

A Model of Data Maturity to Support Predictive Analytics, Part Deux

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Has no real or apparent conflicts of interest to report.

Agenda

- Introduction
- Problem Statement
- Industry Standards / Current Literature
- Data Team Overview / Background
- University of Virginia's Data Model and Architectural Design
- Implications for Practice
- Questions

Learning Objectives

- Describe the data maturity progression that an organization undergoes as it becomes data-driven
- List the data architecture activities that support the data maturity progression journey
- Recognize the various benefits that are achieved as an organization progresses toward agile analytics

Introduction

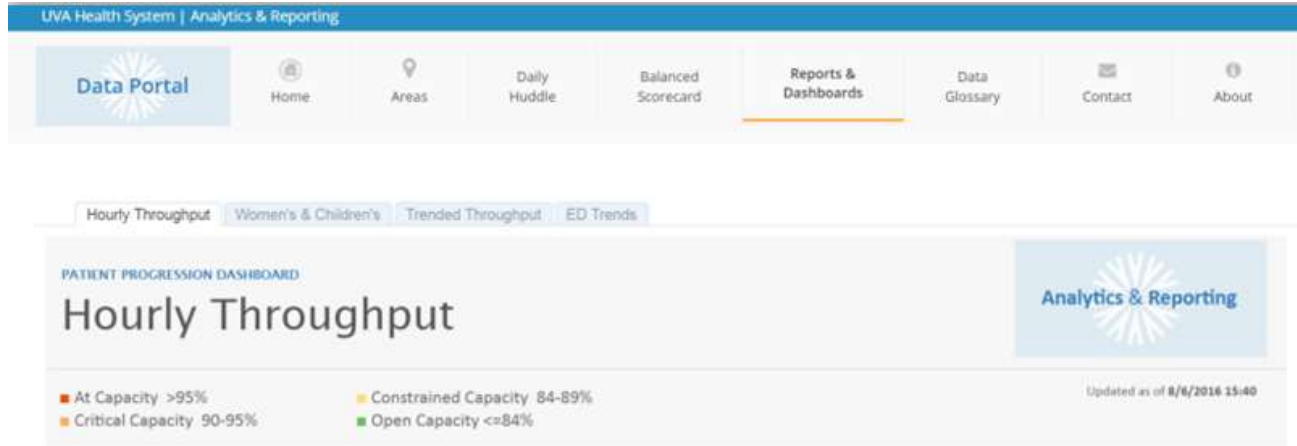
- Use of data within an organization follows a maturity progression:
 - Operational / retrospective -> Strategic / prospective
- Foundational components must be present before advancing, including:
 - Data warehouses / data marts / reporting tables
 - Analysis cubes
 - Intra-day data extraction
 - Advanced data modeling

Problem Statement

The journey toward data use maturity requires expert support and an advanced data infrastructure that increasingly must deliver real-time analysis.

Operational Use Cases

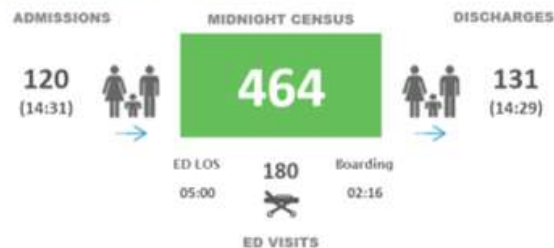
- Hourly Throughput Dashboard
- Infectious Disease Dashboard
- CEO Daily Volumes Dashboard
- NICU Dashboard
- Decompensating Patient



TODAY'S OUTLOOK | August 6, 2016



YESTERDAY IN REVIEW | August 5, 2016



Operational Use Cases

UNIVERSITY OF VIRGINIA HEALTH SYSTEM		MEDICAL CENTER VOLUMES									
		Data through Friday, August 5, 2016									
INPATIENT ADMITTANCE 464 <small>INPATIENT OCCUPANCY</small> 75%	ADMISSIONS IPV16: 190 IPV17: 754 IPV18: 4,252	DISCHARGES Inpatient: 80 Short Stay: 21 Post Proc: 34	ED VISITS 181	OUTPT VISITS 2,400 18,991 77,188	SURGERIES Main OR: 73 OPIC: 43 346 242 1,834 1,178						

MTC ACTUALS AND BUDGET VARIANCE

		MTC Actual	MTC Budget	MTC Variance	Variance %	MTC Budget Variance %
Inpatient	Inpatient Discharges	382	382.0	0.0	0.0%	
	Short Stay Patients	71	92.0	-21.0	-22.9%	
	Post-Procedure Patients	117	94.0	23.0	24.5%	
Emergency Care	ED Visits	881	889.0	-8.0	-0.9%	
	Outpatient Visits	18,991	12,117.0	6,874.0	56.7%	
	Diagnostic Outpatient Procedures	270	286.0	-16.0	-5.6%	
Phys and Services	Cardiac Lab Cases	68	18.0	50.0	277.8%	
	Other Procedures	712	101.0	611.0	604.9%	
	Electrocardiography Cases	19	24.7	-5.7	-23.1%	
Outpatient	Diagnostic Outpatient Procedures	158	118.0	40.0	33.9%	
	Inpatient Cardiac Diagnostics	101	112.0	-11.0	-9.8%	
	Outpatient Diagnostic Procedures	198	110.0	88.0	79.1%	
Non-Op	Main OR Surgeries	44	62.0	-18.0	-29.0%	
	OPIC Surgeries	242	219.0	23.0	10.5%	
	OP Site Procedures	99	99.0	0.0	0.0%	

Unnecessary Lab Orders

What is the trend for unnecessary *C. difficile* lab orders?



By year, which units had the most unnecessary *C. difficile* lab orders?



There are many, many maturity models. Just about every major vendor has a maturity model. Some exemplar articles include:

- CMMI (Capability Maturity Model Integration) – Carnegie Mellon / CMMI Institute
- Sen, A., Ramamurthy, K., & Sinha, A. P. (2012). <https://doi.org/10.1109/TSE.2011.2>
- Danciu, I., Cowan, J. D., Basford, M., Wang, X., Saip, A., Osgood, S., ... Harris, P. A. (2014). <https://doi.org/10.1016/j.jbi.2014.02.003>
- Yoo, S., Kim, S., Lee, K.-H., Jeong, C. W., Youn, S. W., Park, K. U., ... Hwang, H. (2014). <https://doi.org/10.1016/j.ijmedinf.2014.04.001>

Responsible for the data tier of the organization's analytics infrastructure, which includes various data repositories and the enterprise data warehouse

- Organizational data in relational database form
- Analysis cubes (pivot-style analysis)
- Data intake/extract services
- Data transformation services
- Hourly updates for various clinical data

Technologies

Architecture Technologies

- SQL Server 2012 and SQL Server 2014
- SQL Server Reporting Services
- SQL Server Integration Services
- Tableau
- Crystal Reports
- BixPRESS
- SharePoint 2013
- Informatica PowerCenter
- Informatica Data Quality Analyst
- Informatica MDM
- Cloudera Hadoop
- PostgreSQL
- Python
- R
- Knime



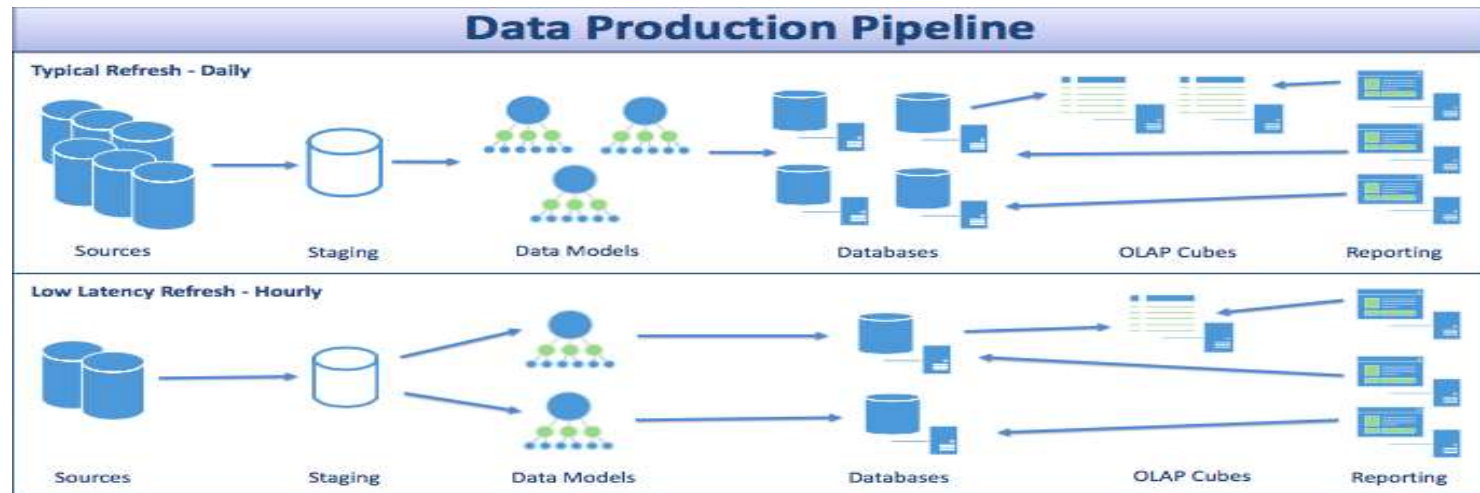
- Our model and architecture:
 - Developed organically (3 stages of data tier maturity)
 - Based on the realities of our reporting requests
 - Time (latency) is a major dimension / consideration

UVA's Data Model and Design

Time, time, time.... (Or, should I say, latency, latency, latency)... Why is it so important?

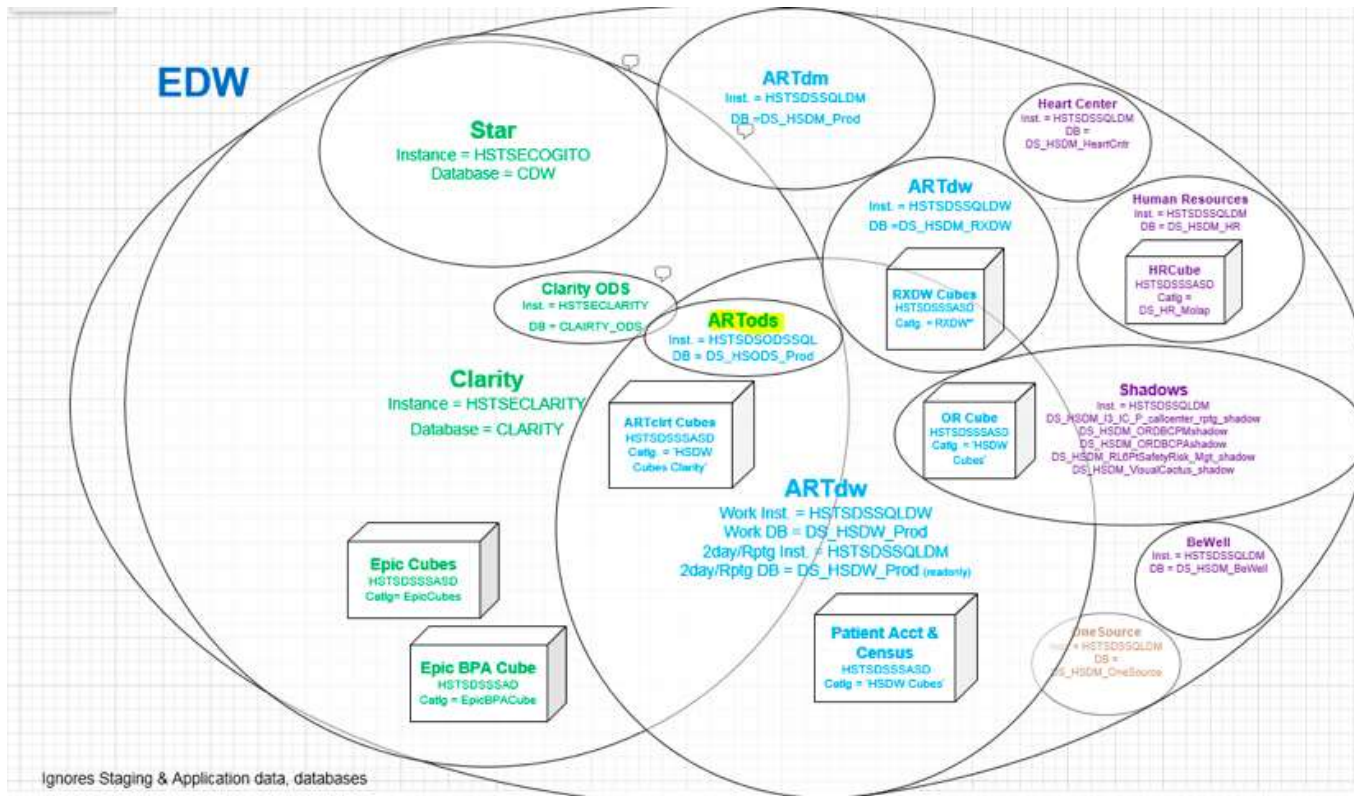
- Data has an expiration date
- Clinical environment / urgency

**The architectural design must accommodate and deeply integrate the time dimension



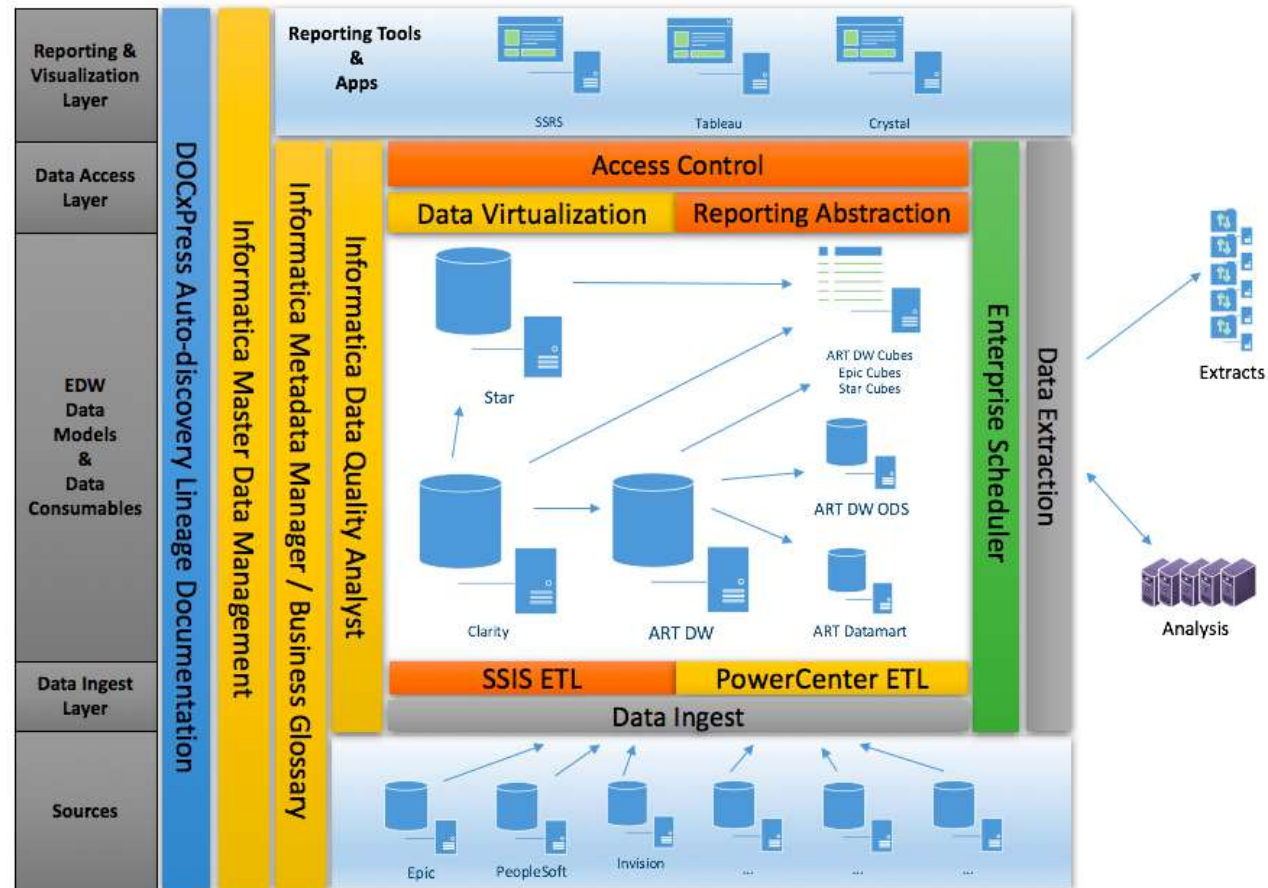
UVA's Data Model and Design

- Clinical data
- Financial data
- Various other domains of data
- Various data types and constructs



UVA's Data Model and Design

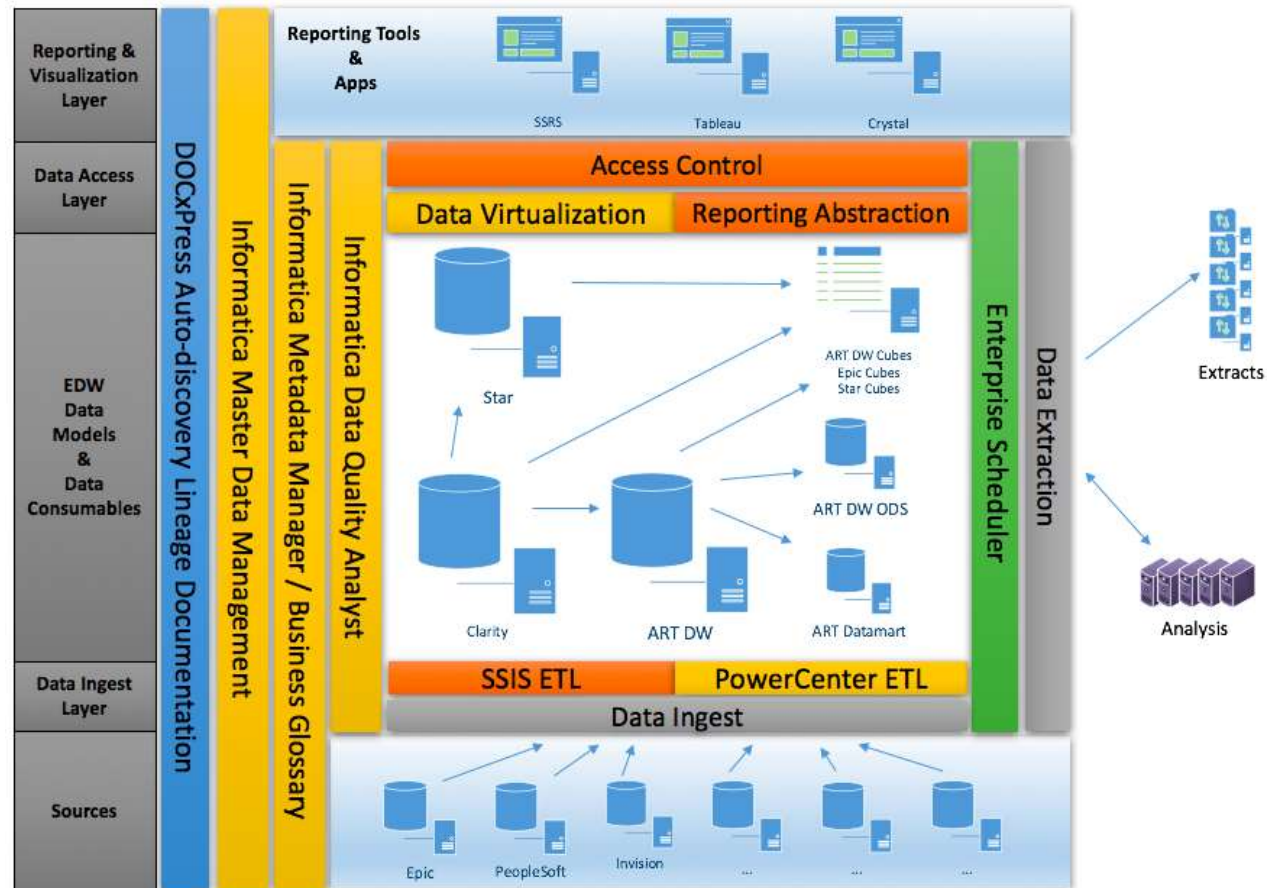
- Complex design
- Multiple data models
- Multiple data refresh latencies



UVA's Data Model and Design

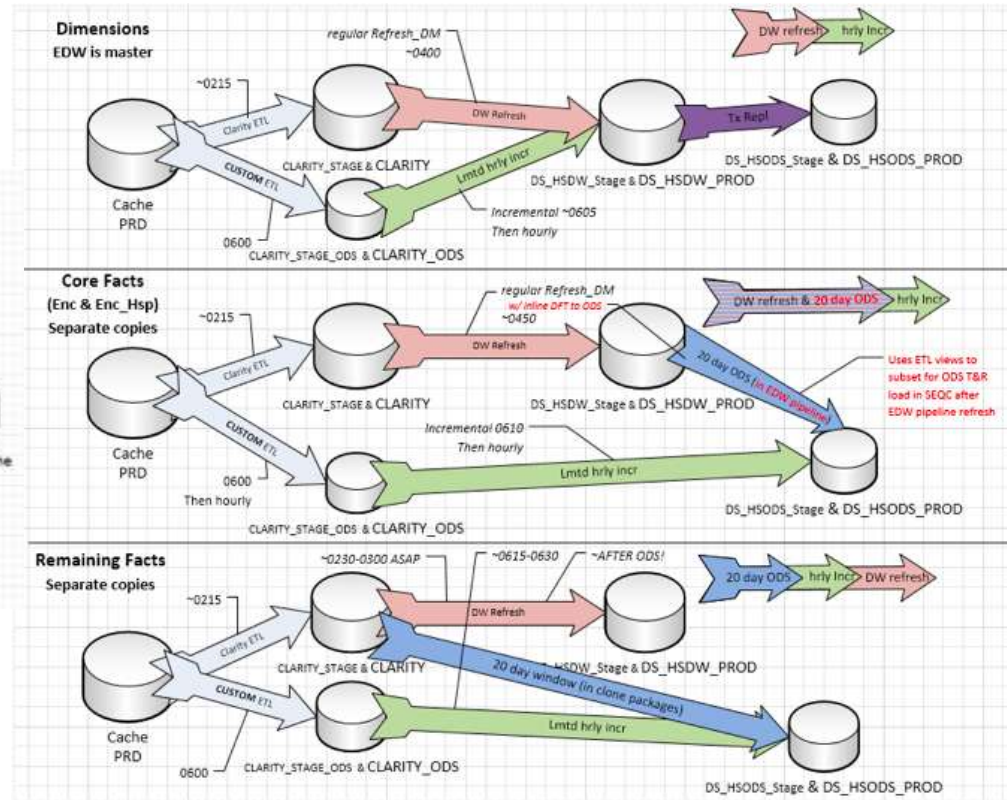
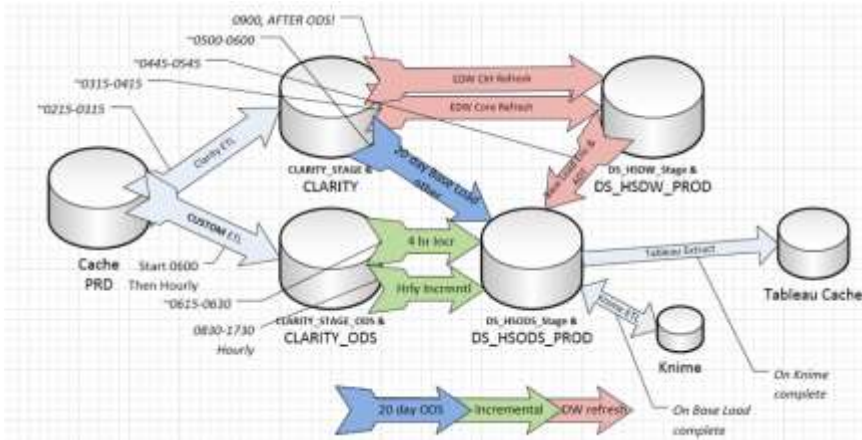
Data Sources (Sample):

- Epic (various)
- Siemens Invision (patient accounting, census, scheduling, registration, etc)
- PeopleSoft (supply chain, employee turnover)
- Teletracking
- CMS (beneficiaries)
- Clinical Staff Office (provider data)
- Be Safe Events
- Active Directory
- GE Centricity (CPM, CPA)
- StrataJazz
- Vizient (UHC)
- Press Ganey
- Locus Health



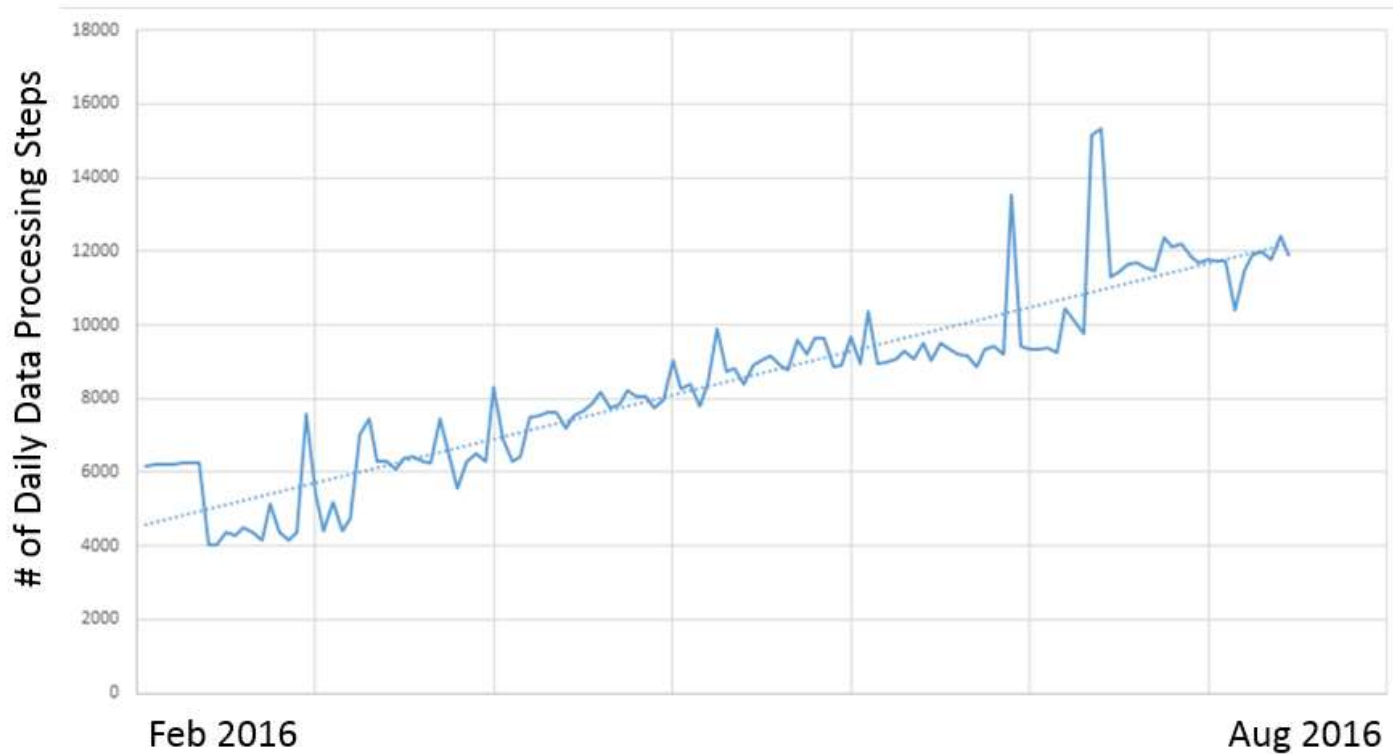
UVA's Data Model and Design

- Multiple refresh rates are complex to manage, hard to conceptualize



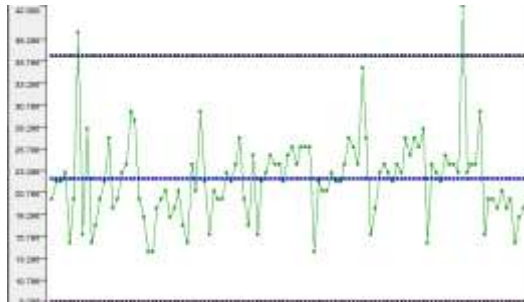
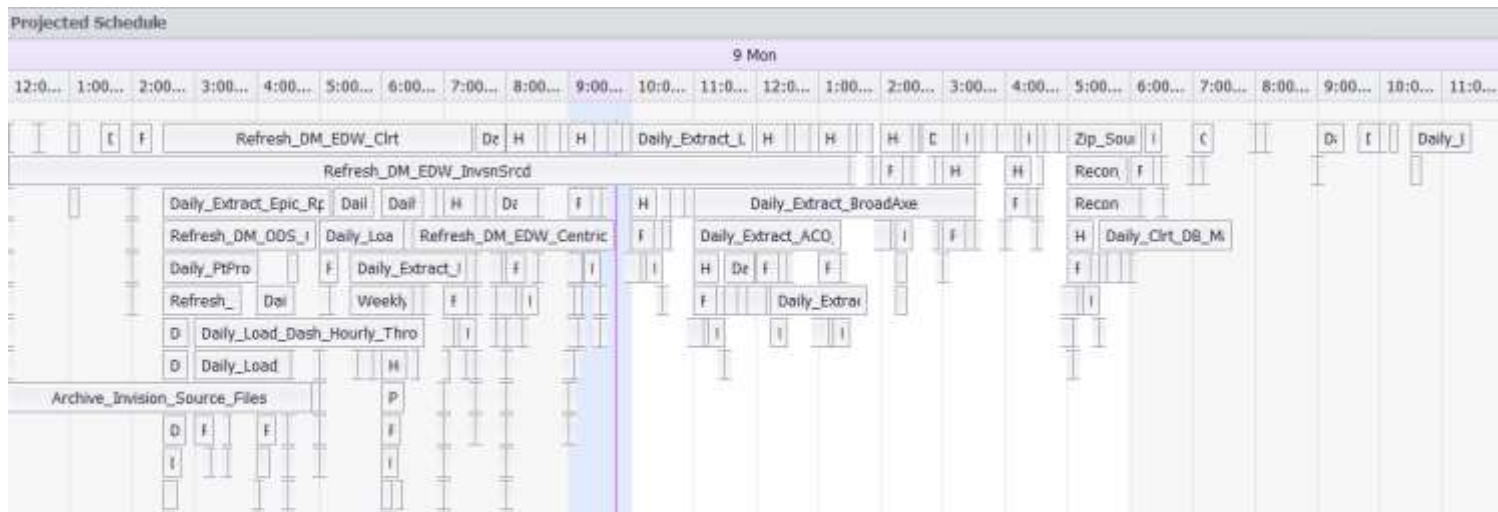
UVA's Data Model and Design

- Daily processing increases rapidly
- It is harder today than yesterday
- Complexity increases over time



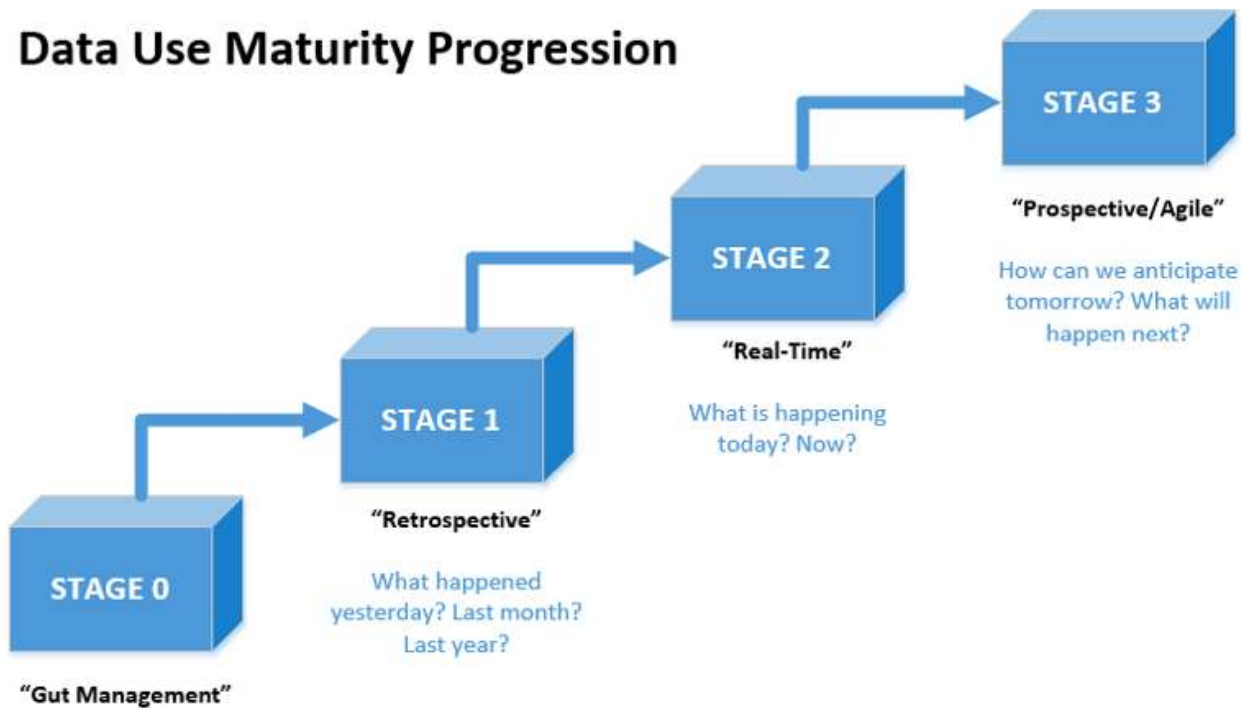
UVA's Data Model and Design

- Complex scheduling needs
- Need to monitor key data processing control limits
- Intervene when processes are outside of control limits
- Proactive monitoring



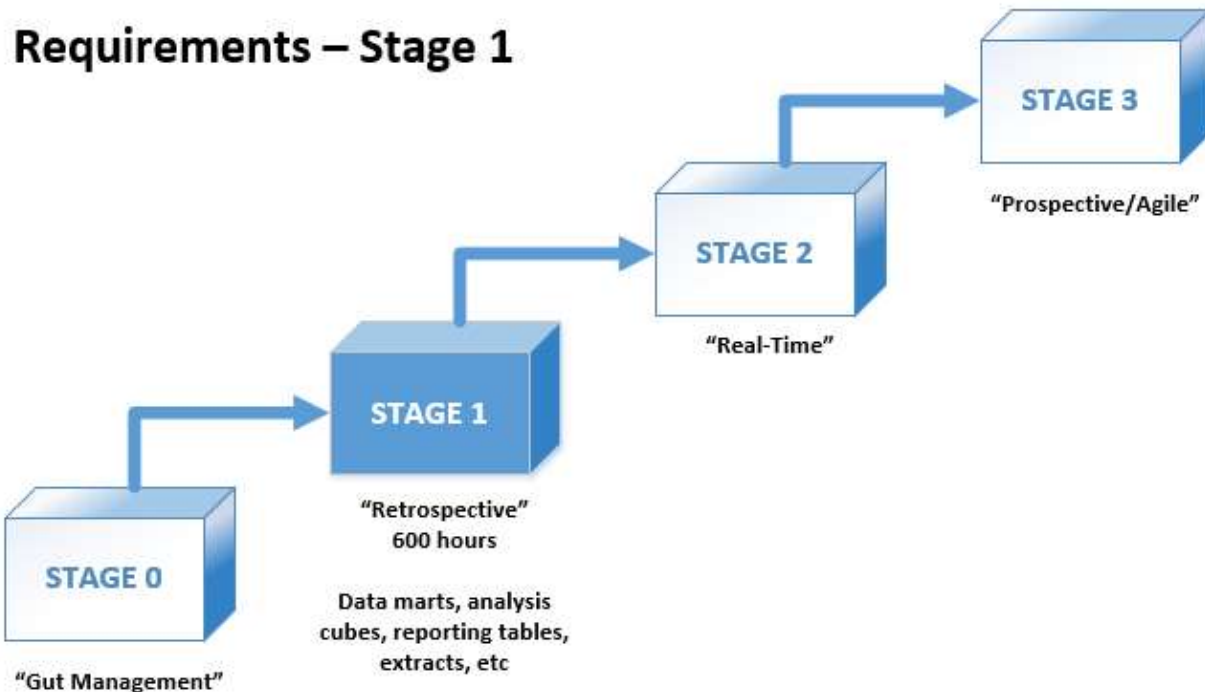
UVA's Data Model and Design

- Three distinct stages
- Each stage builds upon the previous stages
- Change in focus from past to present to future



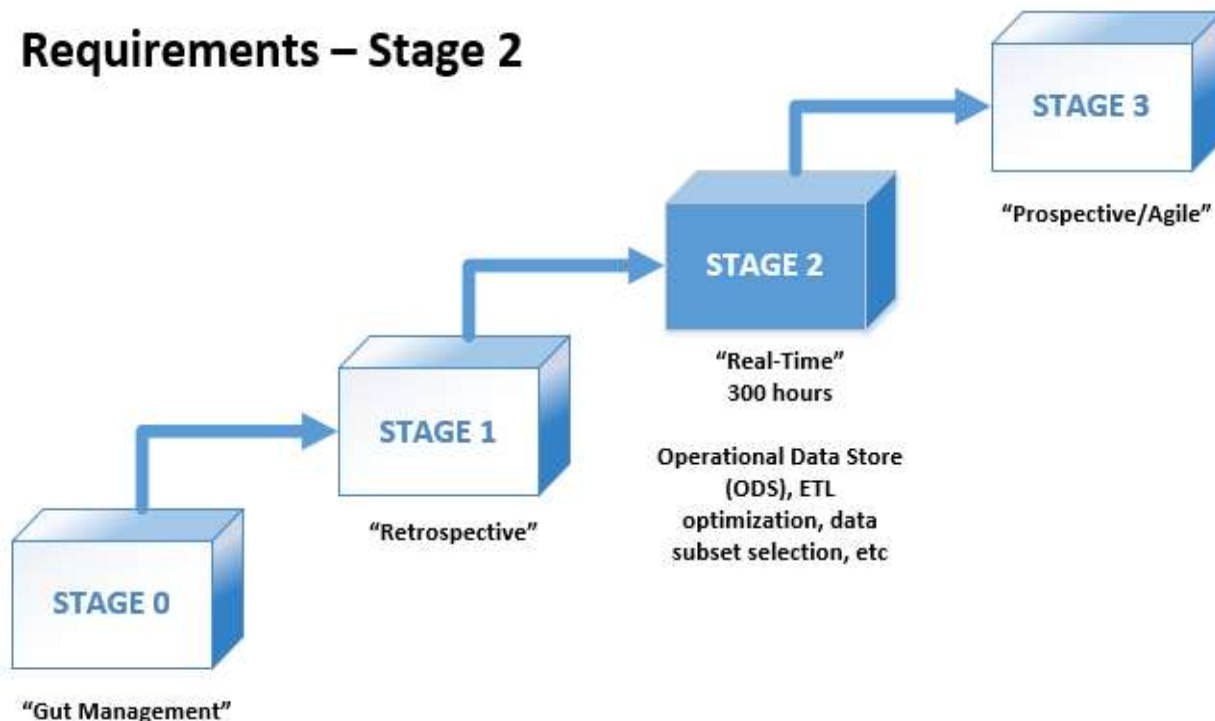
UVa's Data Model and Design

- 600 hours of senior database administrator/data engineering support
- Data model understanding of the business unit or service line
- Reporting tables and/or data mart creation to support required performance
- Analysis cubes that provide drill down and pivot-style interactive analysis



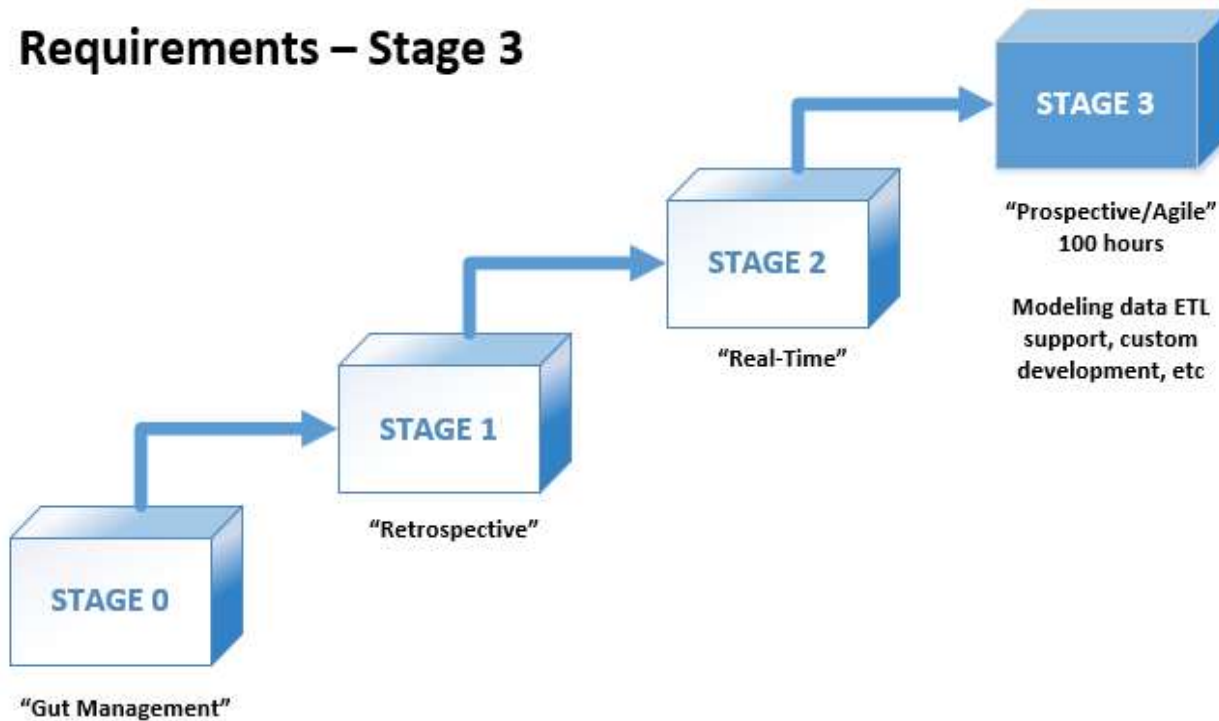
UVA's Data Model and Design

- 300 hours of senior database administrator/data engineering support
- Creation of a business unit or service line ODS
- Optimization of the data pipeline to support a rapid data refresh rate and the data subset
- The formation of basic data governance processes and management



UVa's Data Model and Design

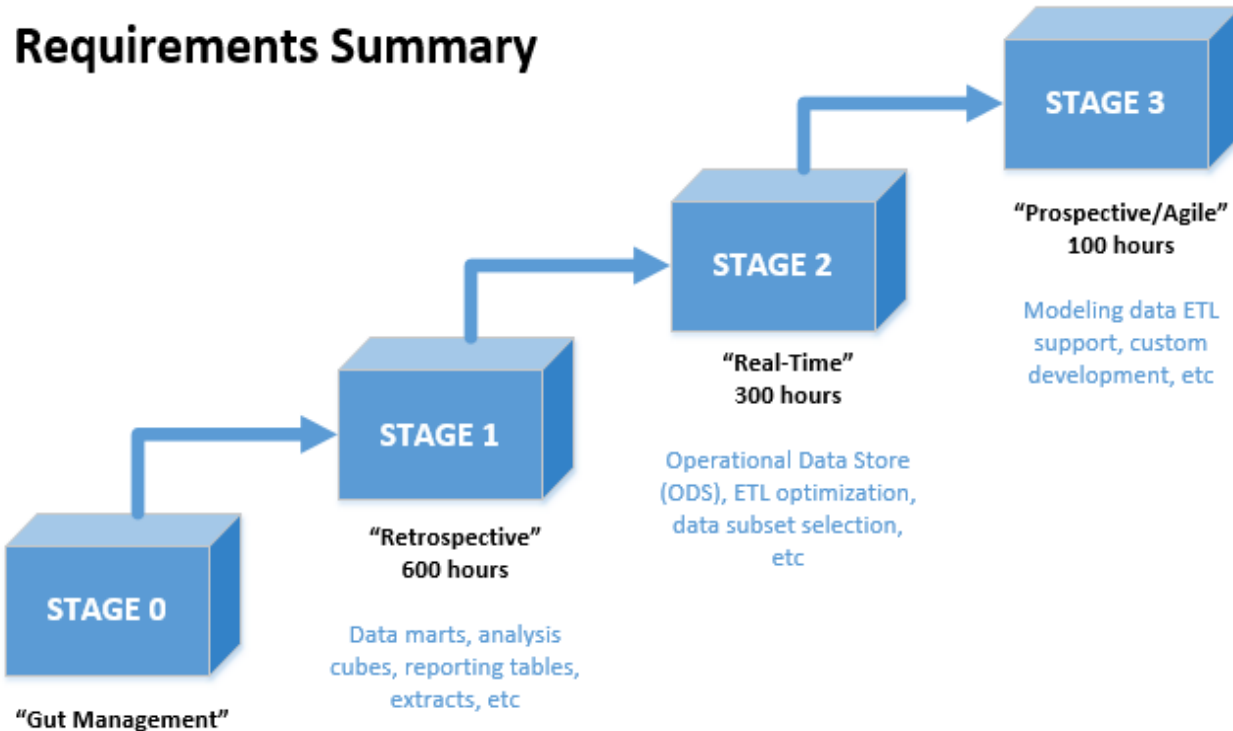
- 100 hours of senior database administrator/data engineering support
- Data format and structure changes to support advanced data modeling
- Custom development to support advanced data techniques
- Advanced data governance methodology utilizing MDM software



UVa's Data Model and Design

- Data maturity progression is cumulative
- Collaborative initiative between customers, data engineering team, and reporting team

***Estimates are only the data engineering team's effort



Our Successes

- Rapid access to clinical data from electronic health record
- Flexible data tier
- Helped to foster the organization's shift to data-driven decision-making
- Customer demand

So What? Why is this important?

- Clinicians and leaders need this data and will get it somehow
- Spreadsheets are not your friends
- 'Analyst' can have many meanings from department to department
- Unified organizational view?
- Metadata management?
- A reliable data tier is rapidly becoming imperative

Implications - Recommendations

- Focus on the quality of the data pipeline first
 - As data becomes more and more crucial, users must learn to first trust the data
- Data production pipeline stability
 - Accurate data is not useful if the users cannot access it
- Strive for data model extensibility
 - Plan for changes to the data architecture—this is one sign of success!

Implications - Recommendations

- Focus on matching the source systems' data, even if they are wrong!
 - The data warehouse should not be the place where 'dirty' data is fixed
- Begin profiling your data and tracking it over time.
 - Key to understanding your data quality current state and progressing to higher quality data

Implications - Recommendations

- Do the hard work of data modeling first
 - Take time to model your data and use cases in order to fully support your customers
- Don't just create rapidly refreshing copies of source systems
 - A system-agnostic data model will save time in the future (e.g., system changes/vendor changes)

Implications - Difficulties

- Victim of our own success?
- Highly dependent on source systems (and their availability / uptime)
- Complex data transformations, with a large number of steps
- Nuanced reporting problems (data mismatch)
- Many of the most important reports need to be ready early in the morning, when there is the least amount of processing capacity/time

Questions?

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