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Business Intelligence

Lecture 03 - Descriptive Analytics Part B
Data Warehousing, Business Performance Management

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With particular thanks to

- Marco Spruits (previous BI lecturer)
- Armel Lefebvre (tutor, A.E.J.Lefebvre@uu.nl)
- Vincent Goris (student teaching assistant, vincent.goris93@gmail.com)
- Kristof Fellegi (student teaching assistant, k.fellegi@uu.nl)

Summary of the Previous Lecture(s)

- The Nature of Data
  See [Sharda et al., 2018, chapter 2.1], [Žliobaitė et al., 2016]
- Data Quality and Integrity
  See [Sharda et al., 2018, chapter 2.2–2.3]
- Data Preprocessing
  See [Sharda et al., 2018, chapter 2.4 & Application Case 2.1]

Figure:
[Sharda et al., 2018, p. 92 & 115]

- Statistics Repetition
  See [Hand et al., 2001, Appendix A.1]
- Statistical Modelling
  See [Sharda et al., 2018, chapter 2.5–2.7],
  [Cover and Thomas, 2006, chapter 2], [Hand, 2008], and others
- Business Reporting
  See [Sharda et al., 2018, chapter 2.7]
- Data Visualization
  See [Sharda et al., 2018, chapter 2.8–2.11] and [Segel and Heer, 2010]

Outline: Today's Lecture in the Context of Business Intelligence

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Figure: Context of Data Warehousing within Business Intelligence (Source: [Sharda et al., 2018, page 84])

Descriptive Analytics Part B: Data Warehousing, Business Performance Management

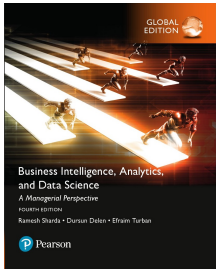

Figure: Textbook [Sharda et al., 2018, Chapter 3]
Sharda, Delen, Turban & King (2018). Business Intelligence, Analytics & Data Science: A Managerial Perspective 4th Global Edition, Pearson. ISBN-13: 9781292220567

Figure: Paper [Chaudhuri et al., 2011]
Chaudhuri, Dayal, Narasayya (2011)). An Overview of Business Intelligence Technology Communications of the ACM, vol. 54, no. 8 DOI:10.1145/1978542.1978562

Advanced Literature (Voluntary Further Reading):

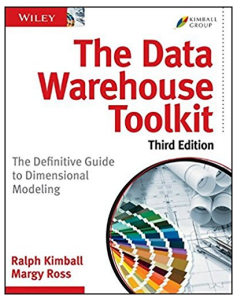

Figure: Textbook [Kimball and Ross, 2013]
Kimball, Ross (2013). The Data Warehouse Toolkit 3rd Edition, Wiley
ISBN-13: 978-1118530801

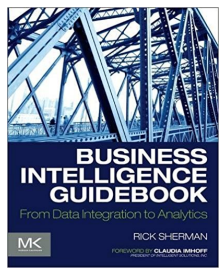

Figure: Textbook [Sherman, 2015, Part III-IV]
Sherman (2015). The Business Intelligence Guidebook 1st Edition, Morgan Kaufmann
ISBN-13: 978-0124114616

Outline and Summary[1]

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Data Warehouse: Motivation

> *The company being profiled within this case study is a privately held Dutch retailer with 2,800 stores across several European countries. This retailer has* **15 different brands** *that include products from toys to cookware,* **each** *brand* **having its own infrastructure**. *Each business entity is* **managed independently** *as one of 15 individual companies in the way they develop their processes, maintain their legacy systems, and make business decisions across finance, IT, supply chain, and general operations.*

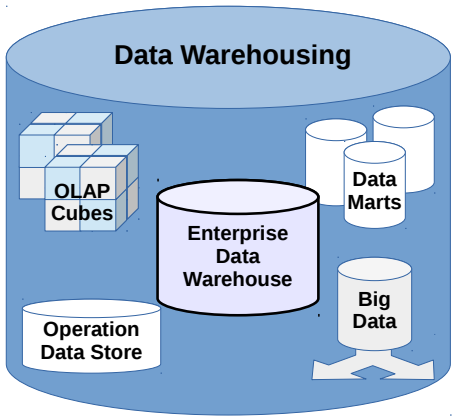
Application Case 3.3
[Sharda et al., 2018, p. 177–179]

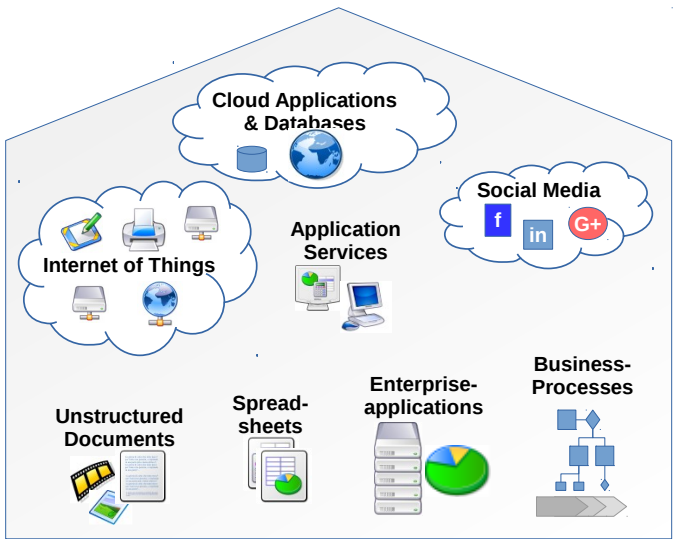
What are the challenges here?

- many organizational units (brands, divisions, . . .)
- managed independently
- heterogenous IS landscape

- *Decision support* require integrating data from many units & systems
- Operational systems and databases (OLTP) are designed independently and with different objectives in mind (*efficiency* and *consistency*)

Data Warehouse: Definition





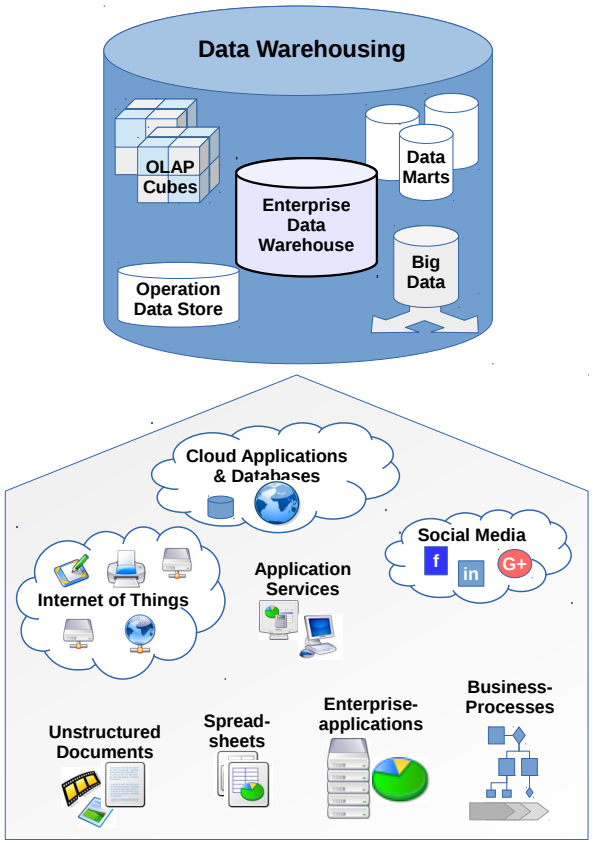
Data Warehouse

- *Central physical* repository
- for *decision support*, providing
- *enterprise-wide*, *cleansed* data
- in a *standardized format*,
- mostly *structured* and *analytics-ready*

Data Warehousing

- subject-oriented
- integrated
- time-variant
- nonvolatile
- collection of data (& metadata)
- often not normalized
- to support decision-making

Data Warehousing: Definition



subject-oriented

- organized by detailed subject
- reduced to decision-relevant info
- *not product-oriented as in operational DBs*

integrated

- fetch data from different sources
- transform into consistent format

time-variant

- temporal quality: time-stamped data
- time as *the* important dimension

nonvolatile

- once stored, data is not to be changed
- obsolete data is discarded, not updated

Data Warehousing: Further (Potential) Characteristics

Web-Based

- designed for web-based applications

Relational / Multidimensional

- either relational structured, or multidimensional structured

Client/Server

- for easy access by end users

Real Time

- real-time, active, data-access and analytics capabilities

Inclusion of Metadata

- metadata describing how data is organized and (to be) used

Data Warehouse: Main Types of DW

Data Marts

- smaller and focused on a particular subject/business unit
- **dependent** of a centralized enterprise data warehouse
  follows a single entreprise-wide data model
- **independent data mart** designed for one unit

Operational Data Stores

- consolidation of data from multiple sources
- near-real-time, integrated view of volatile current data
- used for **short-term decisions**, **short-term memory**
- often used as **interim staging area** for DW

Enterprise Data Warehouse

- **large-scale** data warehouse
- used **accross the enterprise**
- consolidation of data from multiple sources
- standard format for BI/DSS

Data Warehouse: Historical Development

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Timeline of Historical Events in DW Development (Source: [Sharda et al., 2018, page 158])

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Figure: Timeline of Historical Events in DW Development (Source: [Sharda et al., 2018, page 158])

Milestones

1970s	Mainframe computers Data mostly hidden
1980s	Personal Computers Islands of data Distributed DBMS
1990s	Centralized Data Warehouse Data copied & integrated
2000s	DM & Predictive Analytics
2000+	(Big) Data Analytics

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Data Warehousing Process

Data Warehousing

The process

- from data sources
- to data extraction, transformation, loading
- into a comprehensive database
- including managing and retrieving metadata

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Data Warehouse Framework and Views (Source: [Sherda et al., 2018, page 164])

Data Warehousing Architecture: Components

Data Sources

- indep. operational "legacy" systems
- internal OLTP or ERP systems
- external data providers
- web data (logs)

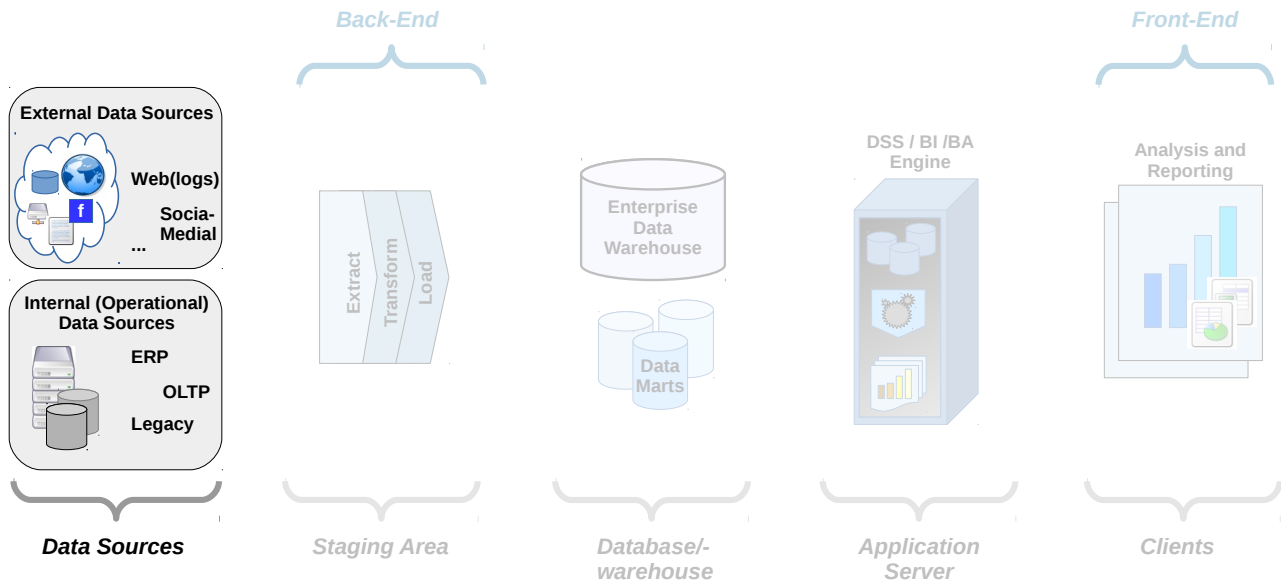

Figure: Data Warehouse Architecture Components

Data Warehousing Architecture: Components

Data Extraction, Transformation

- Subprocess for selection, extraction, transformation of data

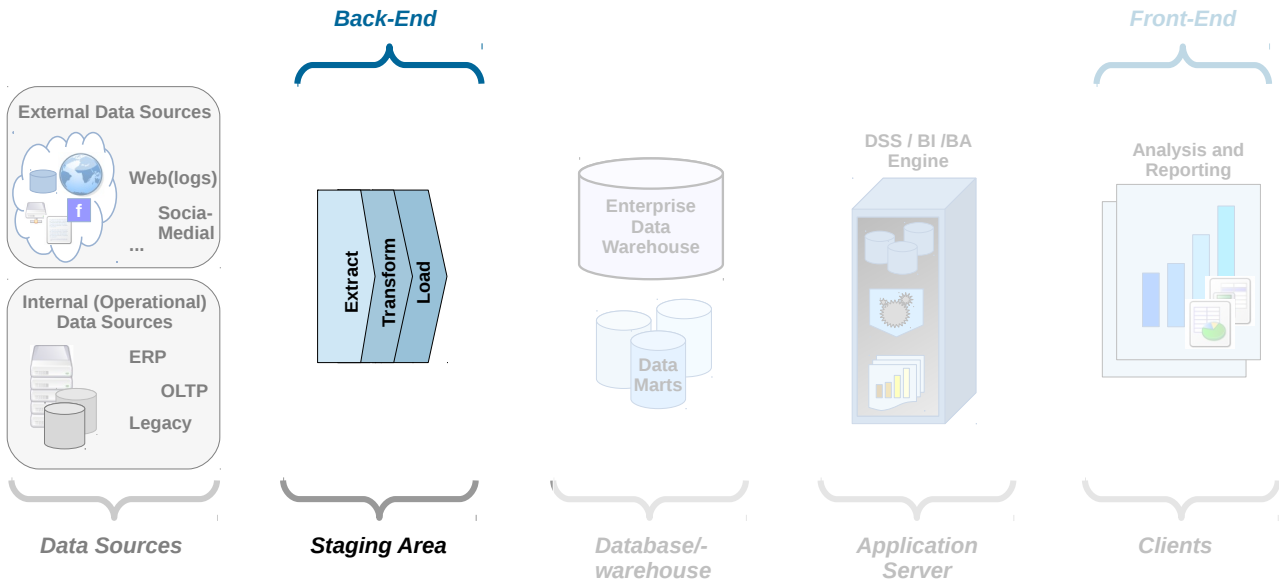

Figure: Data Warehouse Architecture Components

Data Warehousing Architecture: Components

Data Loading

- Loading into a staging area for transformation and cleansing
- Loading into data warehouse

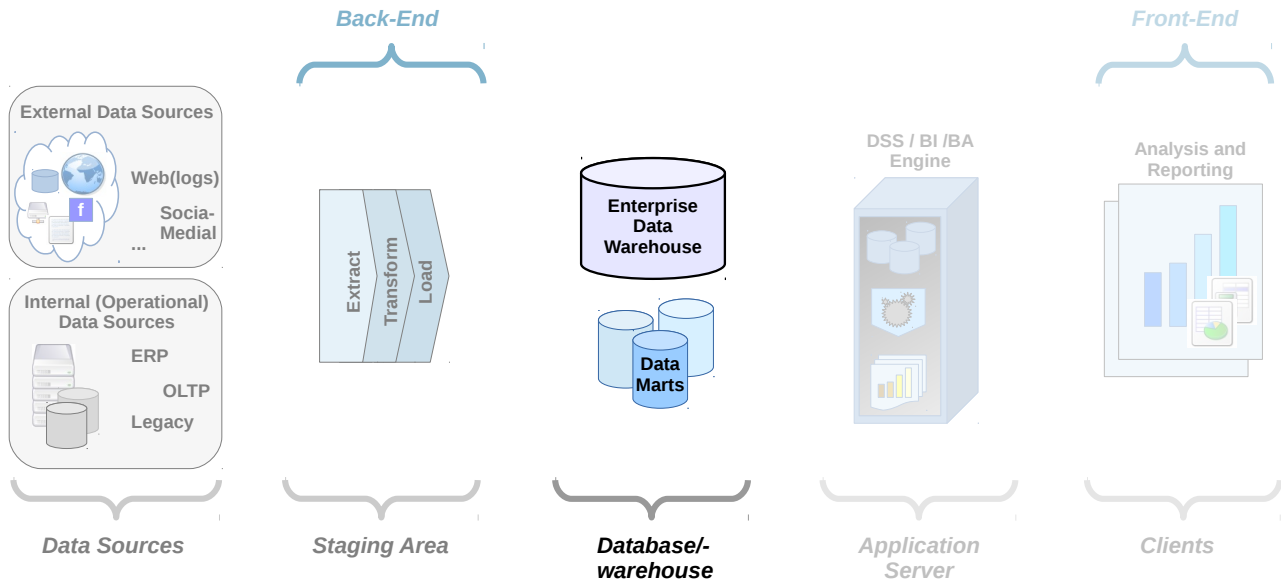

Figure: Data Warehouse Architecture Components

Data Warehousing Architecture: Components

DSS/BI/BA Engine

- Analytics and DSS Software
- Typically an application server

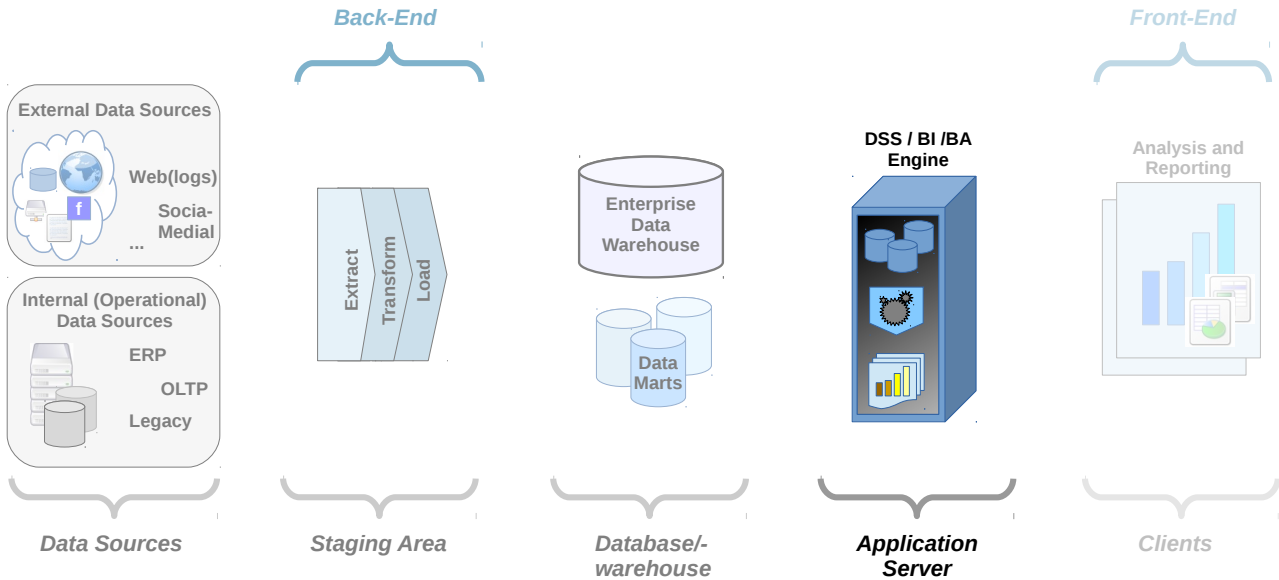

Figure: Data Warehouse Architecture Components

Data Warehousing Architecture: Components

DSS/BI/BA Engine

- Analytics and DSS Software
- Typically an application server
- Sometimes combined with the DB server (two-tier architecture)

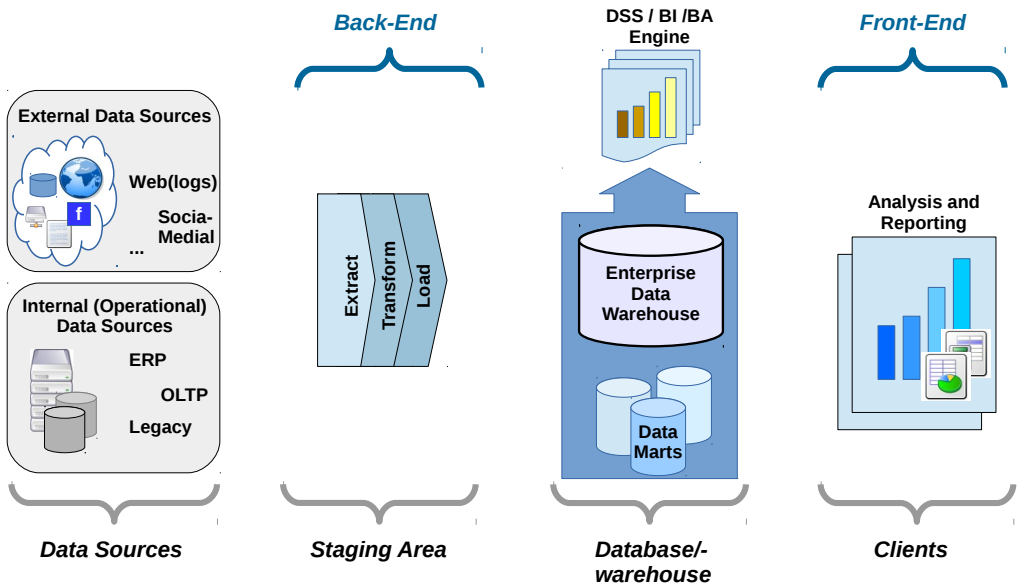

Figure: Data Warehouse Architecture Components

Data Warehousing Architecture: Components

Client / GUI

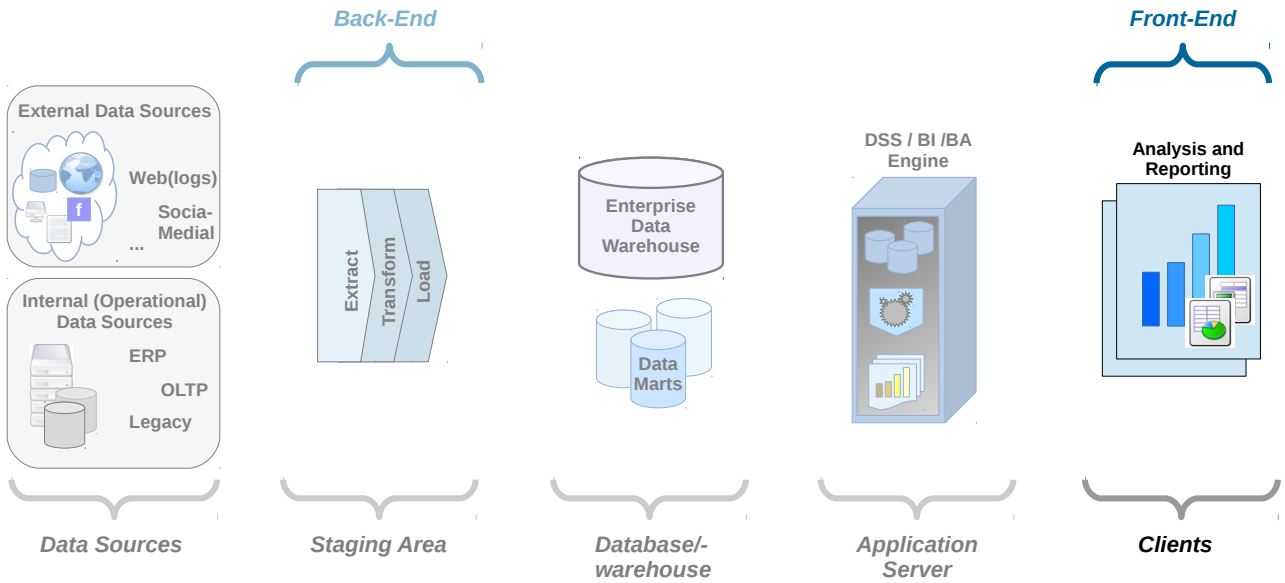

Figure: Data Warehouse Architecture Components

Web-Based Data Warehouse Architecture

- Dedicated Application, Database, and Web-Server

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Web Data Warehouse (Source: [Sharda et al., 2018, page 167])

(Further) Data Warehousing Architectures

Indepedent Data Mart

- Data Marts that are independent of a central Data Warehouse

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Independent Data Mart (Source: [Sharda et al., 2018, page 169])

(Further) Data Warehousing Architectures

Data Mart Bus

- Data Marts are linked by conformed dimensions

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Data Mart Bus (Source: [Sharda et al., 2018, page 169])

(Further) Data Warehousing Architectures

Hub-and-Spoke Architecture

- Normalized Relational Warehouse with
- Dependent Data Marts

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Hub-and-Spoke Architecture (Source: [Sharda et al., 2018, page 169])

(Further) Data Warehousing Architectures

Centralized Data Warehouse

- Normalized Relational Warehouse

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Normalized Relational Warehouse (Source: [Sharda et al., 2018, page 169])

(Further) Data Warehousing Architectures

Federated Architecture

- Several Data Warehouses, Data Marts, and Legacy Systems
- Data Mapping between them

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: The Federated Architecture (Source: [Sharda et al., 2018, page 169])

Data Warehousing Architectures: Comparision[2]

	Indep. D.-Marts	Bus Arch.	Hub-&Spoke Arch.	Centr. Arch.	Fed. Arch.
Popularity	12%	26%	**39%**	17%	4%
Information Quality	4.42	5.16	**5.35**	5.23	4.73
System Quality	4.59	**5.60**	5.56	5.41	4.69
Individual Impacts	5.08	**5.80**	5.62	5.64	5.15
Organiz. Imp.	4.66	**5.34**	5.24	5.30	4.77

Table: Results of an empirical study by Ariyachandra and Watson (2006)

Discussion

- Predominantly used (in 2006) was hub-and-spoke architecture (39%), followed by bus, centralized, and independent architectures
- Hub-and-Spoke: most expensive and time-consuming to implement, mostly with entreprise-wise implementations & larger warehouses
- Bus, Hub- & Spoke, and Centralized architecture perform very similar

[2] Based on Ariyachandra and Watson (2006), cited in [Sharda et al., 2018, p. 170].

Data Warehousing Architectures: Issues to Consider

Which Database Management System (DBMS)?

- Mostly relational DBMS, like Oracle, Microsoft SQL,
- Open Source variantly like PostgreSQL, ...

Will parallel processing / partitioning be used?

- Parallel processing: Enables simultaneous processing of queries
- Partitioning (splitting into smaller subtables) for access efficiency

Use of Data Migration Tools to Load the Warehouse

- Moving data is tedious and costly (see application case study 3.3)
- Tools ease this process (in particular on standard sources)

Tools for Data Retrieval and Analysis

Data Warehousing Architectures: Influence Factors[3]

1. Information interdependence between organizational units
2. Upper managements information needs
3. Urgency of need for a data warehouse
4. Nature of end-user tasks
5. Constraints on resources
6. Strategic view of the data warehouse prior to implementation
7. Compatibility with existing systems
8. Perceived ability of the in-house IT staff
9. Technical issues
10. Social/political factors

[3] Based on Ariyachandra and Watson (2005). Cited from [Sharda et al., 2018, p. 170].

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Data Integration: Preparation for Lecture

Reading assignments

- Application Case Study 3.3
  [Sharda et al., 2018, pages 177–179]
- Paper [Chaudhuri et al., 2011]

Questions?

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Application Case Study 3.3[4]: Discussion

Data Integration: Issues & Lessons Learned

- 6 months for (unsuccessful) integration of SAP ERP
- Estimation of required integration time: 400 days for development of loading from one (out of 15!) SAP ERP system
- Approach using automated system: 5 days for initial SAP ERP loading
  Further 45 days for customising and preparing data for consumption
- Study available (standard) technologies/solutions, focus own development efforts on tasks that require customised/individual solutions

From Prototype to Rollout for Integrating all Brands

- Aim: Integrate all brands (on the long run)
- Approach: Develop a framework for integration (using ETL as ELT tool) on a subset of brands, later apply it to all remaining brands

Further Learning Points

- Keep system design as simple as possible
- Develop standard data governance approach (data integrity beyond implementation!)
- Identify user's needs, e.g., on acceptable latency

[4] See [Sharda et al., 2018, pages 177–179].

Data Integration Capabilities

1. Data Access (from any source)
2. Data Federation (Integration across multiple sources)
3. Change Capture (of changes at the enterprise data source)

Data Integration Capabilities

- Enterprise application integration
  and Service-Oriented Architecture
- Enterprise information integration
- Extraction, Transformation, Load - Process

Data Integration: Enterprise Application Integration (EAI) and Enterprise Information Integration (EII)

Enterprise Application Integration (EAI)

- Integration of application functionality
- Focus on *sharing functionality* rather than data
- Often accomplished by using SOA (Service-Oriented Architecture) Services
- Usable for fast populating of a data warehouse (near real-time)

Enterprise Information Integration (EII)

- Allows virtual data integration by generating views
- Uses predefined Metadata (e.g., XML-based)

Data Integration: Extraction, Transformation, Load - Process

Extraction, Transformation, Load (ETL)

- Extraction: Reading from one/many DBs
- Transformation: Converting to the form needed for the DW or another DB
- Load: Writing the data into the DW

- Often input is written to staging tables to facilitate load
- ETL tools are not only used for populating a Data Warehouse, also for transport between databases
- Automated metadata management (e.g., creation of metadata on how data changes during transport)
- Administration of all runtime processess and operations (e.g., scheduling, error managements, logging)

Image not available due to copyright restrictions. Please refer to the source cited below.

Data Integration: Extraction, Transformation, Load - Process

Issues to Consider when Selecting ETL Tools

- OLAP and Data Mining tools rely no the data transformation!
- ETL tools should support an unlimited number of data source architectures
- Metadata should be automatically handled (capturing, delivering)
- Tools should be conform to open standards
- Interface should be easy to use for developer and functional users
  Complexity in Learning Data Transformation Tools!
- Success only becomes measureable after tools have been learned and the process is completed

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Data Warehouse Development: Main Philosophies

Enterprise Data Warehouse (EDW)

- Propagated by Bill Inmon
- Top-Down approach

Data Mart Approach (DM)

- Propagated by Ralph Kimball
- Bottom-Up approach

Hosted Data Warehouse (HDW)

- Outsourcing DW to external provider ("cloud")
- For small enterprises cheaper
- Privacy and security concerns

Data Warehouse Development: (Dis)Advantages of Hosted Data Warehouses[5]

Possible Advantages

- Minimal investment (in infrastructure) required
- Focus on core competencies/business
- Free-up of money / capacity on in-house systems
- Allows powerful solutions at lower cost
- Scalability/Adaptable to varying needs (e.g., growth)
- Often better integrated & optimised solutions (hard- & software)

Possible Disadvantages

- Loss of competencies & control
- For large enterprises in-house solution might be cheapter on the long-run
- Outsourcing sensible applications and data:
  Security & privacy concerns

[5] See also [Sharda et al., 2018, Technology Insight 3.1].

Data Warehouse Development: Comparison EDW and DM

Characteristics	**EDW Approach**	**DM Approach**
Author	Bill Inmon	Ralph Kimball
Overall	top-down	bottom-up
Architecture	a single enterprise-wide (atomic) Datawarehouse feeds departmental DBs	single business process is modelled; consistency by data bus and conforming dimensions
Complexity	high	simple
Tools	ER-diagrams,	dimensional
Tools	data flow diagrams,	modelling

Table: Comparison between Enterprise Data Warehouse and Data Marts.
Source: Adaptation by [Sharda et al., 2018, p.182] from M. Breslin (2004)

Data Warehouse Development: Comparison EDW and DM

Effort	EDW Approach	DM Approach
Scope	several subject areas	one subject area
Development	years for implementation	months for implementation
	$1,000,000+$ Euros	$10,000 - 100,000+$ Euros
	high difficulty	low-medium difficulty
Data prerequisite	common accross enterprise	common within unit
Sources	many operational & external	only few operational & ext.
Size	Giga- to Petabytes	Mega- to Gigabytes
Time Horizon	Historical Data	Near-Current Hist. Data
Update Freq.	weekly, monthly	weekly, daily, hourly
Hardware	Enterprise Servers, mainframe comp.	Workgroup / standard DB Servers
Simult. Users	100 to 1000+	10*s*
Use	Cross-functional optim. & decision making	Optimization within business area

Table: Comparison between Enterprise Data Warehouse and Data Marts.
Source: Adaptation by [Sharda et al., 2018, p.181] from Van den Hoven, J. (2003)

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Data Modelling[6]

Levels of Data Models

Three levels with increasing complexity and level of detail:

Conceptual Data Model: Business View

Logical Data Model: Architect View

Pysical Data Model: Developer View

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Data Modelling: Recap ER-Diagram and Normalisation[7]

- ER-modelling
- Normalisation
- primary key: used to identify an instance of an entity
- foreign key: reference to an instance of another entity (based on their primary key)
- alternate key: could be used in place of a primary key
- surrogate key: primary key generated by DBMS (e.g., based on counter)

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Data Modelling[8]

Conceptual Data Model

- Overall view of the structure of data in business context
- Independent of any database or physical storage structure
- May contain objects that are never being implemented in physical DB but needed for understanding

Tool for business and IT to define

- Data requirements scope
- Enterprise-wide business terms & measures
- Names, data types, characteristics of entities and their attributes

[8] See [Sherman, 2015, chapter 8].

Data Modelling (2)

Logical Data Model

- Still independent of any database or physical storage structure
- First step in designing architecture of the application
- Specifies the entities & attributes to be implemented
- Identifies relationships between these entities & attributes, and business rules
- Defines primary keys, foreign keys, alternate keys[9]

Physical Data Model

- Represents the logical data model in a DB schema, DBMS specific
- Defines physical objects such as tables and columns
- Specifies referential integrity rules,
  including foreign keys, constraints, event triggers
- Contains DBMS-specific performance and optimisation entities

[9] See [Sherman, 2015, chapter 8, section Entity-Relationship Modelling] for explanations of ER-modelling, primary / foreign / alternate keys, and normalisation.

Data Modelling Workflow[10]

1. Gather business requirements
   - Analyse the data needed by business requirements
   - Identify the data relationships
2. Create the three data models top-down:
   2.1 Conceptual
   2.2 Logical
   2.3 Physical
3. Support the application development
   - Create application specifications
   - Develop applications
   - Deploy applications

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Dimensional Modelling[11]: Multidimensionality

Definition of Multidimensionality

> *"The ability to organize, present, and analyze data by several dimensions, such as sales by region, by product, by salesperson, and by time (four dimensions)" [Sharda et al., 2018]*

Multidimensional Presentation

Dimensions: products, salespeople, market segments, business units, geographical locations, distribution channels, country, or industry

Measures: money, sales volume, head count, inventory profit, actual versus forecast

Time: daily, weekly, monthly, quarterly, or yearly

[11] Recommended reading: [Sherman, 2015, chapter 9].

Dimensional Modelling: Facts and Fact Tables

- (Numerical) measurement of business activity (descriptive dec. analysis attrib.)
- Examples: Sales, expenses, inventory levels
- Ideally stored at the most granular level, leaving aggregation to analytics
  E.g., Salesprice of every unit in euros and eurocents (flexibility vs. storage)
- Primary key: typically combination of foreign keys, or surrogate key

Types of Facts

Is summarisation possible across dimensions?

additive: sum can be calculated across **all** dimensions
Example: Quantity of sold items (sum over time, stores, . . .)

semiadditive: sum can be calculated across **some** dimensions
Example: Bank account balance (sum over accounts but not months)

non-additive: sum **can not** be calculated over **any** dimension
Example: Unit price, ratios, temperature

Note that other aggregation operations (e.g., averaging) might be reasonable.

Fact Tables

Contain columns of two types:

1. Measures of business activity
2. (Foreign) Keys pointing to dimension tables

Dimensional Modelling: Fact Table Example

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Fact Table Example (Source: [Sherman, 2015, page 199])

Dimensional Modelling: Dimensions and Dimension Tables

- Define the Who What Where Why
- Establish business context of the measures
- Used for filtering and aggregating content in fact table
  (e.g., the dimensions used to slice & dice the values in the fact table)
  based on one-to-many relationships with rows in the central fact table
- Descriptive in nature (although some are numeric)
- Often, there is a **dimension hierarchy**
  Example: Geographical dimension (continent:country:province:city)
- Primary key: ideally surrogate key, or source system's primary key

Dimensions

- descriptive, i.e. understandable for business people and BI application designer
- complete, **no missing values! Why?**
- unique, to ensure values are uniquely identifiable
- valid, to be useful for business decisions

Dimensional Modelling: Example

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Dimensional Modelling Example (Source: [Sherman, 2015, page 235])

Dimensional Modelling

- A retrieval-based system supporting high-volume query access

Star Schema

- **Star (join) schema** is the most common and simplest dimensional modelling style
- Comprises a **fact table** surrounded by and connected to several **dimension tables**
- Design aim: fast query response time, simplicity, ease of maintenance for read-only DB
- Consequences of optimisation for analytics rather than storage:
  - to avoid redundancy in fact table, it uses foreign keys pointing to dimension tables
  - dimensions are de-normalised, i.e. a single table per dimension combining attributes that spead across multiple tables in the source system

Snowflake Schema

- Extends the star schema
- Usually only one central fact table, connected to
- multiple dimensions that are normalised into multiple related tables

Dimensional Modelling: Star Schema Example

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Star Schema Example (Source: [Sherman, 2015, page 209])

Dimensional Modelling: Snowflake Schema Example

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Snowflake Schema Example (Source: [Sherman, 2015, page 210])

Dimensional Modelling: Star & Snowflake Schema Examples

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: The Star & Snowflake Schema (Source: [Sharda et al., 2018, page 184])

Dimensional Modelling: Multifact Star Schema Example

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Multifact Star Schema Example (Source: [Sherman, 2015, page 212])

- In practice, multiple facts are required to be considered together
- They share dimensions, called **conformed dimensions**
- For a discussion on conforming dimensions and Master Data Management, see also [Sherman, 2015, p. 220–221]

Dimensional Modelling: Mapping to Business Report

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Mapping from Dimensional Model to Business Report (Source: [Sherman, 2015, page 217])

Dimensional Modelling: ER vs. Dimensional Model

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: ER vs. Dimensional Model (Source: [Sherman, 2015, page 216])

Note: For differences between ER and Dimensional Modelling see also [Sherman, 2015, Table 9.1, p. 215]

Analysis of Data in Data Warehouse: OLAP

Online Analytical Processing (OLAP)

- Approach for answering ad-hoc questions (reports)
- by executing multidimensional analytical queries against Data Warehouses (or other organisational data repositories)
- Convert data into information for decision support
- Conducting statistical and other analyses
- Most common data anylsis technique for DW
- Data cubes, drill-down / rollup, slice & dice, ...
- Compare to Online Transaction Processing (OLTP):
  Capturing and storing data from ERP, CRM, POS, ... (see next page)
  The main focus there is on efficiency of routine tasks

Multidimensional Schema: Online Analytical Processing (OLAP)

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Example of a 3-Dimensional Data Cube (Source: [Sharda et al., 2018, page 186])

Data Cube

- multidimensional array (data structure)
- supports fast analysis of data
- overcomes limitations of traditional RDBMS (those focus on row-wise adding/deleting/updating capabilities)

Slice

- A 2D-subset of a multidim. array
- Example: Sales of a specific product along time & region
- Generalisation beyond 2D: **Dice**

Online Analytical Processing (OLAP)

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: Example of a 3-Dimensional Data Cube (Source: [Sharda et al., 2018, page 186])

Drill Down/Up

- Navigating through levels of aggregation/summarisation
- E.g.: Going from total sales to sales of a specific product at a time & region

Roll-Up

- Computing all of the data relationships for one or more dimensions

Pivot

- Changing dimensional orientation of a report / query page display

Outline and Summary[1]

- Definition & History of Data Warehouses
  See [Sharda et al., 2018, chapter 3.2]
- Data Warehousing Process & Architectures
  See [Sharda et al., 2018, chapter 3.3–3.4]
- Data Integration and ETL Processes
  See [Sharda et al., 2018, chapter 3.5]
- Data Warehouse Development
  See [Sharda et al., 2018, chapter 3.6]
- Data Modelling & Dimensional Modelling
  See [Sherman, 2015, **chapter 9** and parts of 8] and [Sharda et al., 2018, chapter 3.7–3.8]
- Issues, Considerations & Future Trends
  See [Sharda et al., 2018, chapter 3.7–3.8] and **[Chaudhuri et al., 2011]**
- Business Performance Management
  See [Sharda et al., 2018, chapter 3.9-3.11]

▸ Start ▸ Appendix

[1] Note: This lecture integrates knowledge from several further sources (cited where used, except if my own).

Issues and Considerations

- **Sponsorship Chain:** Support from top-level executives
  That is, a resouce-providing "sponsor" and a decisive but flexible "project driver"
  Why: DW needs architectural framework for decision analysis throughout enterprise
- **Expectation Management:** Realistic expectations, plan capacity & speed reserves
- **Data Landfill:** Filling Data Warehouse with irrelevant data
- **Awareness of DW DB Design Particularities:**
  redundant, not normalized, multidimensional
  (vs. transactional DB design: non-redunant, normalized, relational)
- **User before Technology:** DW must serve the user
  Focus on user- rather than technology-orientation
- **Moving from Reports to Alerts:** Periodical reports are a 1st step, but event-triggered as-soon-as-possible alerts are the aim
- **Clear and Simple:** Avoid conflicting data definitions and formats

Securing a Data Warehouse[12]

1. Establish Corporate & Security Policies & Procedures
   Communicate them to employees on all levels
2. Develop logical security procedures & access restriction techniques
   This comprises authentication, access control, encryption
3. Limit physical access to data center
4. Establish an internal control review process
   Should focus on security & privacy

[12] Based on [**?**], cited in [Sharda et al., 2018, p.190–191].

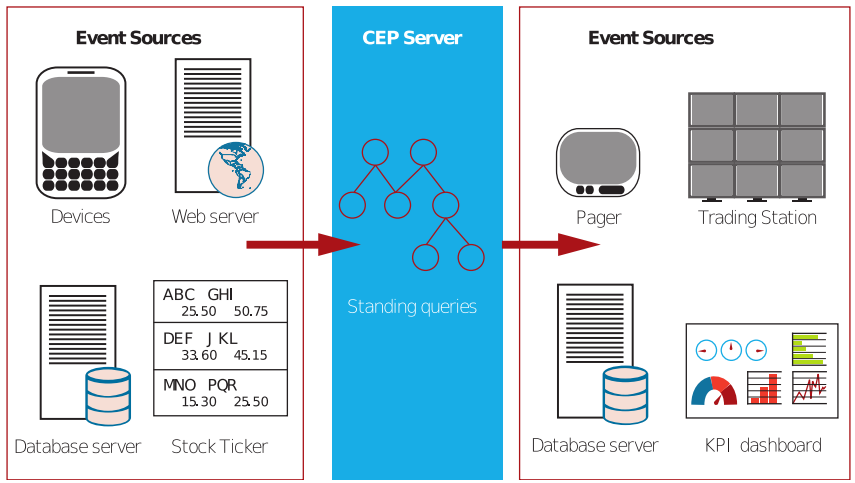
Current Trends & Developments

Big Data

- Recap: Velocity, Volume, and Variety
- Data from many sources (Web, Social Media, Internet of Things)
- Data of many kind (structured, semi- and unstructured)
- Already discussed: Streaming/Online processing

Near Real-Time Streaming BI

- Complex Event Processing (CEP) Engines
- Search for **events** over streaming operational data: pre-specified patterns or temporal trends
- Do not require data being loaded into warehouse
- Define so-called **standing** (or continuous) queries that use operations such as filtering, windowing, aggregation, unions, joins



Current Trends & Developments: Data Lakes

Data Lakes

- Data Warehouse: focus on cleaned, structured & tabular data
  Schema-on-write: Shape & structure data when writing it into DW

- **Data Lake:** Large storage for all types of data
  Loosely defined, stored in native/raw format
  Schema-on-read: Shape & structure data when reading it from DL
  Flexible, but sophisticated (requires specialists as users)
  Low cost storage, but limitations in speed

Current Trends & Developments: DB Technologies

In-Database Processing

- "Put the algorithm where the data is"
- Integrate analytics algorithms into DW
- Advantage: Performance improvements, high-throughput
- Disadvantage: Complexity, requires specialised tools

Database Technologies

- **Columnar:** column-oriented processing
  Efficient when doing operations over most rows but (few) columns
  Allows better compression (due to homogenity of data within each column)
- **In-Memory Storing:** (RAM rather than hard disk, fast but costly)

Current Trends & Developments: Distributed Systems

Distributed Systems

- Platforms based on distributed file systems
- Highly parallel processing using **MapReduce**
- Open Source Apache **Hadoop** Ecosystem
- Tools for translating SQL-like queries
  (also available for R!)

Further Trends

- Open Source Software
- Software as a Service, extending the Application Service Provider model
- Virtualisation & Cloud Computing

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Data Warehousing: Aligning it with Business Strategy

Expedias **problem was not lack of data**. *The customer satisfaction group at Expedia knew that it had lots of data. In all, there were 20 disparate databases with 20 different owners. [. . .]*

The business analyst spent 2 to 3 weeks every month pulling and aggregating the data, leaving virtually no time for analysis. Eventually, the group realized that **it wasnt enough to aggregate the data**. *The* **data needed to be viewed in the context of strategic goals**, *and individuals had to take ownership of the results.*

Application Case 3.6
[Sharda et al., 2018, p. 208–209]

Key Messages:

- data alone is worthless: "data landfill"
- view it in context of strategy!

Approach:

1. Analyse fundamental performance drivers, and the link between performance & costs
2. Decide how to measure satisfaction
   Basis for scorecards & KPIs
3. Set right performance targets
4. Put data into context
   Link to ongoing actions

Data Warehousing: Aligning it with Business Strategy

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: The closed-loop BPM cycle (Source: [Sharda et al., 2018, page 197])

Strategy:

- Where do we want to go?
- Long-time perspective (several years)
- Identify & state organisation's mission, vision, objectives
- Develop according plans (strategic, tactical, operational)

Plan:

- How do we get there?
- Detailed **operational plan**
  1. Start with revenue-generating tactics
  2. Next, focus on their associated costs
  3. Finally, overhead & financing costs

Data Warehousing: Aligning it with Business Strategy (2)

Image not available due to copyright restrictions. Please refer to the source cited below.

Figure: The closed-loop BPM cycle (Source: [Sharda et al., 2018, page 197])

Monitor/Analyse:

1. How are we doing?
2. Identify indicators or measures
3. Develop measuring strategy
4. Examples of Measures:
   Key performance indicators (KPIs)
   See next slides ...

Act and Adjust:

1. What needs to be done differently?

Performance Measurement: Key Performance Indicator (KPI)

Key Performance Indicator

- A **strategically aligned** measure
  embodies a strategic objective
- Measures **performance against a target**
  E.g., achievment target
- with a **performance range** (above/on/below target)
- **Encoding** that alows visual display (e.g., percentage)
- Assigned to **time frame**

Performance Measurement: Key Performance Indicator (KPI) (2)

Categories of KPIs

- Outcome KPIs or lagging indicators
  measure output of past activity
- Driver KPIs or leading indicators
  measure activities that will impact outcome KPIs (later)

Examples

- Customer performance: Customer satisfaction/retention, ...
- Service performance: Metrics for service-call resolution rates, ...
- Sales operations: New pipeline accounts, sales meetings secured, ...
- Sales plan/forecast: Metrics for price-to-purchase accuracy, ...

Business Performance Management

- A set of integrated, closed-loop management & analytic processes
- Tools for defining strategic goals, operationalising (making them measurable) & evaluating achievment of them
- Methods & tools for monitoring key performance indicators (KPIs), linked to organisational strategy

BPM Instruments Overview

Balanced Scorecard

Indicators along 4 dimensions

- customer
- financial
- business process
- learning & growth

Dashboard

Graphical presentation of several performance indicators
in a single page using dials/gauges

Key Performance Indicator (KPI)

A strategically aligned measure of performance against a target,
suited for visual display

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Outlook: Predictive Analytics

Next Lecture

- Predictive Analytics: Data Mining: [Sharda et al., 2018, chapter 4–5]

Any More Questions?

Thank you!

Appendix

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