ETL and Data Warehouses

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Disclosures

I have no relevant financial relationships with commercial interests to disclose in relation to the content of this presentation.

Learning Objectives

- Describe a Data Warehouse
- Define the ETL (extract-transform-load) process
- How does a Data Warehouse add value

Agenda



The economy, stupid.

-James Carville

Competitive (and noncompetitive) forces are driving down reimbursements





What's the *VALUE*?



What's the *RISK*?

Quality

Occasional disconnect between Perception and Reality

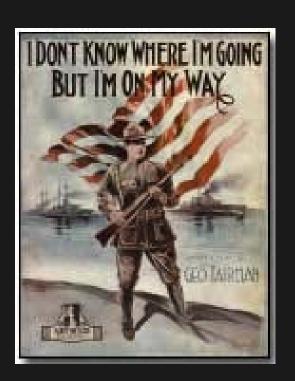


High Performing Enterprises

are Innovators



Healthcare Systems are in the Information
Business, some of them act like it



Clinical Use of an Enterprise Data Warehouse

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Abstract

The enormous amount of data being collected by electronic medical records (EMR) has found additional value when integrated and stored in data warehouses. The enterprise data warehouse (EDW) allows all data from an organization with numerous inpatient and outpatient facilities to be integrated and analyzed. We have found the EDW at Intermountain Healthcare to not only be an essential tool for management and strategic decision making, but also for patient specific clinical decision support. This paper presents the structure and two case studies of a framework that has provided us the ability to create a number of decision support applications that are dependent on the integration of previous enterprise-wide data in addition to a patient's current information in the EMR.

Introduction

Inpatient and outpatient electronic medical records (EMR) are accumulating enormous amounts of patient, provider, facility, financial and process information. During the early 1990s, this information began to be recognized as an extremely valuable and untapped resource for management and clinical research. However, EMR administrators were concerned about the impact of running large research queries on the clinical database. It was determined that healthcare needed to convert this data into aggregated and separate information systems that could support retrospective and population-based analysis¹. Data warehouses had emerged in other industries; however, their adoption by healthcare was slow due to the complexity and heterogeneity of medical, operational, and clinical data².

As an effort to facilitate access to this wealth of medical information, data warehouses that contained clinical and administrative data from healthcare organization began to be developed³. Using network technologies, interfaces were developed to collect the data from the different databases and stored in a single large database. However, early on, it was recognized that the data from many sources not only needed to be integrated, but also cleansed, and formatted. Data semantics were then used to regroup and merge patients' medical data from the autonomous and heterogeneous health information systems⁵. As expected, this raised concerns of data security and patient privacy. Solutions supporting U.S. and European laws for high level of security, retrieval audit, and user authentication needed to be incorporated to ensure privacy and confidentiality^{2,5}. As further uses for data warehouses were identified, image data using the (digital imaging and communication in medicine) DICOM standard was used to integrate information from picture archiving and communication system (PACS)⁶⁻⁸. The advantage of sharing data owned by different organizations was identified and federated information models were developed⁹⁻¹¹. While HL7 is often used as the interface standard for integrating the data from divergent data silos, other data standards including RxNorm¹², SNOMED-CT, ICD, CPT, LOINC, UMLS and DRG codes^{3,13,14} are also often included within the data warehouses. The data stored within these data warehouses can be managed and accessed through direct Structured Ouery Language (SOL) calls or SOL that is imbedded inside of Application Programming Interfaces (APIs) that are programmed in C++, Java, Perl, etc. User interfaces have also been developed in Visual Basic and distributed as ActiveX objects embedded in an HTML page 15 or information retrieval can be performed using metadata-based semantic and full-text search methods¹⁰. Web front-ends using i2b2 and caGrid frameworks

Intermountain Healthcare

Established EDW ~20 yrs ago

Data Driven Enterprise

Business Intelligence

Clinical Operations

Research

Evans, R.S, et. al. (2012) Clinical Use of an Enterprise Data Warehouse. *AMIA Annu Symp Proc.* .p189-198 PMID: 23304288

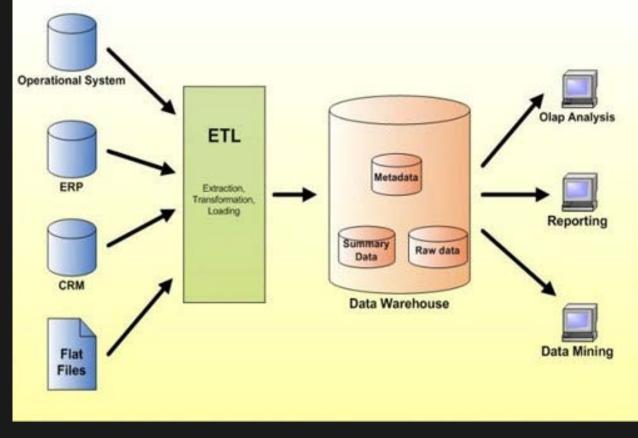
How to define a Data Warehouse?



How to define a Data Warehouse?

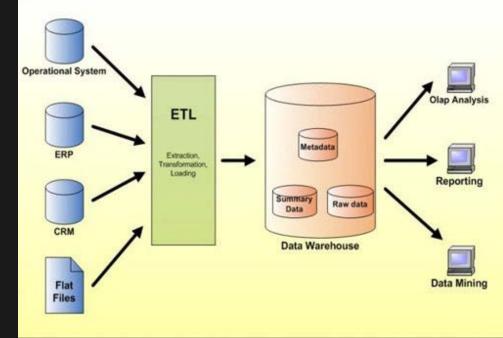
Wikipedia = No Help



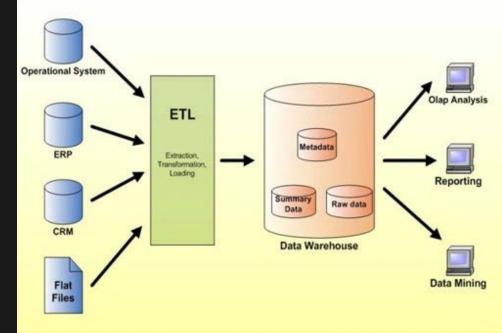


Distillation of every Data Warehouse diagram

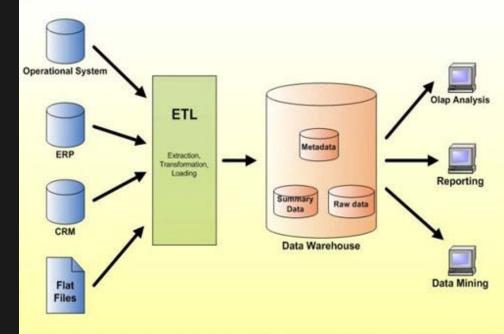
1. Ambiguous cylinders



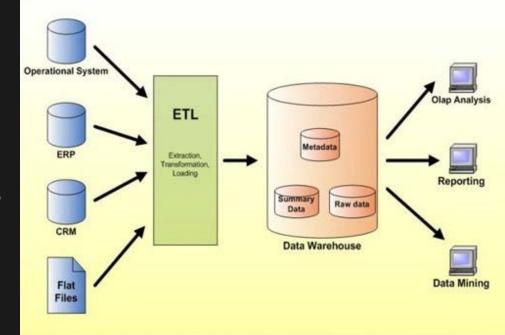
- 1. Ambiguous cylinders
- 2. Magic Box



- 1. Ambiguous cylinders
- 2. Magic Box
- 3. Larger cylinder



- 1. Ambiguous cylinders
- 2. Magic Box
- 3. Larger cylinder
- 4. 80's era terminals



Common Characteristics of a Data Warehouse

1. Multiple sources of data

Common Characteristics of a Data Warehouse

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- 2. Data Transformation/Normalization

Common Characteristics of a Data Warehouse

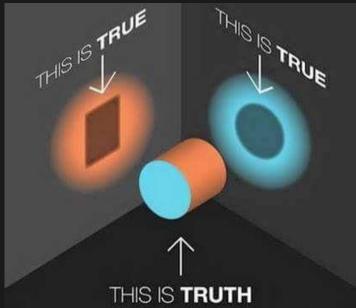
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Common Characteristics of a Data Warehouse

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- 4. Reporting Tools

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Define the source of "Truth"



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Define the source of "Truth"

Source systems vs. Local Copy

Federated Model

Upfront Cost



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Recurring Effort



Local Copy

Upfront Cost



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Recurring Effort



Data Model



Enterprise data model

- 1. Multiple sources of data
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Data Lake

- . Multiple sources of data
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Enterprise Data Model

"A place for everything, and everything in its place."



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Enterprise Data Model

Effort is theoretically front-loaded in setup and design, reporting should easier since data is "clean"



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ETL - Extract, Transform, Load,

Import data from source system

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ETL - Extract, Transform, Load

Convert formatting to conform to destination data format

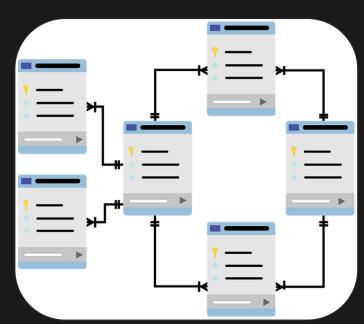
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ETL - Extract, Transform,

Load

Star schema - Dimensions and Facts

Database Normalization



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ETL - Extract, Transform, Load

After conversion, store data in to the data warehouse

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ETL - Extract, **Transform**, Load

Data conversion is one way...

Potential for loss of meaning, may not be able to reconstruct original data

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ETL - Extract, Transform, Load

Trending values over time... have methods and reference ranges remained constant?

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ETL - Extract, **Transform**, Load

What version of AJCC or WHO were used for diagnosis or classification?

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ETL - Extract, Transform, Load

May need to consider Metadata

"Metadata is just data about data"

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Enterprise Data Model

Inability to recover the original data is not ideal



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Enterprise Data Model

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Falling storage costs have enabled the Data Lake concept



Data Lake

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Complete Copy - Native Format

Data Lake

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ETL

CompleteCopy - NativeFormat

Data Lake

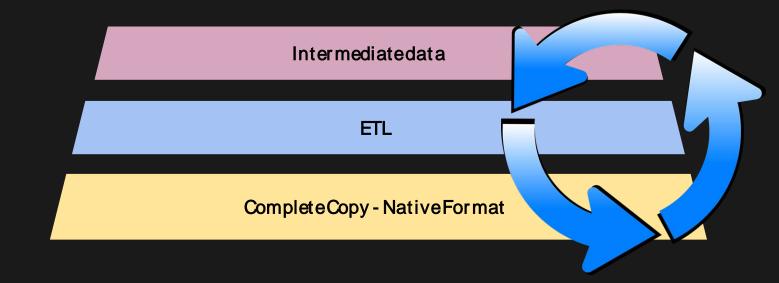
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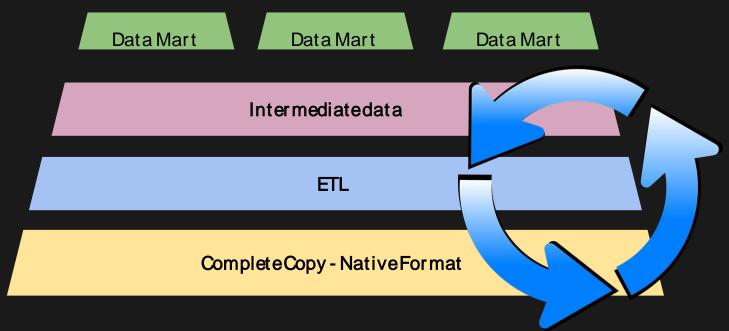
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Data Marts

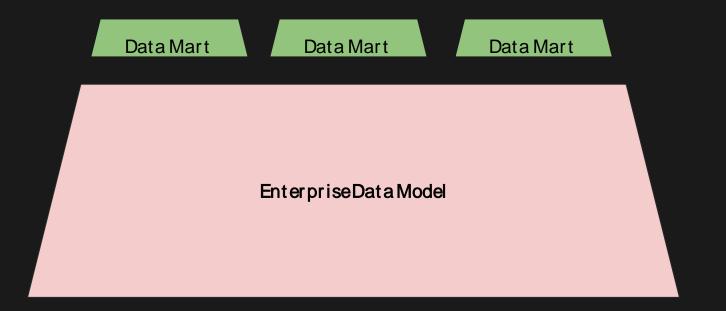
- Smaller DBs with limited scope
- Designed for a specific purpose

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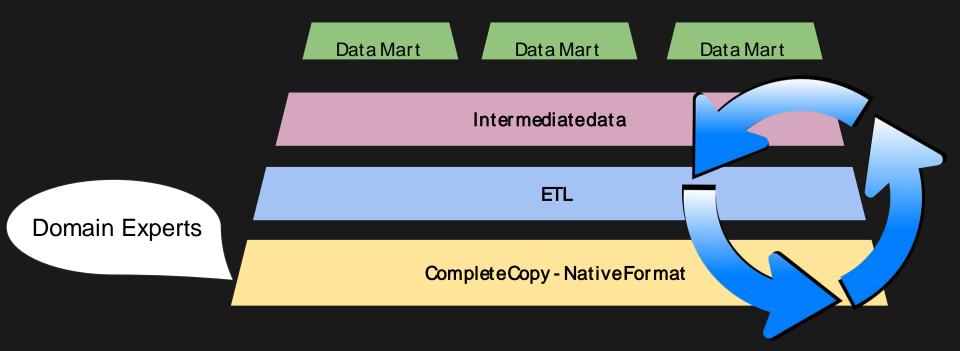
- Smaller DBs with limited scope
- Designed for a specific purpose
- Enhanced performance

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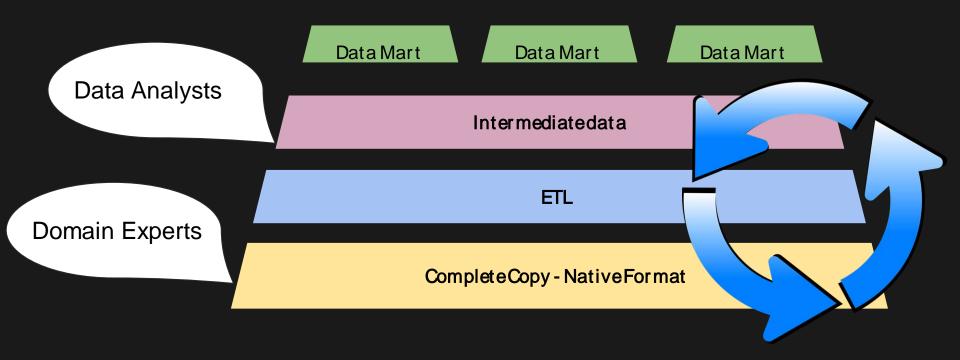
Data Marts

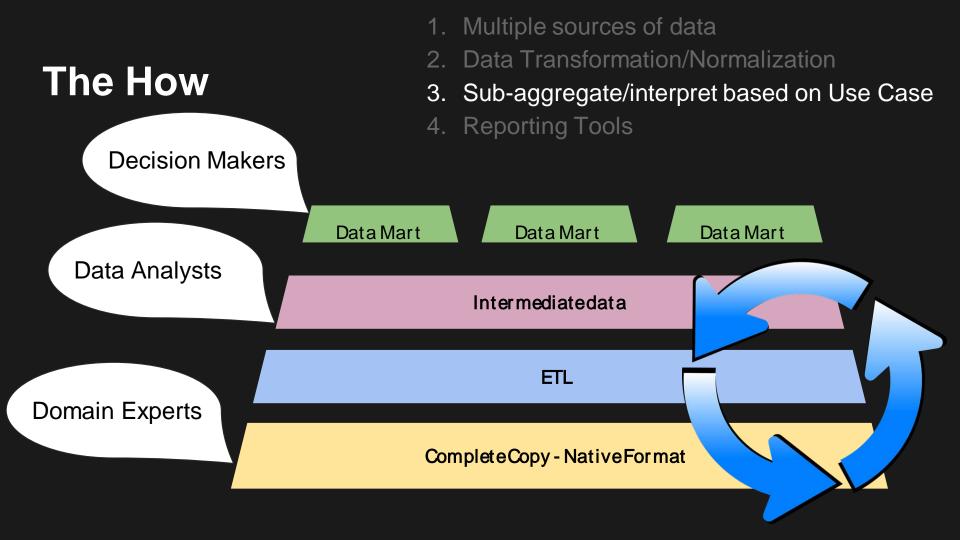
- Smaller DBs with limited scope
- Designed for a specific purpose
- Enhanced performance
- Encapsulate Domain Specific Knowledge

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Often overlooked but Critical to the success of a data warehouse

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Often overlooked but Critical to the success of a data warehouse

The purpose of the data warehouse is to empower end users

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Typically referred to as "Business Intelligence"

Applications:

Tableau, Sisense, MS Power BI, Crystal Reports, Excel, etc.

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Questions?

Thank you

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