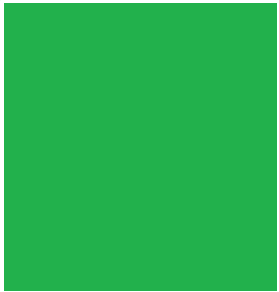
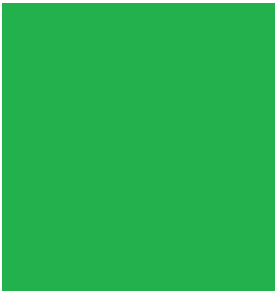
Course Introduction



Course Target



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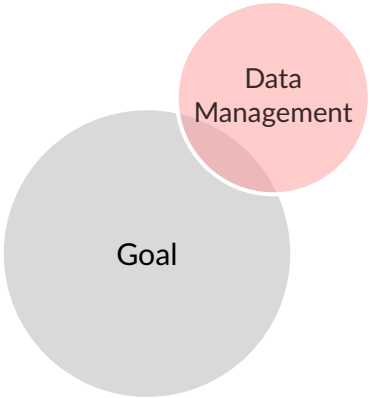

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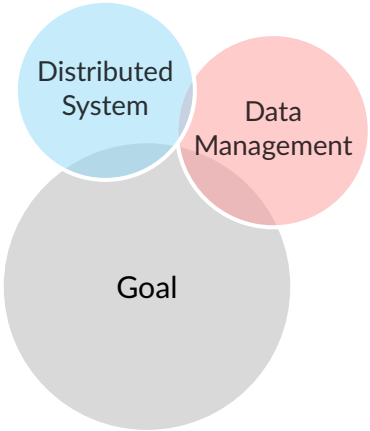

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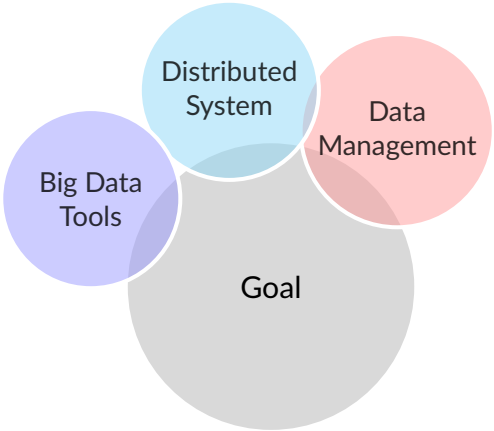

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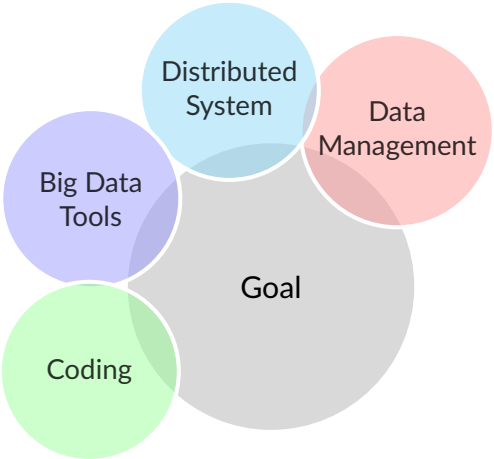

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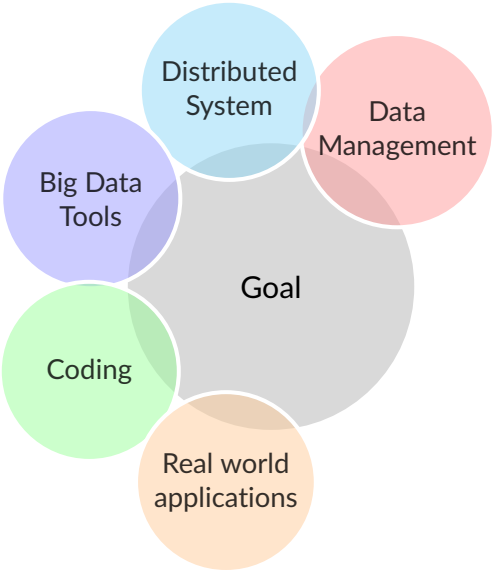
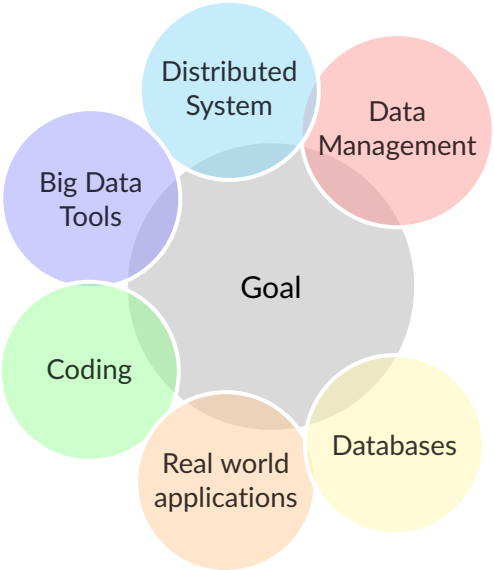


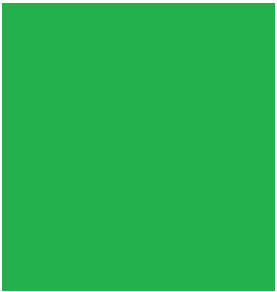
Course Target



Course Target

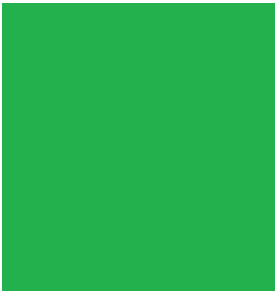
Learning Objectives

- Simplify the concepts in data management.



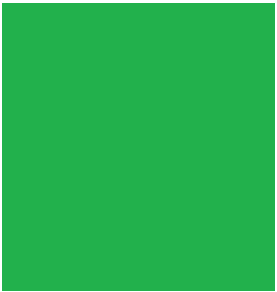
Learning Objectives

- Simplify the concepts in data management.
- Understand the data management life-cycle.



Learning Objectives

- Simplify the concepts in data management.
- Understand the data management life-cycle.
- Illustrate the basics of distributed systems concepts



Learning Objectives

- Simplify the concepts in data management.
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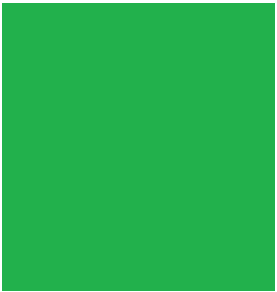
- Be familiar with ETL for (batch/steaming) data over distributed systems ex: Hadoop & Spark.



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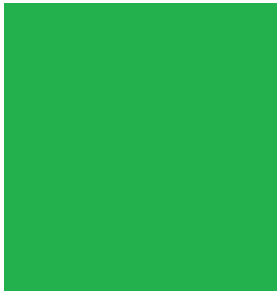

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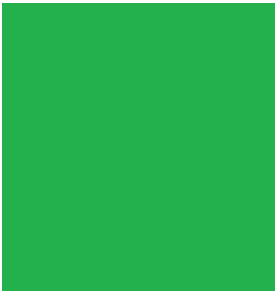

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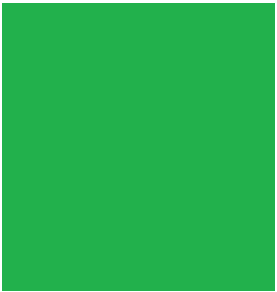

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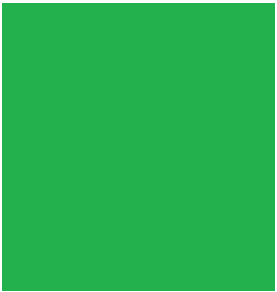

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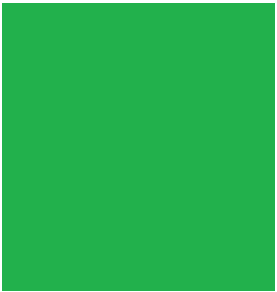
- Automate the data life-cycle process end-to-end (e2e).



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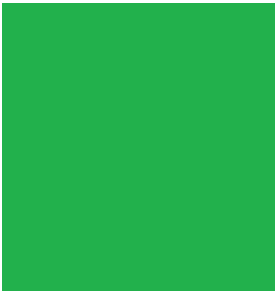
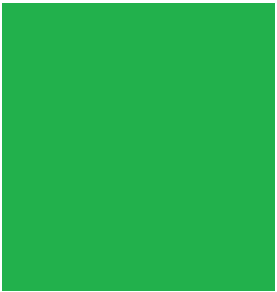
- Understanding of the DevOps tools and functions in data life-cycle.



Audience: Who Should Take This Course?

- Data Engineer who needs to get more knowledge in distributed systems and Big Data.



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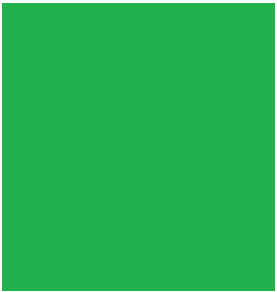
- Data Engineer who needs to get more knowledge in distributed systems and Big Data.
- Data Warehouse Engineer who needs to know more about big data.



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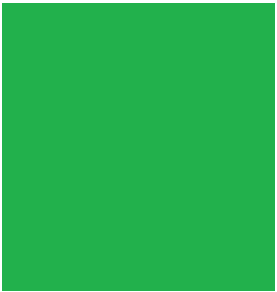
- Software developer who needs to change to data engineering track.



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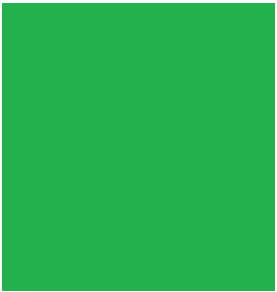

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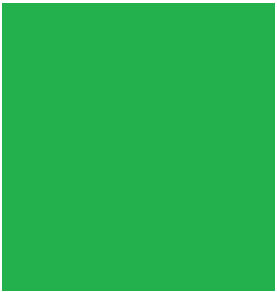
- Data Warehouse Engineer who needs to know more about big data.
- Software developer who needs to change to data engineering track.
- DevOps engineers who needs to understand the concepts of big data.
- Business or entrepreneur who needs to get more information about how to build or manage a data product.



Getting max benefit from this course

Take the course advantage

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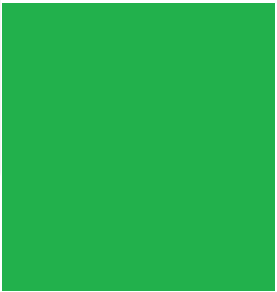

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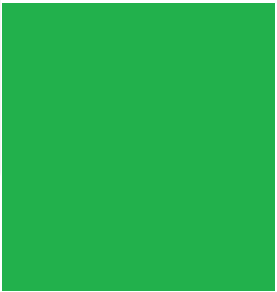

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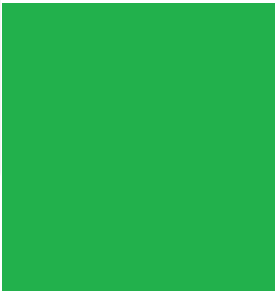

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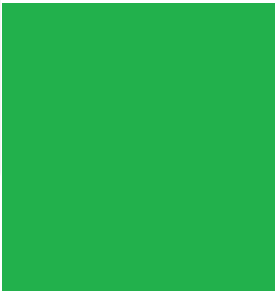

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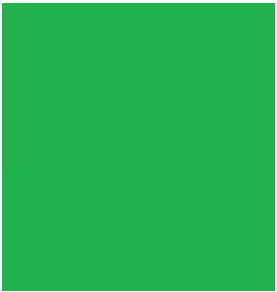

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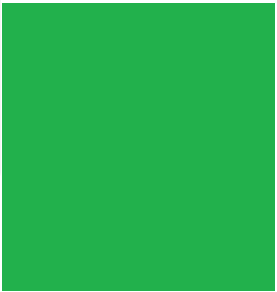

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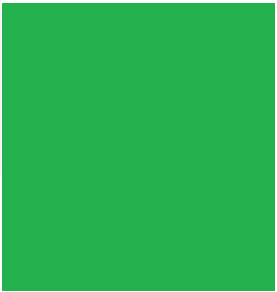
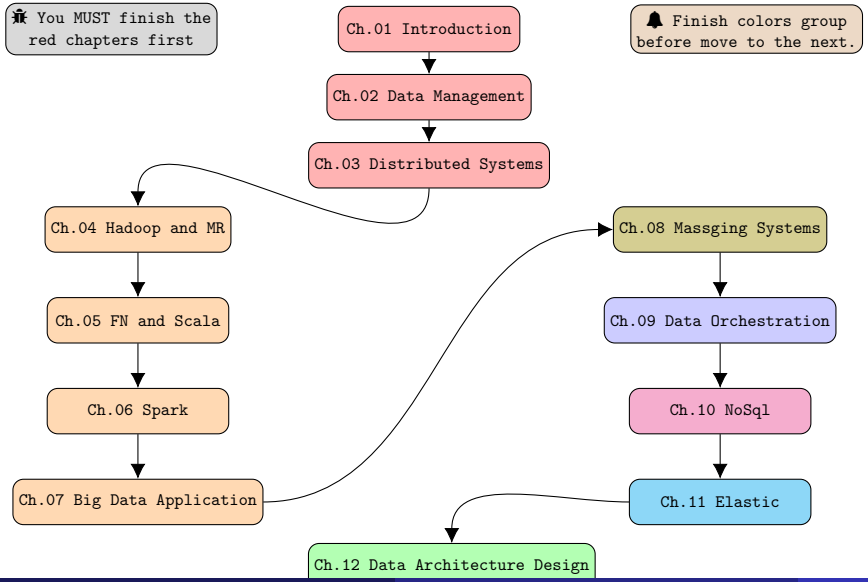
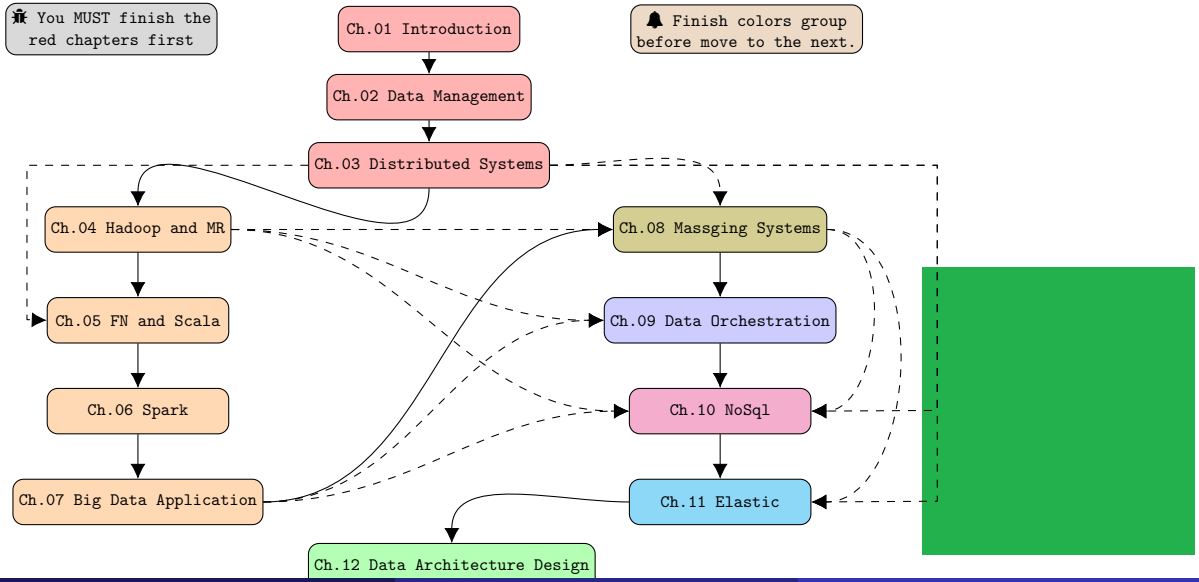


Chapter Dependencies



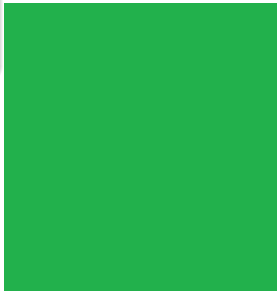
Chapter Dependencies (Jump Out Path)



Assignments and Labs

Remark

- Full project code.



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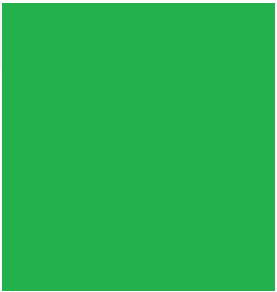

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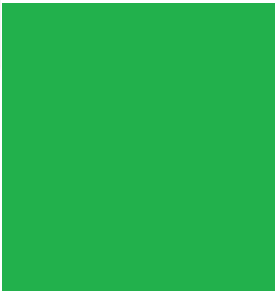
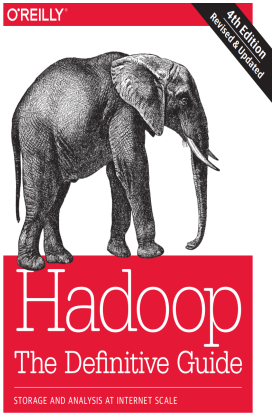


Textbooks-1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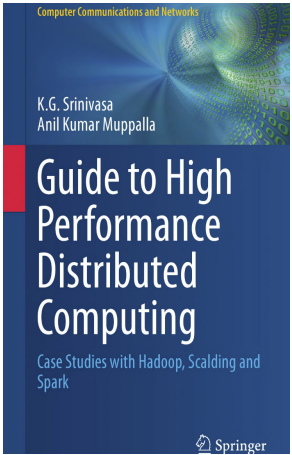
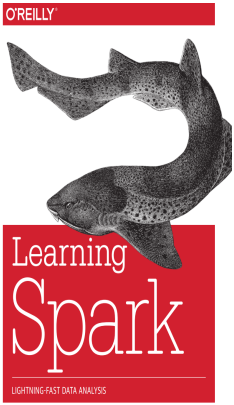
4th Edition
Revised & Updated
Hadoop
The Definitive Guide
STORAGE AND ANALYSIS AT INTERNET SCALE
Tom White


Computer Communications and Networks
K.G. Srinivasa
Anil Kumar Muppalla
Guide to High Performance Distributed Computing
Case Studies with Hadoop, Scalding and Spark
Springer

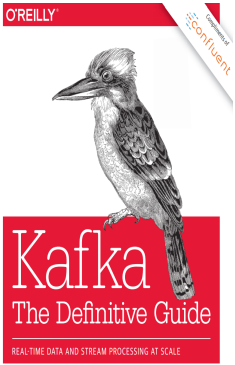
Textbooks-2

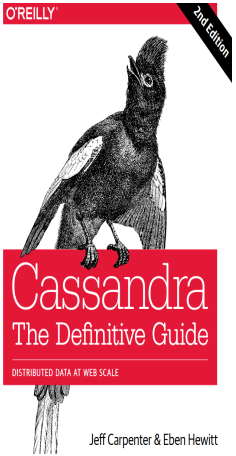
Holden Karau &
Rachel Warren

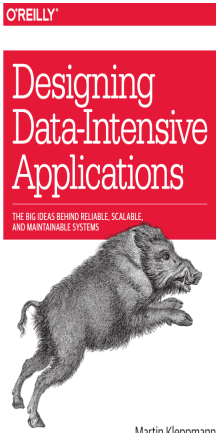


Holden Karau, Andy Konwinski,
Patrick Wendell & Matei Zaharia

Textbooks-3

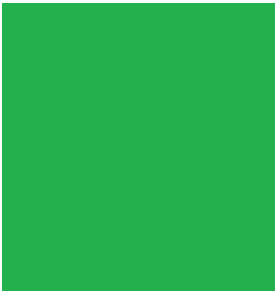

O'REILLY
Compliments of
Confluent
Kafka
The Definitive Guide
REAL-TIME DATA AND STREAM PROCESSING AT SCALE
Neha Narkhede,
Gwen Shapira & Todd Palino


O'REILLY
2nd Edition
Cassandra
The Definitive Guide
DISTRIBUTED DATA AT WEB SCALE
Jeff Carpenter & Eben Hewitt


O'REILLY
Designing
Data-Intensive
Applications
THE BIG IDEAS BEHIND RELIABLE, SCALABLE,
AND MAINTAINABLE SYSTEMS
Martin Kleppmann

Ugly but important

- User stories or technical discussions are not related to any of my current work or my previous companies.
- I am working at EPAM Systems. My company approved me for doing this online course public but the materials are not reviewed or assessed by my company. It is on my own responsibilities.



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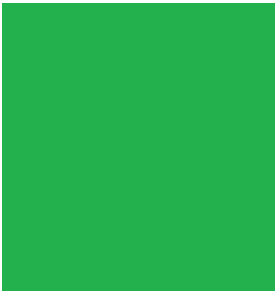

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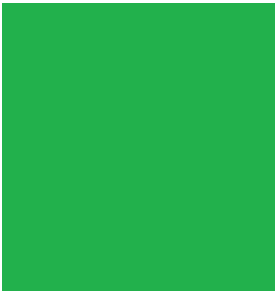

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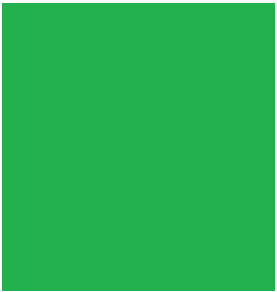

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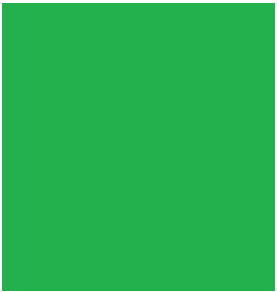

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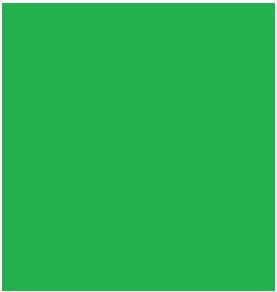

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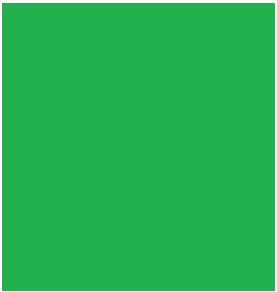

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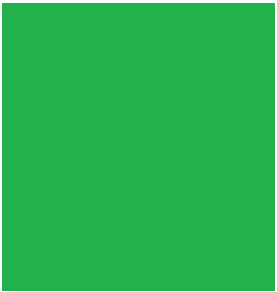

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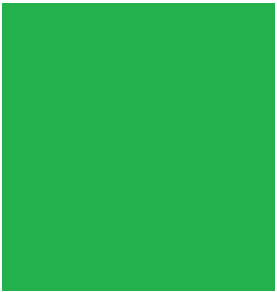
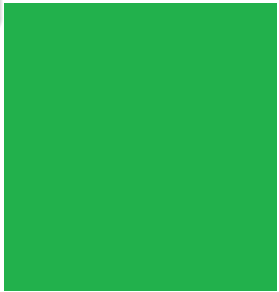


Introduction To Data Management and Data Warehouse



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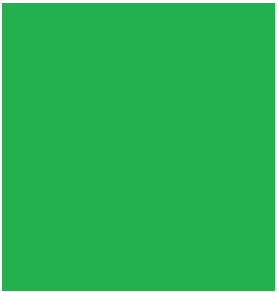

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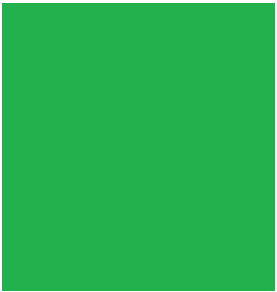

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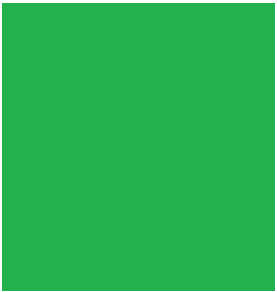

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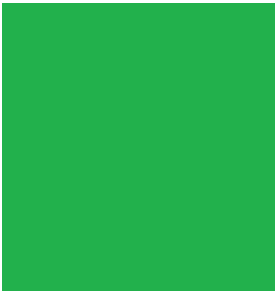

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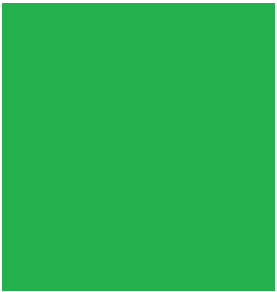

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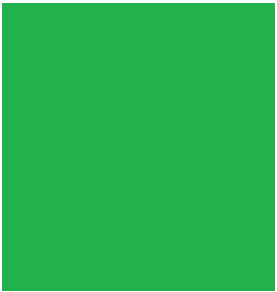

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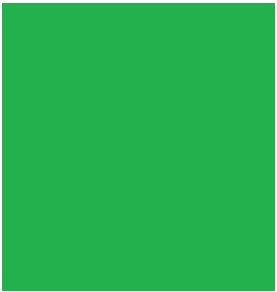

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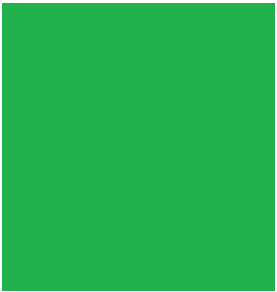

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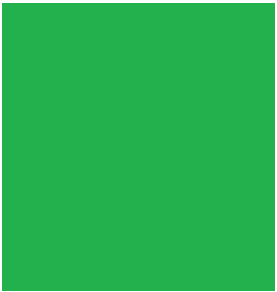

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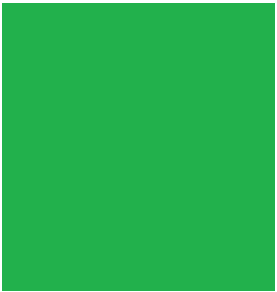

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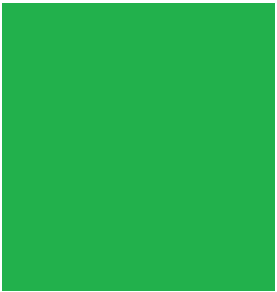

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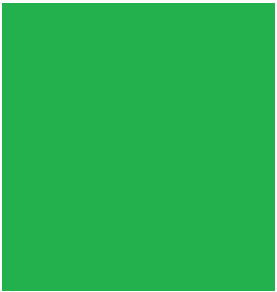

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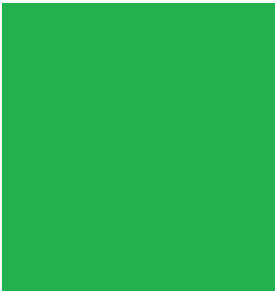

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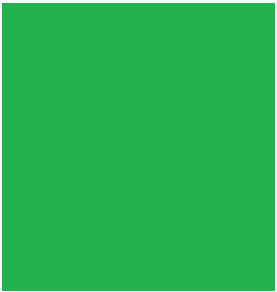

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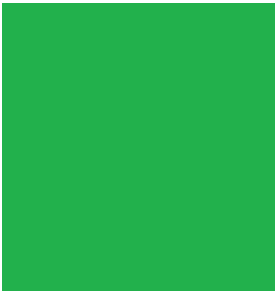

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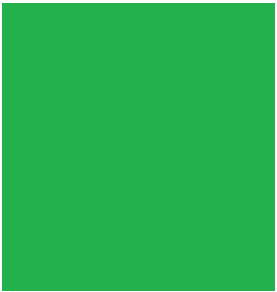

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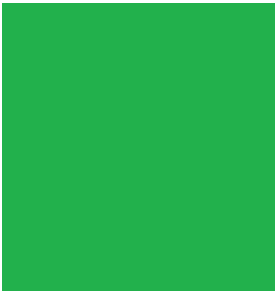

Data Management

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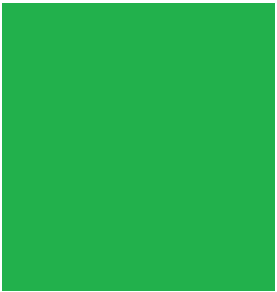

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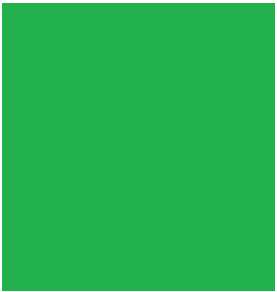

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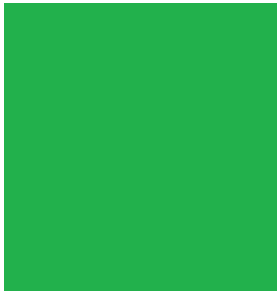

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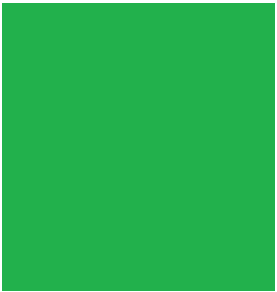

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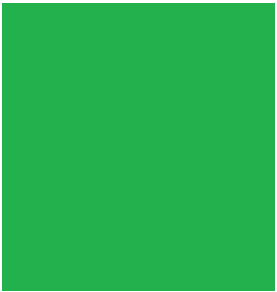

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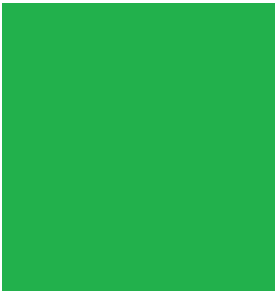

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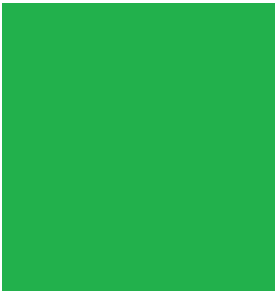

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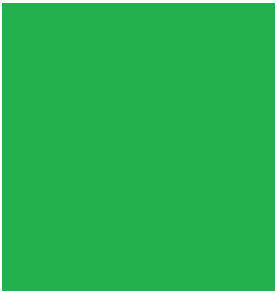

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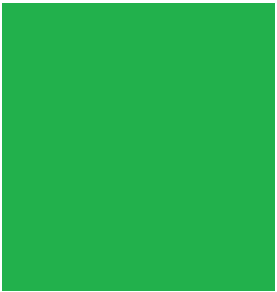

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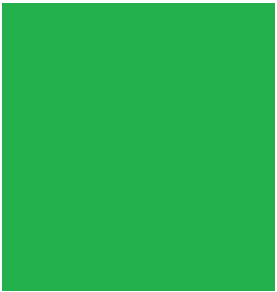

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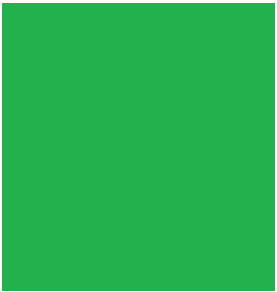

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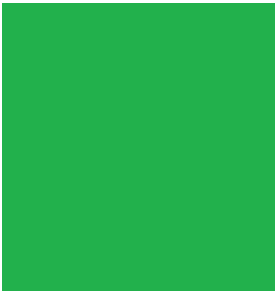
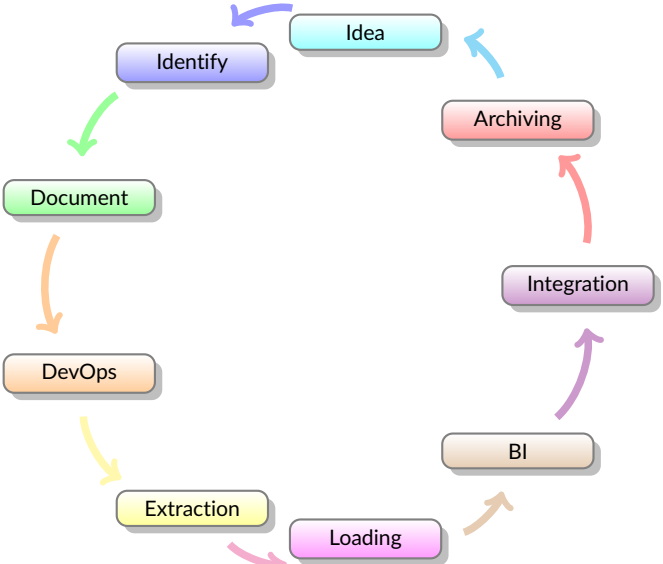
  - **Integration** and publishing.
  - Data retention or **archiving** process ex: (Hot or Cold storage).



Data Management Life-Cycle



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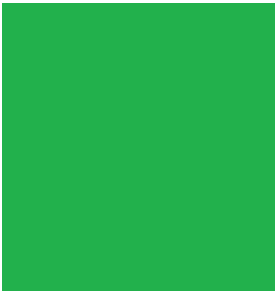

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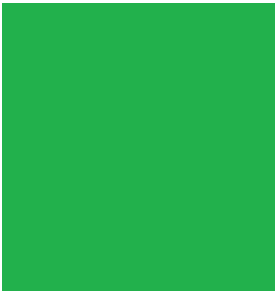

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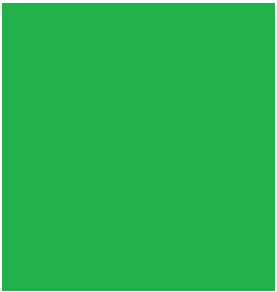

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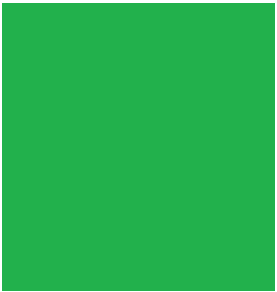

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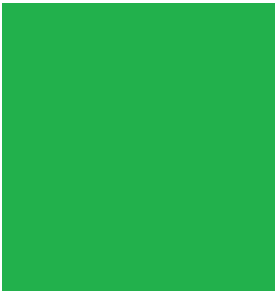

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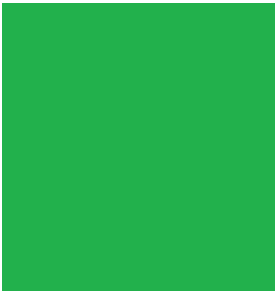

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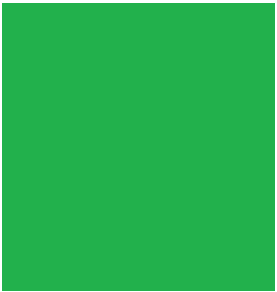

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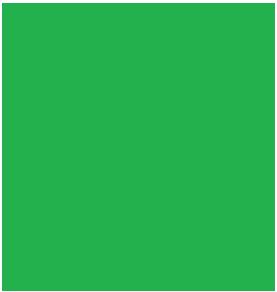
- Vendors who are working to solve the above challenges creating their own product of DWH and their ultimate work is to optimize the above points.

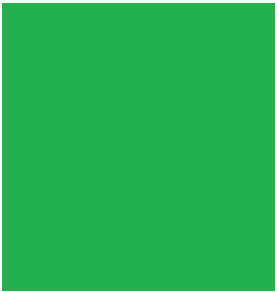


Motivation to Data Warehouse (DWH)

Definition (What is Data Warehousing?)

A DWH is defined as a technique for collecting and managing data from varied sources to **provide meaningful business insights**. It is a blend of technologies and components which aids the strategic use of data.

- The DWH is not a product but an environment.



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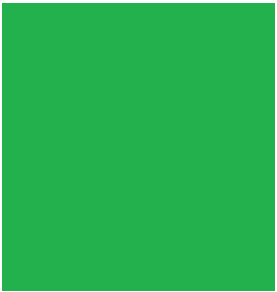

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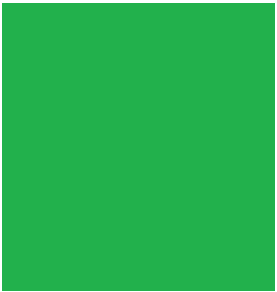

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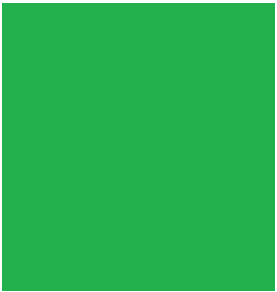
- The DWH is the core of the BI system which is built for data analysis and reporting.

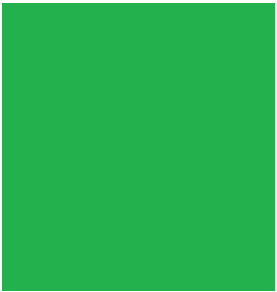


Motivation to Data Warehouse

Data warehouse system is also known by the following names:

- Decision Support System (DSS).
- Business Intelligence Solution.
- Executive Information System.
- Management Information System.
- Analytic Application.
- Data Warehouse.

The real concept was given by Inmon Bill. He was considered as a father of the DWH. He had written about a variety of topics for building, usage, and maintenance of the warehouse & the Corporate Information Factory



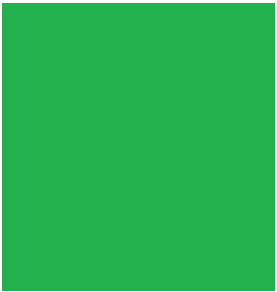
Motivation to Data Warehouse

Types of Data Warehouse

Enterprise Data Warehouse (EDWH) It provides decision support service across the enterprise. It offers a unified approach for organizing and representing data (DWH Model). It offers data classifications according to the subject with privileges policy.

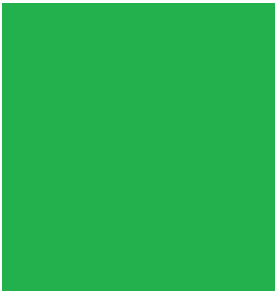
Operational Data Store (ODS): is a central database that provides an up-to-date (real-time) data from multiple transnational systems for operational reporting into a single DWH.

Data Mart: A data mart is a subset of the data warehouse. It specially designed for a particular line of business, such as sales, finance, sales or finance. In an independent data mart, data can collect directly from sources.



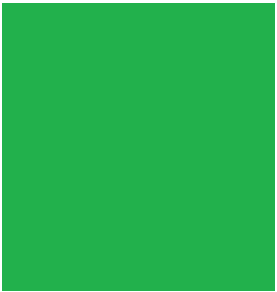
DWH vs ODS vs Data Mart

Metric	DWH	ODS	Data Mart
Latency	Day -1	Real-time	Day -1
Data level	Transnational	Transnational	Summary
Historical	Long-term	Snapshot	Aggregated Long-Term
Size	TB/PB	GB	GB/TB
Orientation	Multi sources	Multi sources	Product
Business Units	Multi organizational units	Product team	Business team



DWH vs Operational databases

Metric	Transactions DB	DWH
Volume	GB/TB	TB/PB
Historical	Short-term	Long-Term
rows	¡1000M	1000M¿
Orientation	Product	Subject or multi products
Business Units	Product team	Multi organizational units
Normalization	Normalized	Not required (De-normalized in many use cases)
Data Model	Relational	Star Schema or Multi-dim
Intelligence	Reporting	Advanced reporting and Machine Learning
Use cases	Online transactions & operations	Centeralized storage (360°)



Transnational DB Use cases

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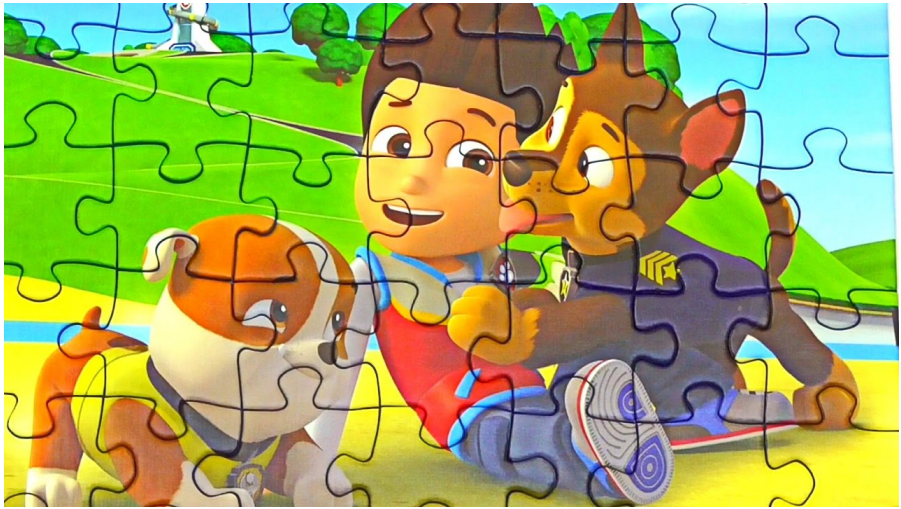

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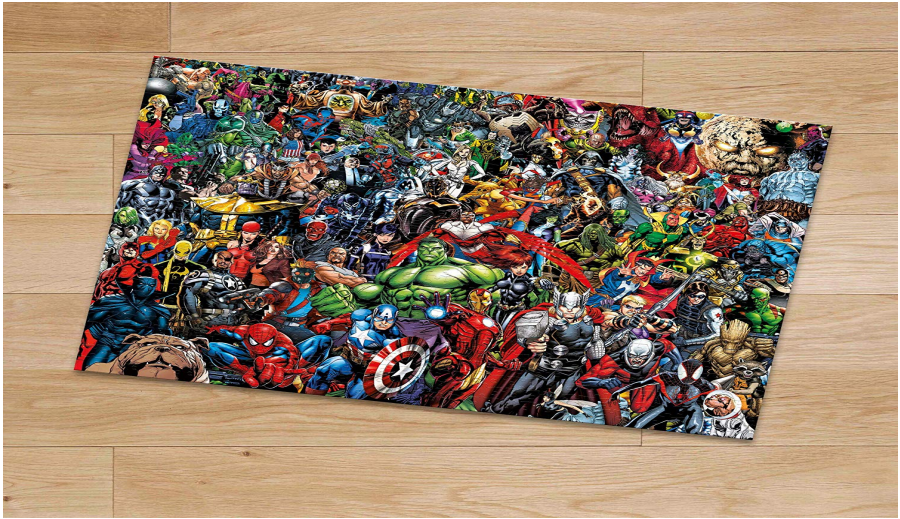
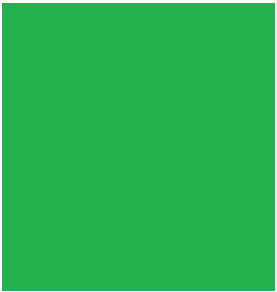


DWH Use cases

Use case (Operational DB)

- A telecommunication company named **XTec**.



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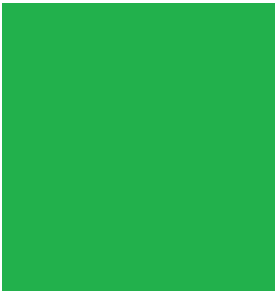
- They have lots of systems. One of this systems is a CRM system as example of operational DB.



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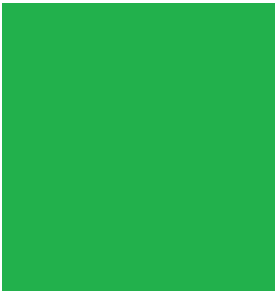

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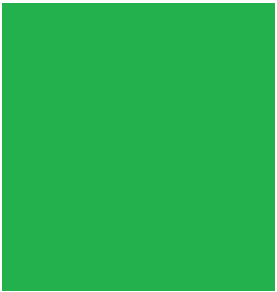

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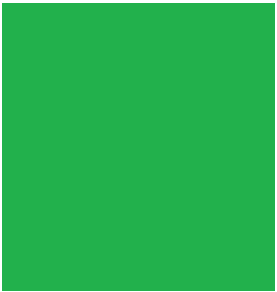

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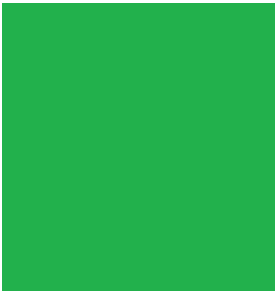
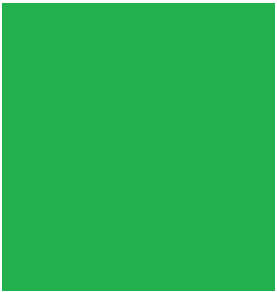
  - Product owner can take a decision based on their system backend reports.



Use case (DWH)

- What is the need for DWH?



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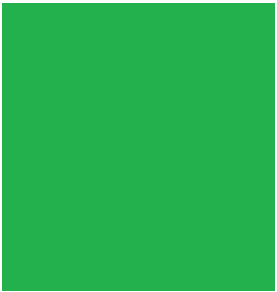
  - This company has other systems for example: billing, charging, signaling.



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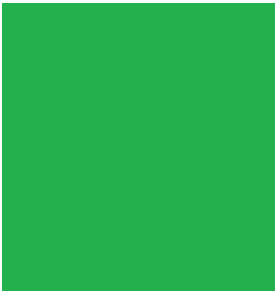

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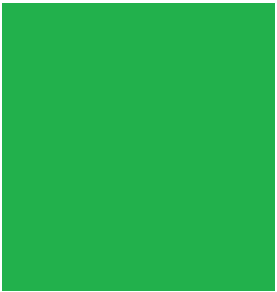

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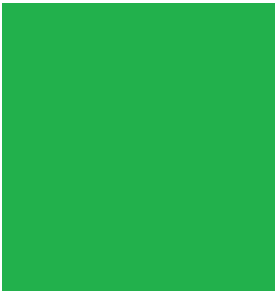

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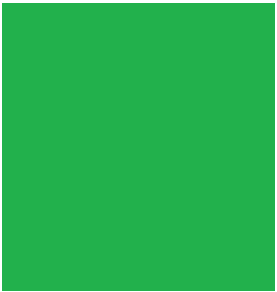
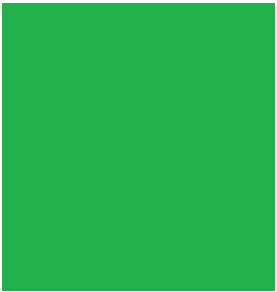
  - If the company needs to build a machine learning model which needs data from different sources. They need to load the data from a centralized database rather than read each source alone.



Use case (DWH)

The Full picture required a DWH. However, we still need the other operational databases for product development perspective.



Use case (ODS)

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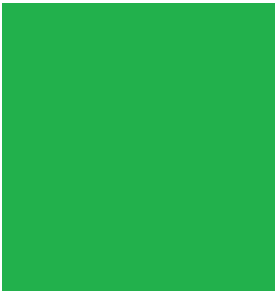
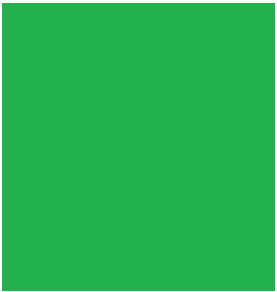


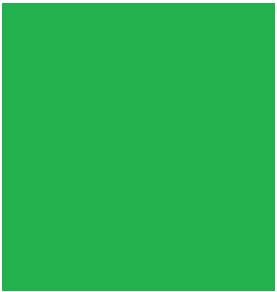
Use case (ODS)

- Why do we need the ODS?
- How does it fit in our system?



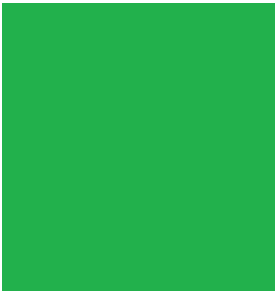
Use case (ODS)

XTec has a call center system which handles the customer inquiries. This system requires the some data related to usage, customer information, billing details to be calculated and accumulated in **real-time** to be able to give the customer the right answer for his inquires.



Use case (ODS)

- So, What is the challenge for this system?



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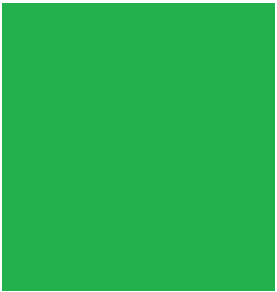

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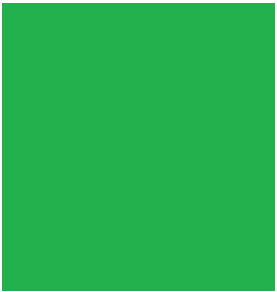

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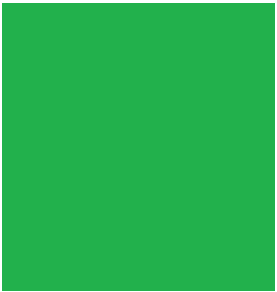
  - It needs specific information from different source systems.
  - It requires to track the source system database changes or update in real-time.
  - It's functionality is based on the aggregate data not the transactions for example (It needs the total outgoing calls till time or it needs the total charging amounts from prepaid or the available limits from billing if it is postpaid).



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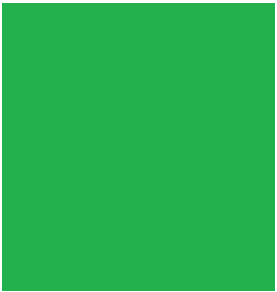

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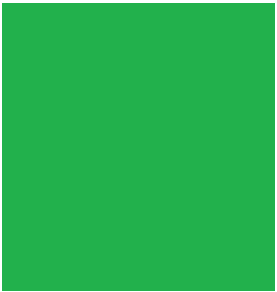
- ODS uses the real-time aggregations to support the online systems from different source systems.



DWH Architecture Overview

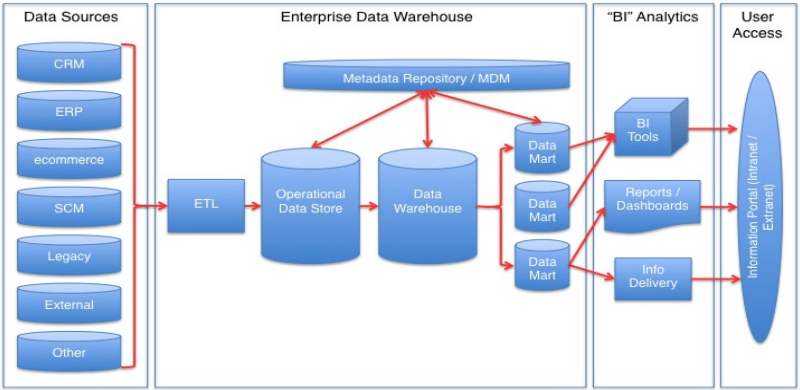
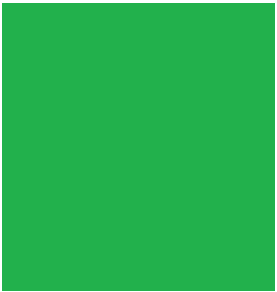


Figure: taken from XXXX

Thinking about data as a product

- How can we think about a data solution?



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- How can we think about a data solution?
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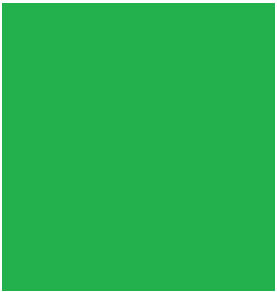

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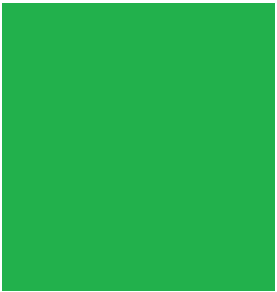

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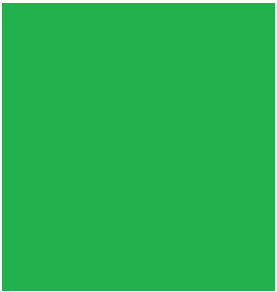

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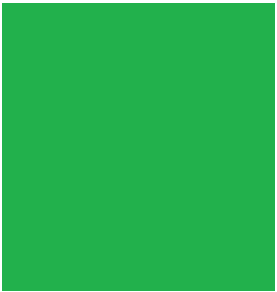

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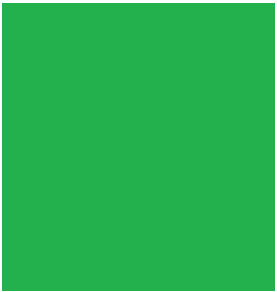

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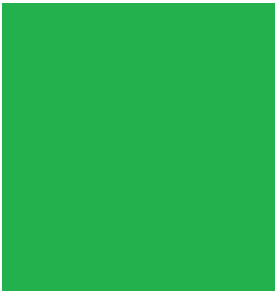

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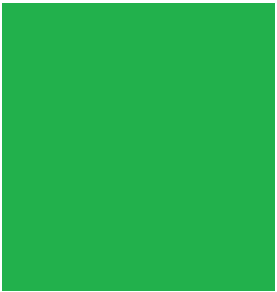

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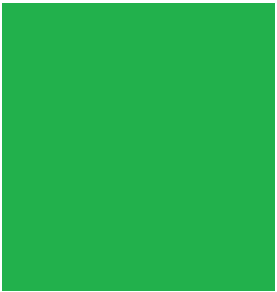
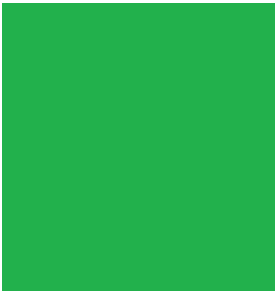
- To answer these questions you need to understand the **data layers**.



Data Layers (Abstraction)

- Any data product (database) contains multi-layers.



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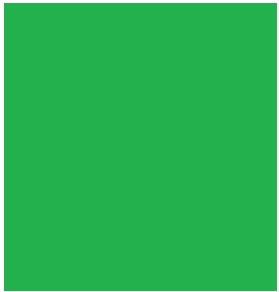

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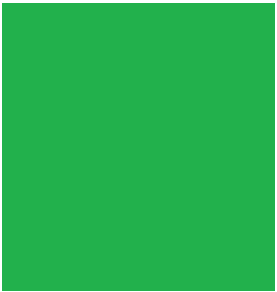

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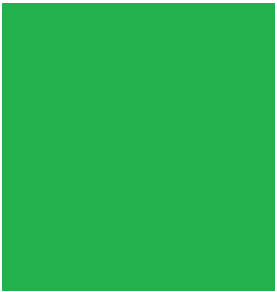

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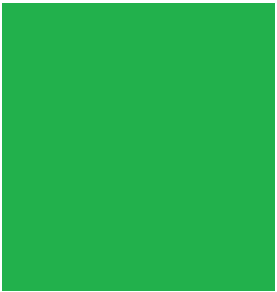

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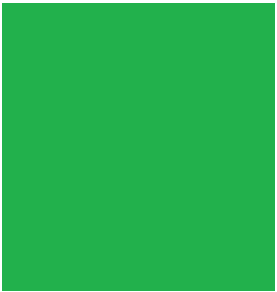
- The process of **hiding** irrelevant details from developer (user) is called data **abstraction**.



Data Layers (Abstraction)

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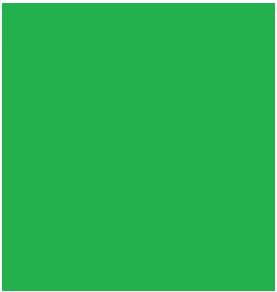
Data Abstraction and Data Independence: Database systems comprise of complex data-structures. In order to make the system efficient in terms of retrieval of data, and reduce complexity in terms of usability of users, developers use abstraction i.e. hide irrelevant details from the users. This approach simplifies database design.

- There are 3 levels of data abstraction.



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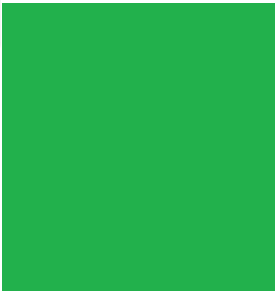

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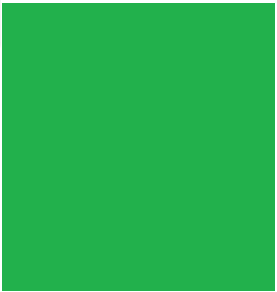

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