-making.”

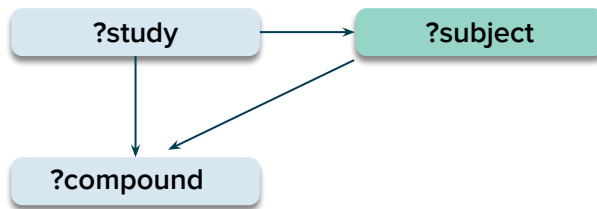
*Gartner, Making Machine Learning Explainable*

# Knowledge graphs enable discoverability

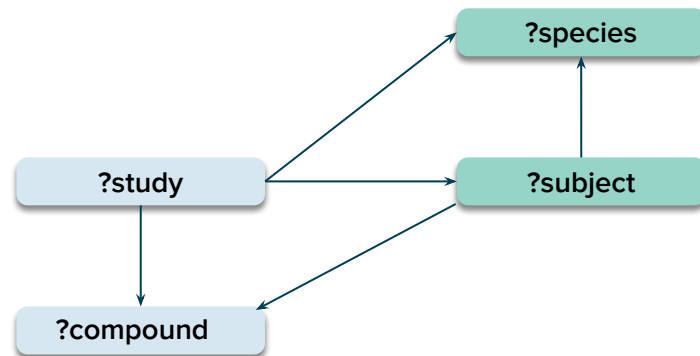
Knowledge graphs enable you to walk through data and understand the connections. You can easily jump from question to question and test new hypotheses.



*Which studies included this compound?*



*Which subjects were also in common with this compound?*



*What was the species mix of the studies for this compound?*



# Developing a data strategy

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## Identify an internal use case

Layer on incrementally

- Start with a key use case with a strong advocate
- Strengthen value of knowledge graph with additional sources; value is accretive over time

## Evaluate prime data sources

Look for opportunities in your data

- Proprietary data
- Accurate/precise data (that you can warrant)
- Siloed data - exposing and connecting to relevant data across the org can be very powerful

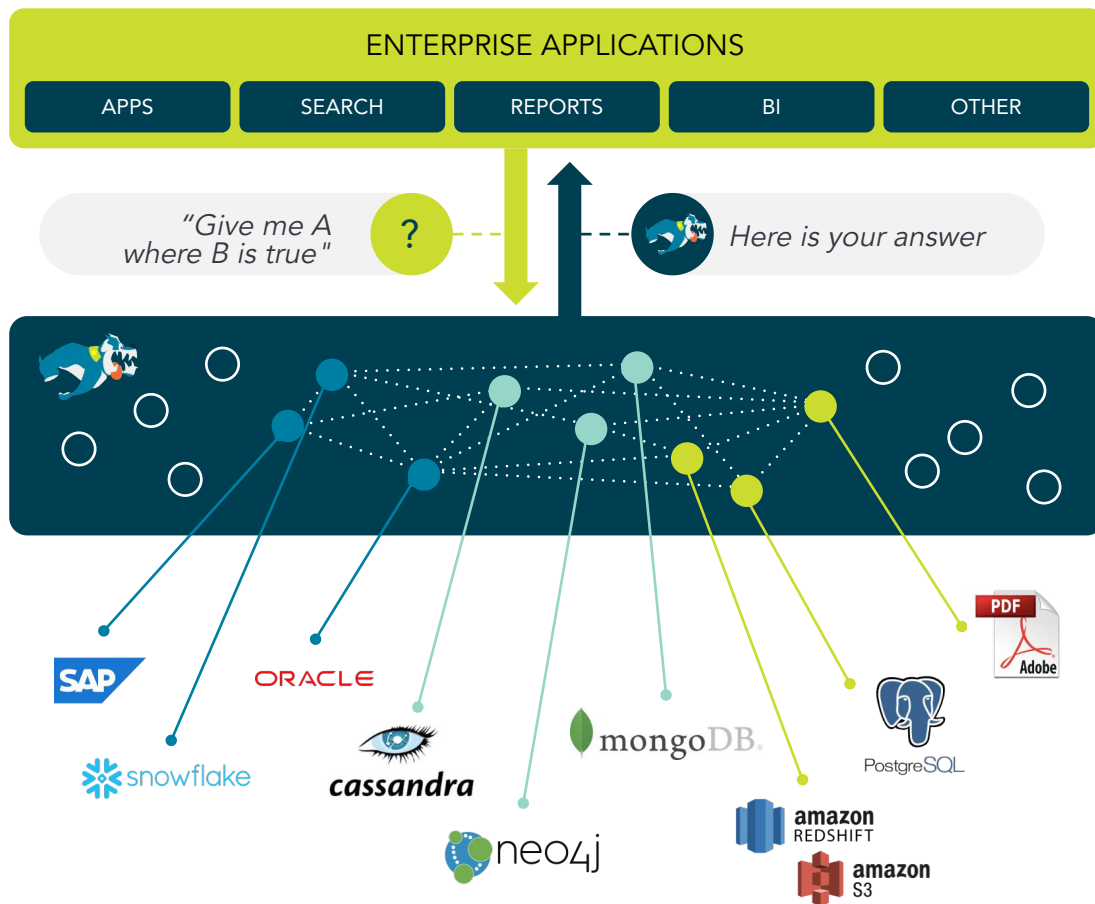


# How Stardog is unique

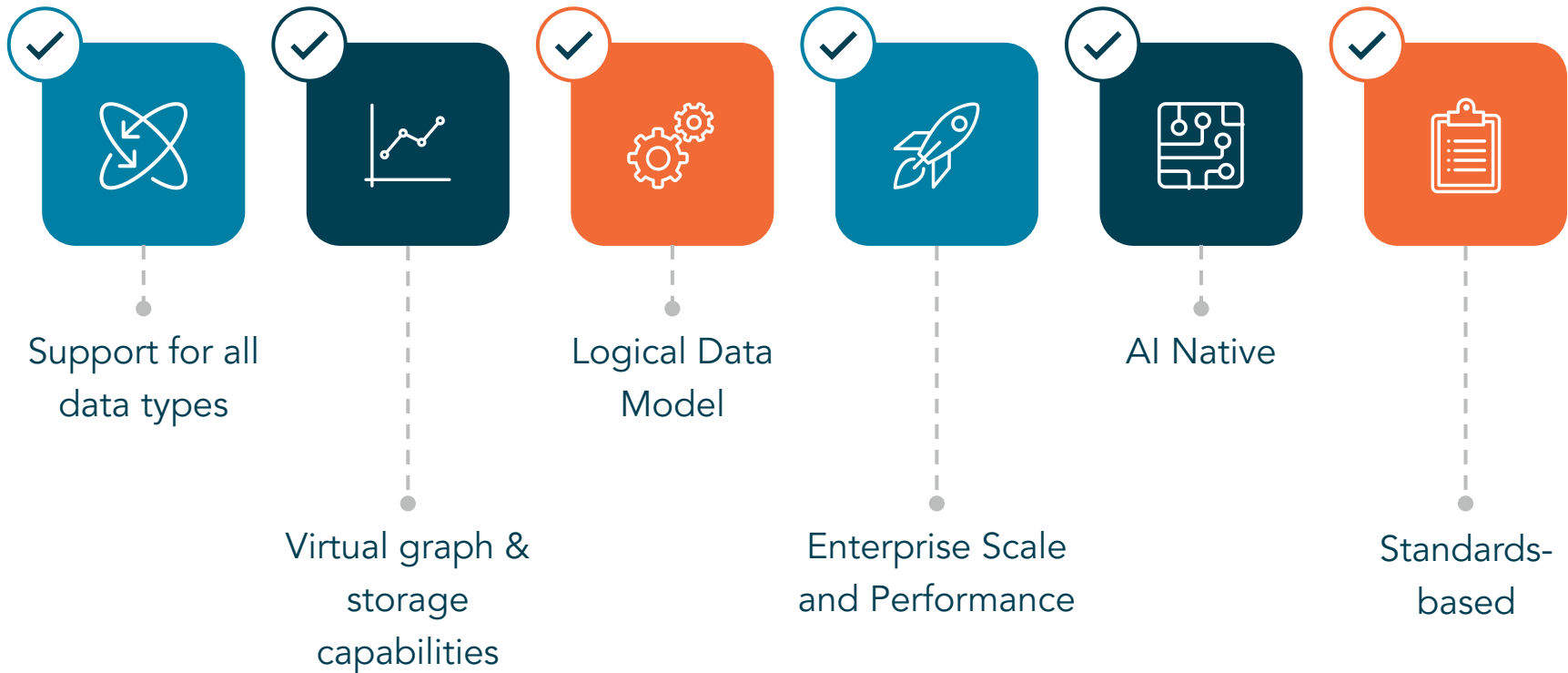
# HOW STARDOG WORKS

Stardog queries data across the enterprise by:

- Using a high-level data model based on semantics
- Mapping data locations and meanings
- Virtualizing and storing as needed
- Running graph queries against the data model to return answers



# Our differentiated features



# MAJOR COMPANIES RECOGNIZE THE VALUE



SPRINGER NATURE



Morgan Stanley



SCHAEFFLER



Raytheon



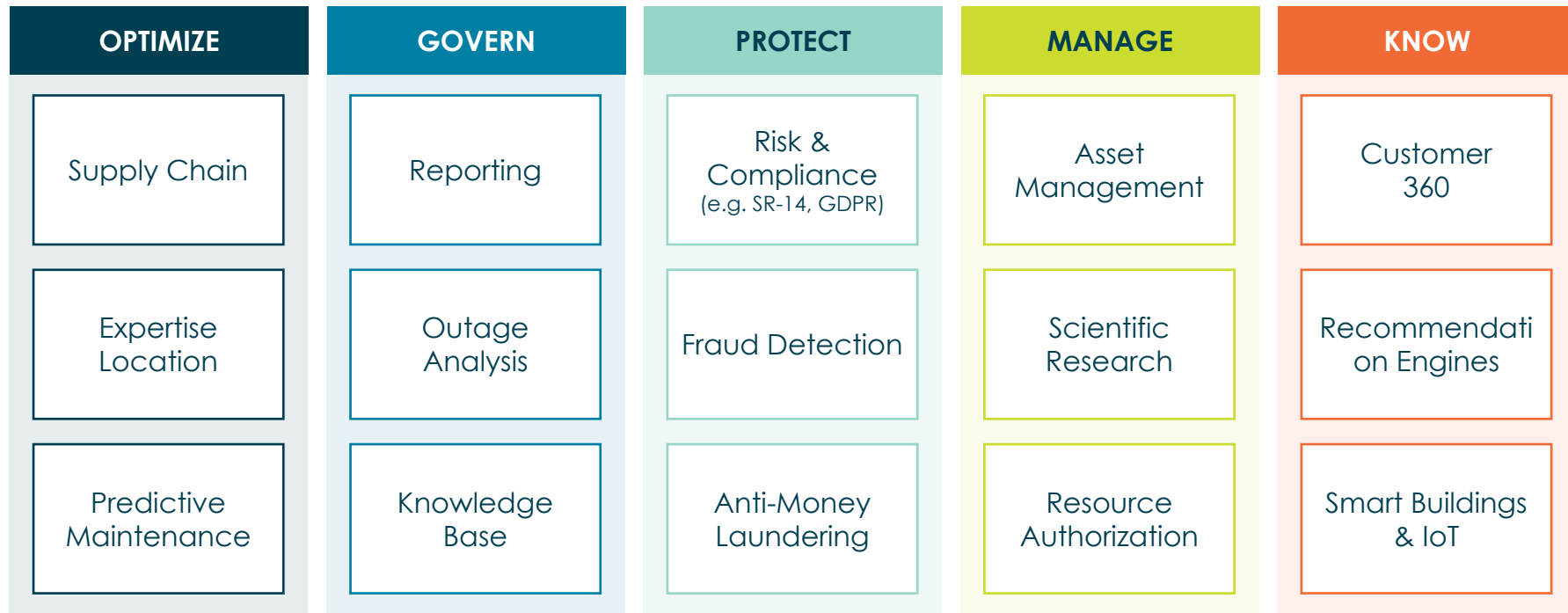
NOKIA



MOODY'S



# Our use cases span across your business



# Ways to learn more

## Download the whitepaper

Read the Knowledge Graphs 101 whitepaper for additional details:

[fetch.stardog.com/web-enterprise-knowledge-graph/](https://fetch.stardog.com/web-enterprise-knowledge-graph/)

## Try out a knowledge graph

Download Stardog's knowledge graph to connect and query your own data:

[\*\*stardog.com/download\*\*](https://stardog.com/download)

# Q&A



Thank you!



STARDOG

# Knowledge Graph can drive significant business value

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Deploying a knowledge graph addresses the following market realities:

Organizations continue to spend 60%-80% of data analysis workflow on finding, accessing, preparing and sharing data for further analysis

- Gartner: *Market Guide for Data Preparation*

Companies today are sitting on “dark data” - defined as data not generally accessible or structured sufficiently for analysis. Parsing, tagging, linking or otherwise structuring and extracting information from this data represents “the greatest immediate opportunity for most businesses among all types of information”

- Gartner: *Applied Infonomics: Seven Steps to Monetize Available Information Assets*

While data is an unquantifiable asset from an accounting standpoint, companies that are leveraging their data to improve their operations and product are recognized by the market with a 2x market-to-book value

- Gartner: *The Birth of Infonomics, the New Economics of Information*

# Silos are a reality

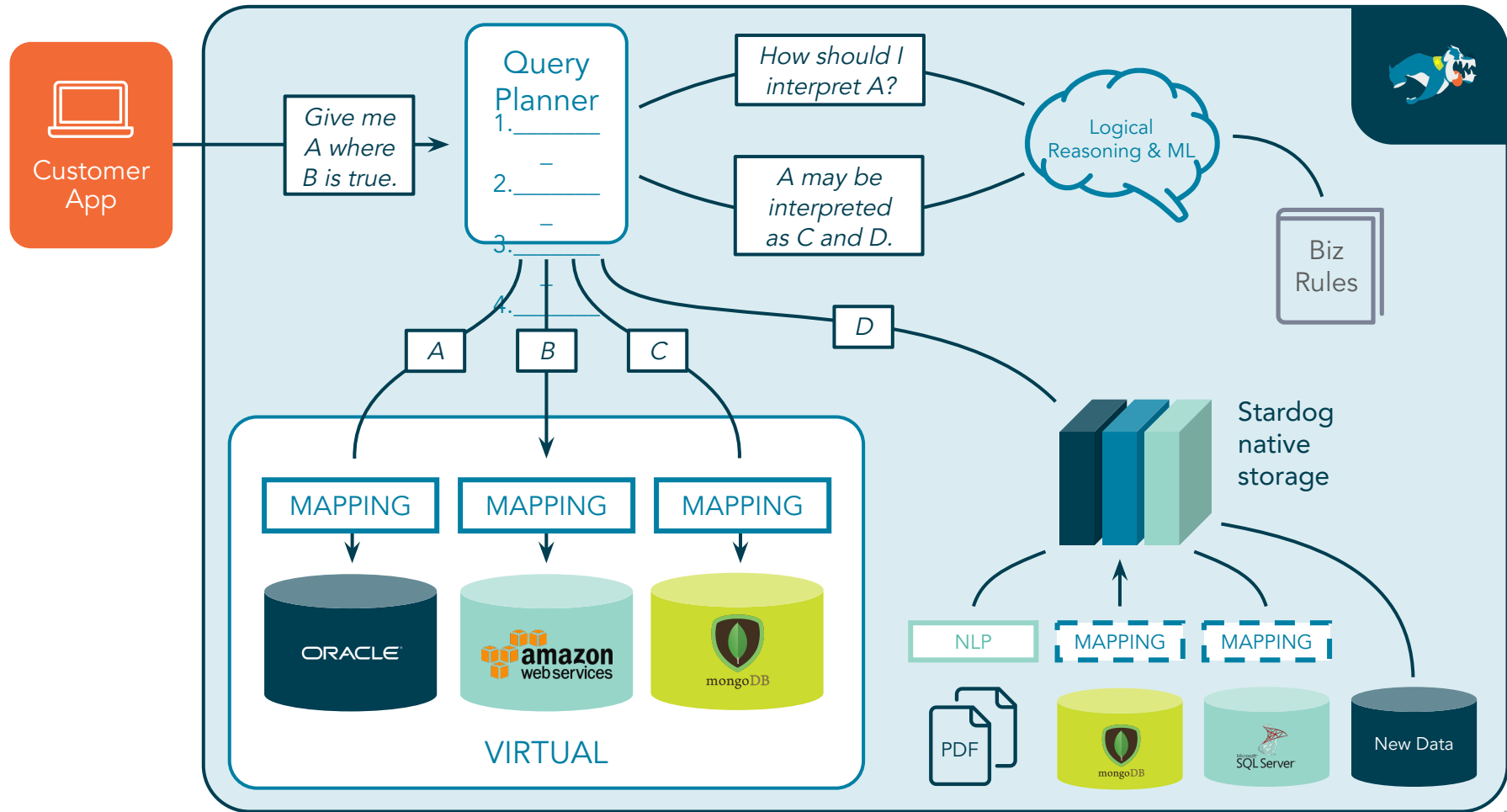


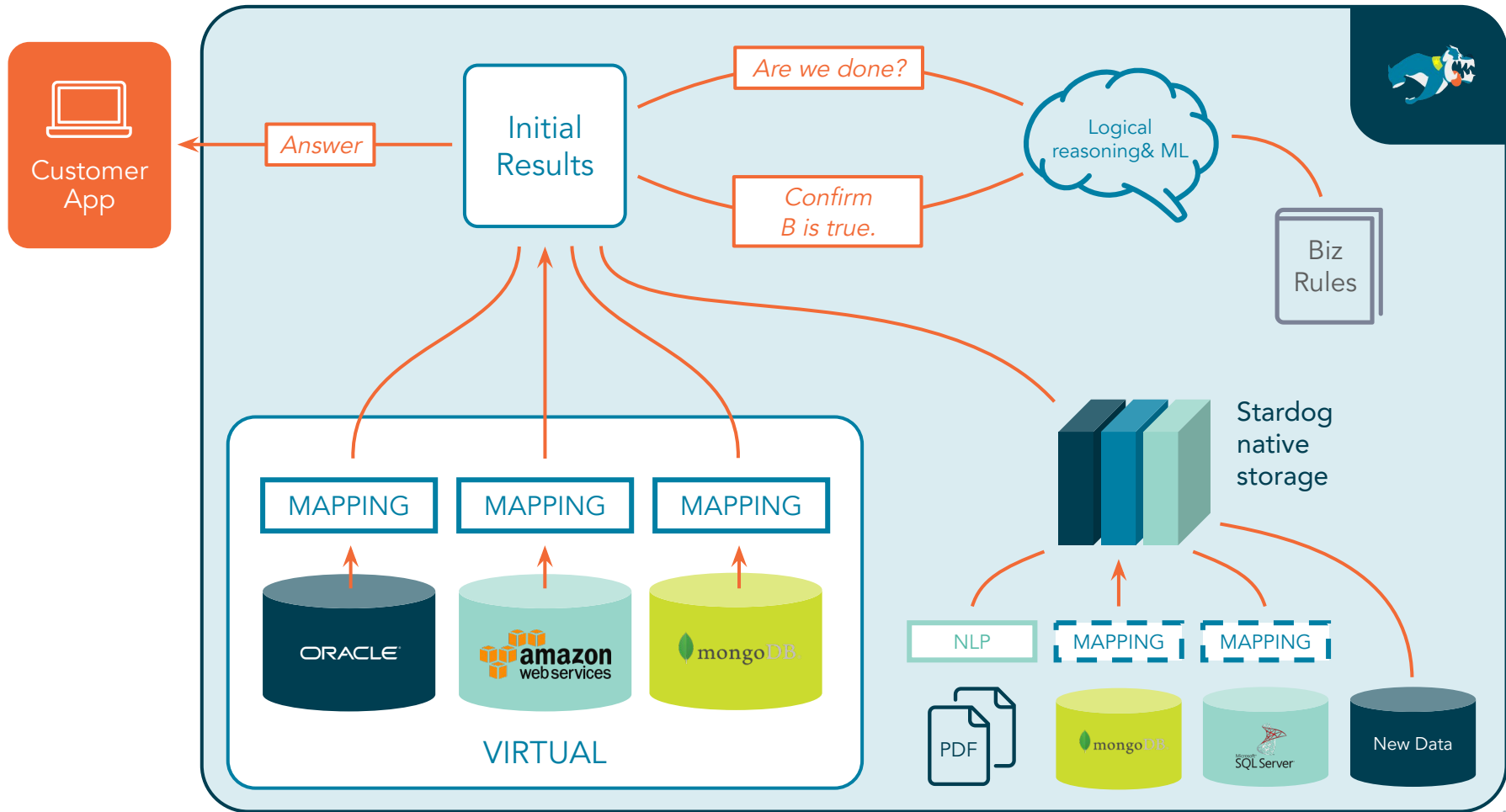
Source: Dun & Bradstreet, Are Data Silos Killing Your Business, May 7 2018

# 69%



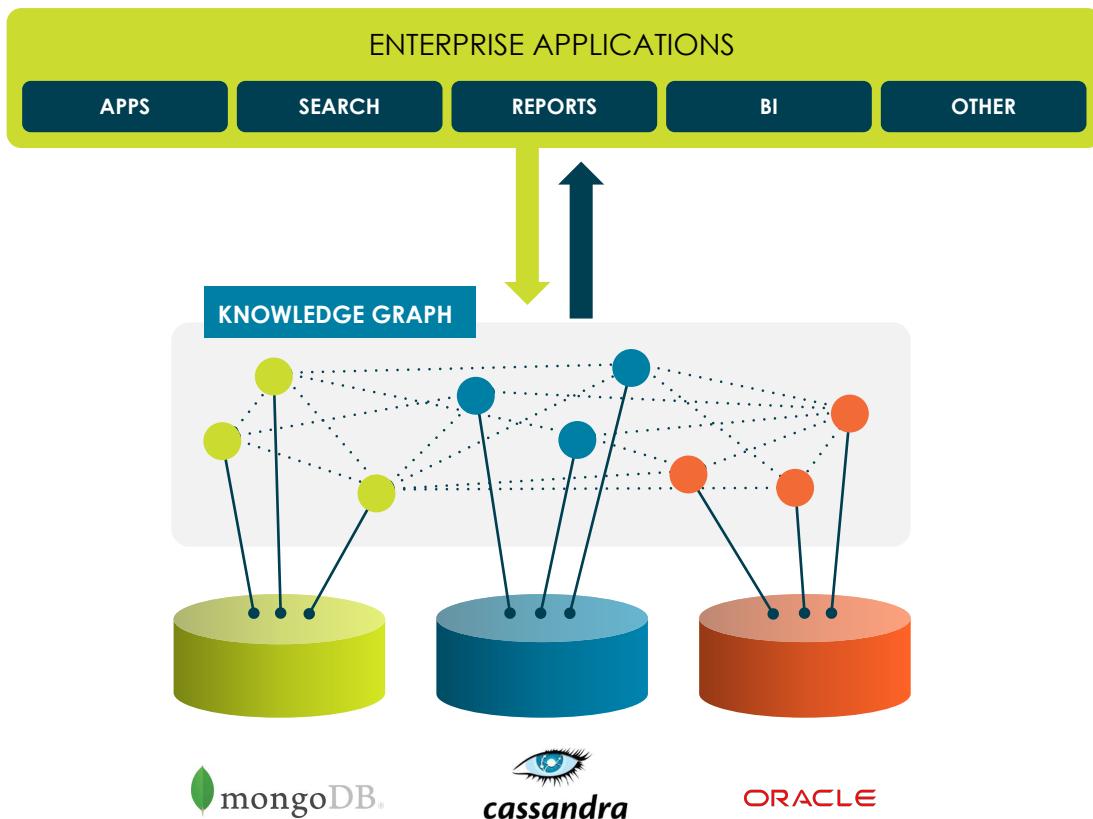
of Customer 360  
projects **FAIL**





# What is a knowledge graph?

A knowledge graph leverages graph technology and a declarative model to connect, query, and retrieve data.



*Examples of data*