

# PURPOSE OF TODAY'S PRESENTATION

- To provide a broad understanding of:
  - Data Warehouses/Data Marts
  - How to collect the data
  - · How to convert data into information
  - Examples

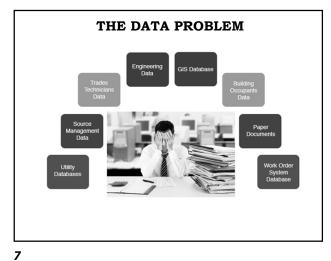
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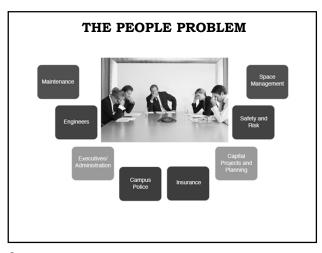
# WORDS OF WISDOM I DIDN'T HAVE ANY ACCURATE NUMBERS SO I JUST MADE UP THIS ONE. STUDIES HAVE SHOUN THAT ACCURATE NUMBERS AREN'T ANY MORE USEFUL THAN THE ONES YOU MAKE UP. WE SHOULD THAT? WE SHOULD THAT?

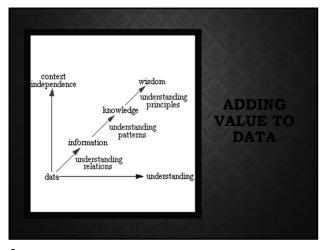
If you torture the data enough, it will confess to anything.

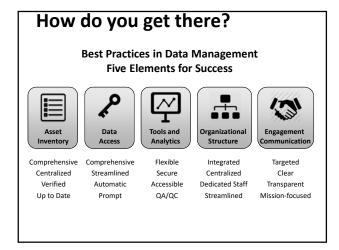
**DISCUSSION**  Create a report of energy consumption and cost for each building owned by your institution: If served by a District Energy System or local system(s): · Chilled Water Steam or Hot Water Electricity · Fuel-Gas/Oil/Coal If served by the local utility Electricity Fuel-Gas/Oil/Coal Water
 This year versus last year information: Consumption and cost Hours used and weekly schedule Average number of occupants, i.e. staff, students, faculty
Square footage of building including classification(s), i.e. instructional space, administrative,
research, housing, etc. Departmental ownership
 Weather, e.g. average temperatures, % sun, etc. HVAC system type WHERE WOULD YOU GET THE INFORMATION TO PRODUCE THIS REPORT?

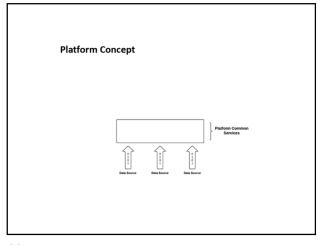
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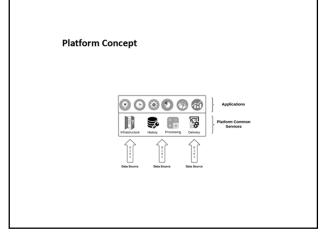


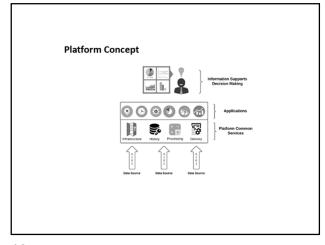






Platform Cor	ncept
	Financial Posterior Common Services
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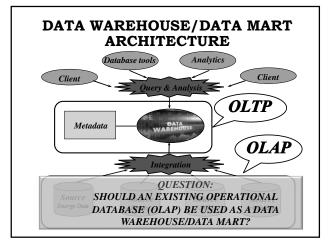


### INTEGRATE THE DATA

**Data Warehouse** operates on an enterprise level and contains all data used for reporting and analysis, while **Data Mart** is used by a specific business department and is focused on a specific subject (business area).

- Aggregate data into a single centralized repository available to all authorized stakeholders
- Integrate the data into consistent subject categories based on how users refer to them
- Apply consistent value representation, units, and descriptors to the data

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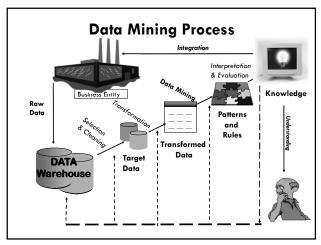
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### MINE THE DATA

Data mining is the

non-trivial process of identifying

- valid
- novel
- potentially useful
- $\blacksquare$  and ultimately  $understandable\ patterns$  in data.



## DATA MINING TECHNIQUES

Classification

The process uses predefined classes to assign to objects such as "dog", "cat", "hat", etc. These classes describe the characteristics of items or represent what the data points have in common with each other. This data mining technique allows the underlying data to be more neatly categorized and summarized across similar features or product lines.

Clustering

Like classification, clustering identifies similarities between objects, then groups those items based on what makes them different from other items. While classification may result in groups such as "shampoo," "conditioner," "soap," and "toothpaste," clustering may identify groups such as "hair care" and "dental health."

Regression

 $A statistical \ method \ that \ attempts \ to \ create \ a \ mathematical \ relationship \ between \ one \ dependent \ variable \ and \ a \ series \ of \ other \ variables \ (known \ as \ independent \ variables).$ 

Association

Association (or relation) is probably the better known, most familiar and straightforward data mining technique. Here, you make a simple correlation between two or more items, often of the same type to identify patterns. For example, when tracking people's buying habits, you might identify that a customer always buys cream when they buy strawberries, and therefore suggest that the next time that they buy strawberries they might also want to buy cream.

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# **DATA MINING TECHNIQUES**

Prediction

Used in combination with other data mining techniques, prediction involves analyzing trends, classification, pattern matching, and relation. By analyzing past events or instances, you can make a prediction about an event.

· Sequential patterns

Often used over longer-term data, sequential patterns are a useful method for identifying trends, or regular occurrences of similar events. For example, with customer data you can identify that customers buy a particular collection of products together at different times of the year. In a shopping basket application, you can use this information to automatically suggest that certain items be added to a basket based on their frequency and past purchasing history.

Decision trees

Related to most of the other techniques (primarily classification and prediction), the decision tree can be used either as a part of the selection criteria, or to support the USE and selection of specific data within the overall structure. Within the decision tree, you start with a simple question that has two (or sometimes more) answers. Each answerf leads to a further question to help classify or identify the data so that it can be categorized, or so that a prediction can be made based on each answer.



HOW IS MACHINE LEARNING RELEVANT TO FACILITIES MANAGEMENT?	
Predicting Problems  When a facility manager tracks operations with machine learning, the disruptions in normal patterns are just as relevant as the consistencies. For example, if a process suddenly fails to meet its routine performance levels, it's possible to isolate and replace a failing part — before it becomes a problem. Smart technology can be programmed to set alerts when the facility displays	
inconsistencies, all through self-monitoring data collection.  Tracking Usage  By establishing operational patterns, it's easy for facilities managers to develop proactive system scheduling: parts ordering, cleaning, routine shutdowns, and equipment replacement can all be arranged at the most cost-effective and efficient times.	
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HOW IS MACHINE LEARNING RELEVANT	]
TO FACILITIES MANAGEMENT?  Optimizing Energy Efficiency  A recent study investigated deep learning for asset optimization throughout a regular office building. The vast system of sensors tracked 35,000 measured data points per minute and drew insights on everything from prioritized elevator scheduling to	
kitchen odors, automated temperature adjustments, and lighting controls.  While this project proves an elaborate example, smart tech systems can outpace static programs in balancing building load. For example, most usage — even in HVAC and lighting alone — goes beyond the binary weekday/weekend or workday/holiday schedule. Weather events, holidays, and even major sporting events routinely alter attendance levels, and a smart system can mine historical performance data and respond	
accordingly.  Savvy Storage  In addition to predicting patterns for real-time applications, machine learning tech can also help to sort, prepare, and store data — suddenly, all this information can be significantly more useful to a manager.	
For example, a tech can automatically group and sort data according to time of year, a particular machine performance, or even a type of maintenance. These analyzed, categorized data sets prepare the foundation for smart, organized action.	
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	]
CONVERT DATA TO INFORMATION	
Microsoft Office	
<ul> <li>Third party reporting tools and</li> </ul>	
applications	
• Analytics, AI	
Web applications	

Knowing that a tomato is a fruit?
That's Data.

Knowing not to put one in a fruit salad? That's Knowledge.

# **GROUP DISCUSSION**

- · What are our FM functions?
- What data is collected by other functions in your organization that you can/want to use?
- What data is collected institutionally that can be used to meet your needs?
- What formats does the data require, i.e. spreadsheet, dashboard, formal reports, etc.?
- Can you currently convert the data into information in the required format(s)? How?

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### **EXAMPLE APPLICATIONS**

- Convert INFORMATION into KNOWLEDGE
  - · Energy Management
  - · Operational and Decision Support
  - Maintenance Management
  - · Analytics, AI, Fault Detection
  - Reporting

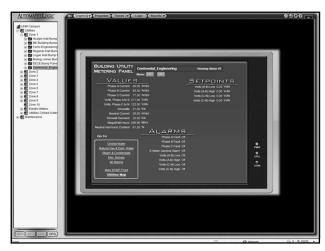
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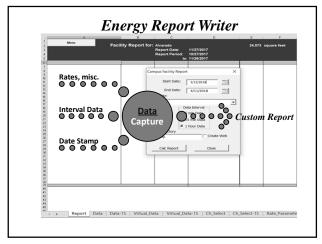
ASHRAE- Great Energy Predictor III- A Machine Learning Case Study

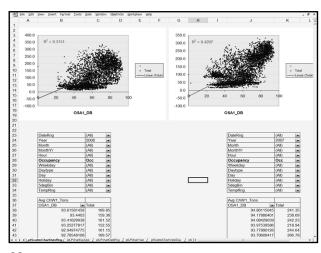
The competition focused on predicting the energy savings of a retrofit in the measurement and verification (M&V) process. Assessing the value of energy efficiency improvements can be challenging as there's no way to know how much energy a building would have used without the improvements.

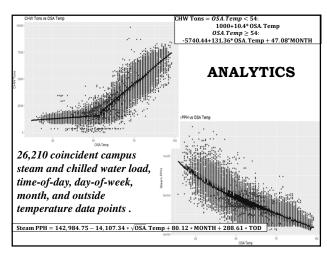
Competitors were challenged to build counterfactual models across four energy types based on historic usage rates and observed weather. The dataset includes three years of hourly meter readings from over one thousand buildings, extensive characterization of the various buildings, and comprehensive weather data at over a 1,000 different sites around the world.

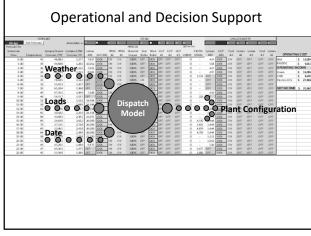
Data	Weather data	Buildings metadata	Meters usage data			
<b>Train</b> — 19 millions rows from around 1500 buildings and 4 meters						
<b>Test</b> — around 42 millions rows from same buildings but for different period of time		All data over a three-year timeframe				
	Train		Test			

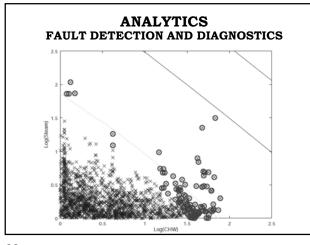












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