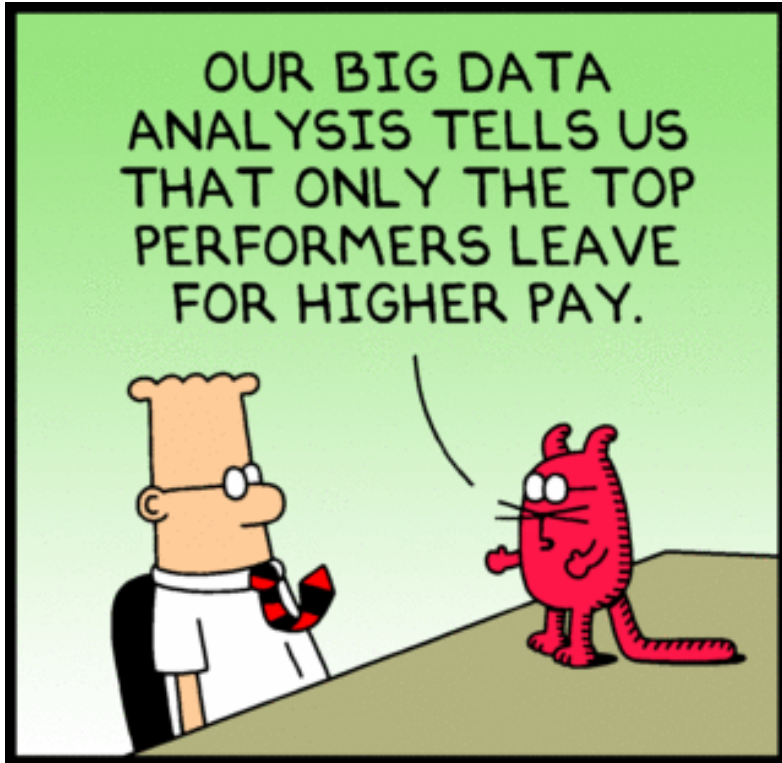


Business Analytics (M.Sc.)  
IT in Business Analytics

# IT APPLICATIONS IN BUSINESS ANALYTICS

SS2016 / Lecture 02 – CRISP DM  
Thomas Zeutschler

# Let's get started...



Dilbert.com DilbertCartoonist@gmail.com



1-27-14 ©2014 Scott Adams, Inc. /Dist. by Universal Uclick



# Data Mining

# Data Mining

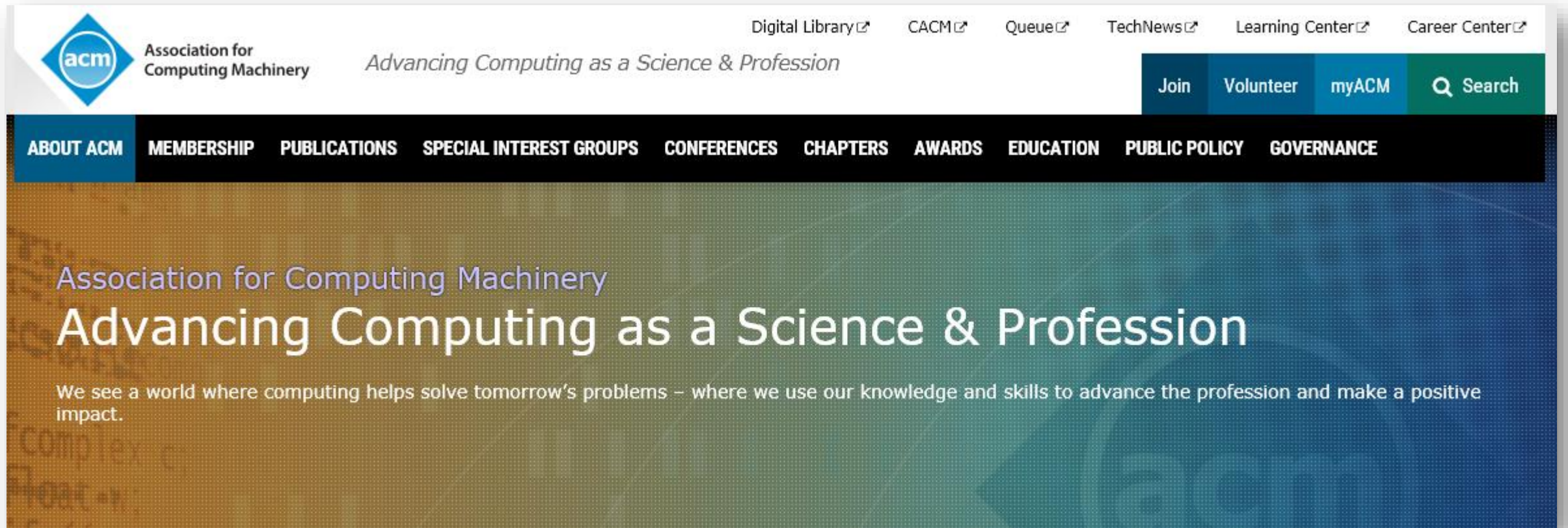
*“Data Mining is an **interdisciplinary** subfield of computer science. It is the **computational process** of **discovering patterns** in large data sets involving methods at the intersection of **artificial intelligence, machine learning, statistics, and database systems.**”*

*Source: Wikipedia “Data Mining”*

*“The core endeavor in data mining is to extract knowledge from data; this knowledge is captured in a human-understandable structure.”*

*Source: Data Mining Curriculum, ACM, 2006*

# Data Mining is about Computing



The image shows the homepage of the Association for Computing Machinery (ACM). At the top left is the ACM logo, a blue diamond with 'acm' inside, followed by the text 'Association for Computing Machinery' and the tagline 'Advancing Computing as a Science & Profession'. To the right of the logo are several links: 'Digital Library', 'CACM', 'Queue', 'TechNews', 'Learning Center', and 'Career Center'. Below these links is a navigation bar with buttons for 'Join', 'Volunteer', 'myACM', and a search icon labeled 'Search'. A dark blue navigation menu contains the following items: 'ABOUT ACM', 'MEMBERSHIP', 'PUBLICATIONS', 'SPECIAL INTEREST GROUPS', 'CONFERENCES', 'CHAPTERS', 'AWARDS', 'EDUCATION', 'PUBLIC POLICY', and 'GOVERNANCE'. The main content area features a large blue background with the text 'Association for Computing Machinery' in a smaller font, followed by the tagline 'Advancing Computing as a Science & Profession' in a large, bold white font. Below this, a smaller line of text reads: 'We see a world where computing helps solve tomorrow's problems – where we use our knowledge and skills to advance the profession and make a positive impact.'

<http://www.acm.org>



# Data Mining – Steps, Challenges and Issues

## Data Mining Curriculum: A Proposal (Version 1.0)

Intensive Working Group of ACM SIGKDD Curriculum Committee:  
Soumen Chakrabarti, Martin Ester, Usama Fayyad, Johannes Gehrke,  
Jiawei Han, Shinichi Morishita, Gregory Piatetsky-Shapiro, Wei Wang

April 30, 2006

### 1 Introduction

Recent tremendous technical advances in processing power, storage capacity, and inter-connectivity of computer technology is creating unprecedented quantities of digital data. *Data mining*, the science of extracting useful knowledge from such huge data repositories, has emerged as a young and interdisciplinary field in computer science. Data mining techniques have been widely applied to problems in industry, science, en-

[http://www.kdd.org/exploration\\_files/CURMay06.pdf](http://www.kdd.org/exploration_files/CURMay06.pdf)



# Data Mining – Steps, Challenges and Issues

## 1. Database and Data Management Issues

- Where does the data reside? How is it to be accessed?
- What forms of sampling are needed? are possible? are appropriate?
- What are the implications of the database or data warehouse structure and constraints on data movement and data preparation?



# Data Mining – Steps, Challenges and Issues

## 2. Data Preprocessing

- What are the required data transformations before a chosen algorithm or class of algorithms can be applied to the data?
- What are effective methods for reducing the dimensionality of the data so the algorithms can work efficiently?
- How are missing data items to be modelled?
- What transformations properly encode a priori knowledge of the problem?





# Data Mining – Steps, Challenges and Issues

## 3. Choice of Model and Statistical Inference Considerations

- What are the appropriate choices to ensure proper statistical inference\*?
- What are valid approximations?
- What are the implications of the inference methods on the expected results?
- How is the resulting structure to be evaluated and validated?

\***Statistical Inference** is the process of deducing properties of an underlying distribution by analysis of data



# Data Mining – Steps, Challenges and Issues

## 4. Interestingness Metrics

- What makes the derived structure interesting or useful?
- How do the goals of the particular data mining activity influence the choice of algorithms or techniques to be used?



# Data Mining – Steps, Challenges and Issues

## 5. Algorithmic Complexity Considerations

- What choice of algorithms based on the size and dimensionality of data?
- What about computational resource constraints?
- Requirements on accuracy of resulting models?
- What are the scalability considerations and how should they be addressed?



# Data Mining – Steps, Challenges and Issues

## 6. Post-processing of Discovered Structure

- How are the results to be used?
- What are the requirements for use at prediction time?
- What are the transformation requirements at model application time?
- How are changes in the data or underlying distributions to be managed?





# Data Mining – Steps, Challenges and Issues

## 7. Visualization and Understandability

- What are the constraints on the discovered structure from the perspective of understandability by humans?
- What are effective visualization techniques for the resulting structure?
- How can data be effectively visualized in the context of or with the aid of the discovered structures?





# Data Mining – Steps, Challenges and Issues

## 8. Maintenance, Updates, and Model Life Cycle Considerations

- When are models to be changed or updated?
- How must the models change as the utility metrics in the application domain change?
- How are the resulting predictions or discovered structure integrated with application domain metrics and constraints?



# CRISP DM

# The Data Mining Process

## CRoss-InduStry Process for Data Mining

- A **methodology** covering the typical phases of an analytical project, the tasks involved with each phase, and an explanation of the relationships between these tasks.
- A **process model**, as CRISP-DM provides an overview of the data mining life cycle.

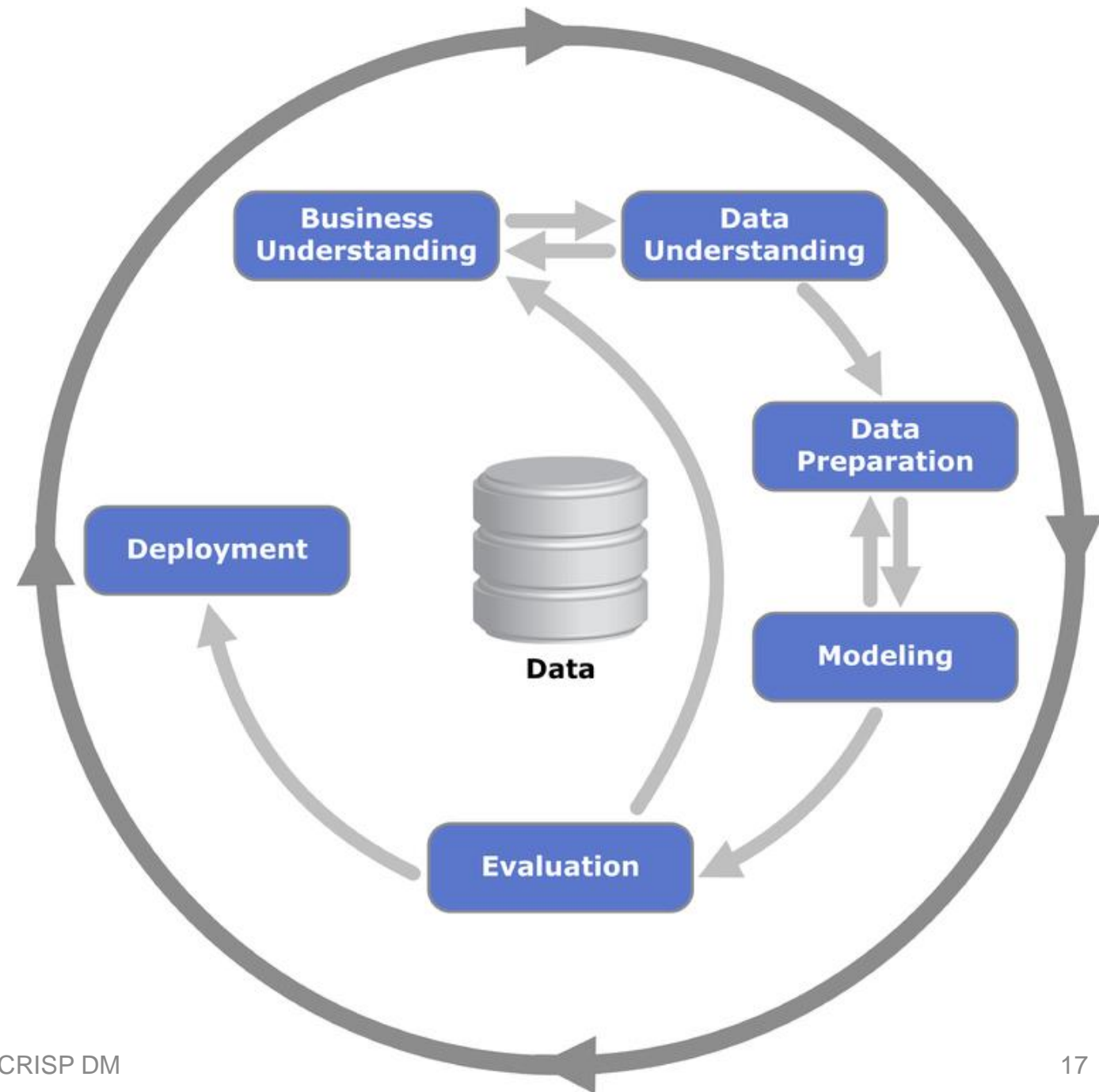
CRISP-DM was conceived in 1996 and first published in 1999 by SPSS, NCR and Mercedes and is reported as the **leading methodology for data mining/predictive analytics projects**.

IBM has released a new implementation method for Data Mining/Predictive Analytics projects in 2015 called **Analytics Solutions Unified Method for Data Mining & Predictive Analytics (ASUM-DM)** which is a refined and extended CRISP-DM. *But it's a little bit too complex start with...*

# Introduction

*„The process of knowledge discovery in data mining has to be reproducible and reliable.*

*Especially for people who have no background in data science.“*



# CRISP DM

## CRoss-InduStry Process for Data Mining

- A **methodology** covering the typical phases of an analytical project, the tasks involved with each phase, and an explanation of the relationships between these tasks.
- A **process model**, as CRISP-DM provides an overview of the data mining life cycle.

CRISP-DM was conceived in 1996 and first published in 1999 by SPSS, NCR and Mercedes and is reported as the **leading methodology for data mining/predictive analytics projects**.

IBM has released a new implementation method for Data Mining/Predictive Analytics projects in 2015 called **Analytics Solutions Unified Method for Data Mining & Predictive Analytics (ASUM-DM)** which is a refined and extended CRISP-DM. *But it's a little bit too complex start with...*



# CRISP DM – Current Industry Standard

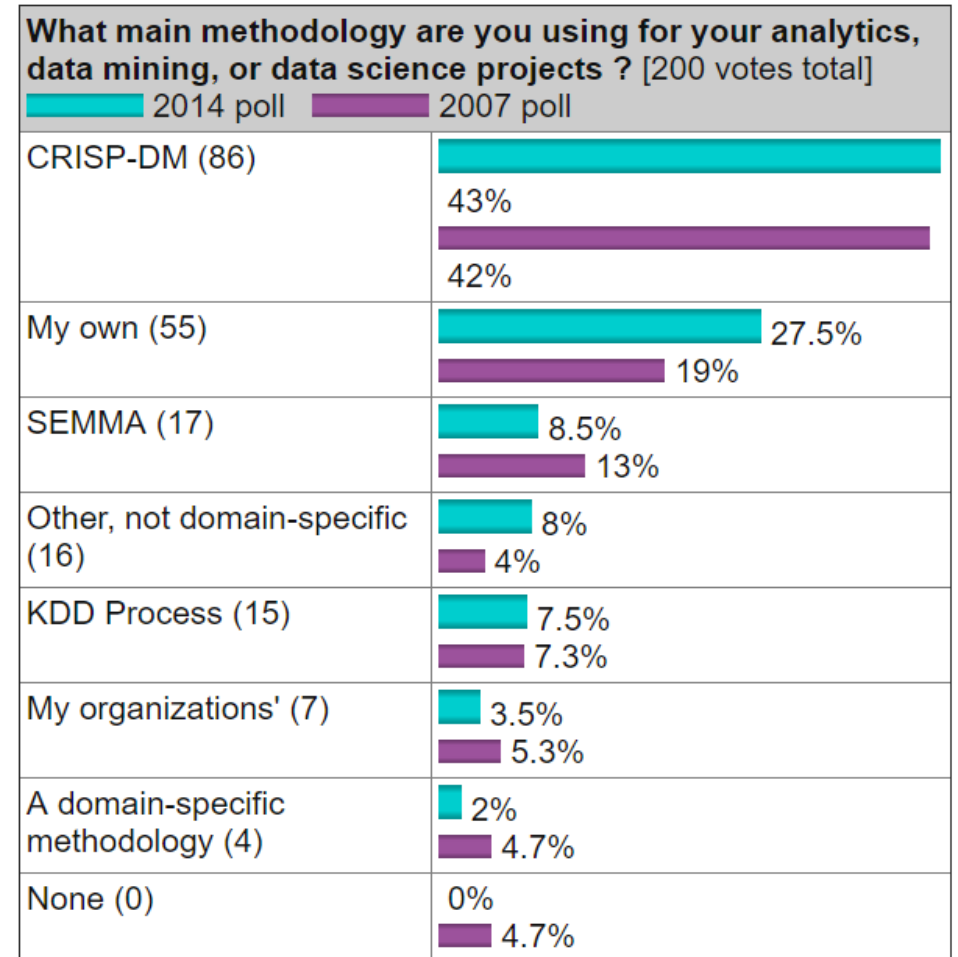
Other approaches:

## KDD

- „**K**nowledge **D**iscovery in **D**atabases“ developed by Usama Fayyad (Microsoft Research, 1996) describes methods and technologies to assist humans in extracting useful information (knowledge) from the rapidly growing volumes of digital data.

## SEMMA

- SEMMA is an acronym that stands for **S**ample, **E**xplore, **M**odify, **M**odel and **A**ssess. It is a list of sequential steps developed by SAS Institute in 2009.
- **Criticism:** SEMMA mainly focuses on the modeling tasks of data mining projects, leaving the business aspects out. Focussed on the usage of SAS products.



Source:

<http://www.kdnuggets.com/2014/10/crisp-dm-top-methodology-analytics-data-mining-data-science-projects.html>

# CRISP DM – Objectives and Benefits

- Ensure quality of knowledge discovery project results
- Reduce skills required for knowledge discovery
- Reduce costs and time
  
- General purpose (i.e., stable across varying applications)
- Robust (i.e., insensitive to changes in the environment)
  
- Tool and technique independent
- Tool supportable
  
- Support documentation of projects
- Capture experience for reuse
- Support knowledge transfer and training

# CRISP DM – Phases and Tasks

## Business Understanding

### Determine Business Objectives

Background.  
Business Objectives.  
Business Success Criteria.

### Assess Situation

Inventory of Resources, Requirements, Assumptions and Constraints.  
Risks and Contingencies Terminology.  
Costs and Benefits.

### Determine Data Mining Goals

Data Mining Goals.  
Data Mining Success Criteria.

### Produce Project Plan

Project Plan.  
Initial Assessment of Tools and Techniques.

## Data Understanding

### Collect Initial Data

Initial Data Collection Report.

### Describe Data

Data Description Report.

### Explore Data

Data Exploration Report.

### Verify Data Quality

Data Quality Report.

## Data Preparation

### Select Data

Rationale for Inclusion/Exclusion.

### Clean Data

Data Cleaning Report.

### Construct Data

Derived Attributes.  
Generated Records.

### Integrate Data

Merged Data.

### Format Data

Reformatted Data.

### Dataset

Dataset Description.

## Modelling

### Select Modelling Technique

Modelling Technique.  
Modelling Assumptions.

### Generate Test Design

Test Design.

### Build Model

Parameter Settings  
Models.  
Model Description.

### Assess Model

Model Assessment.  
Revised Parameter Settings.

## Evaluation

### Evaluate Results

Assessment of Data.  
Mining Results w.r.t. Business Success Criteria.  
Approved Models.

### Review Process

Review of Process.

### Determine Next Steps

List of Possible Actions.  
Decision.

## Deployment

### Plan Deployment

Deployment Plan.

### Plan Monitoring and Maintenance

Monitoring and Maintenance Plan.

### Produce Final Report

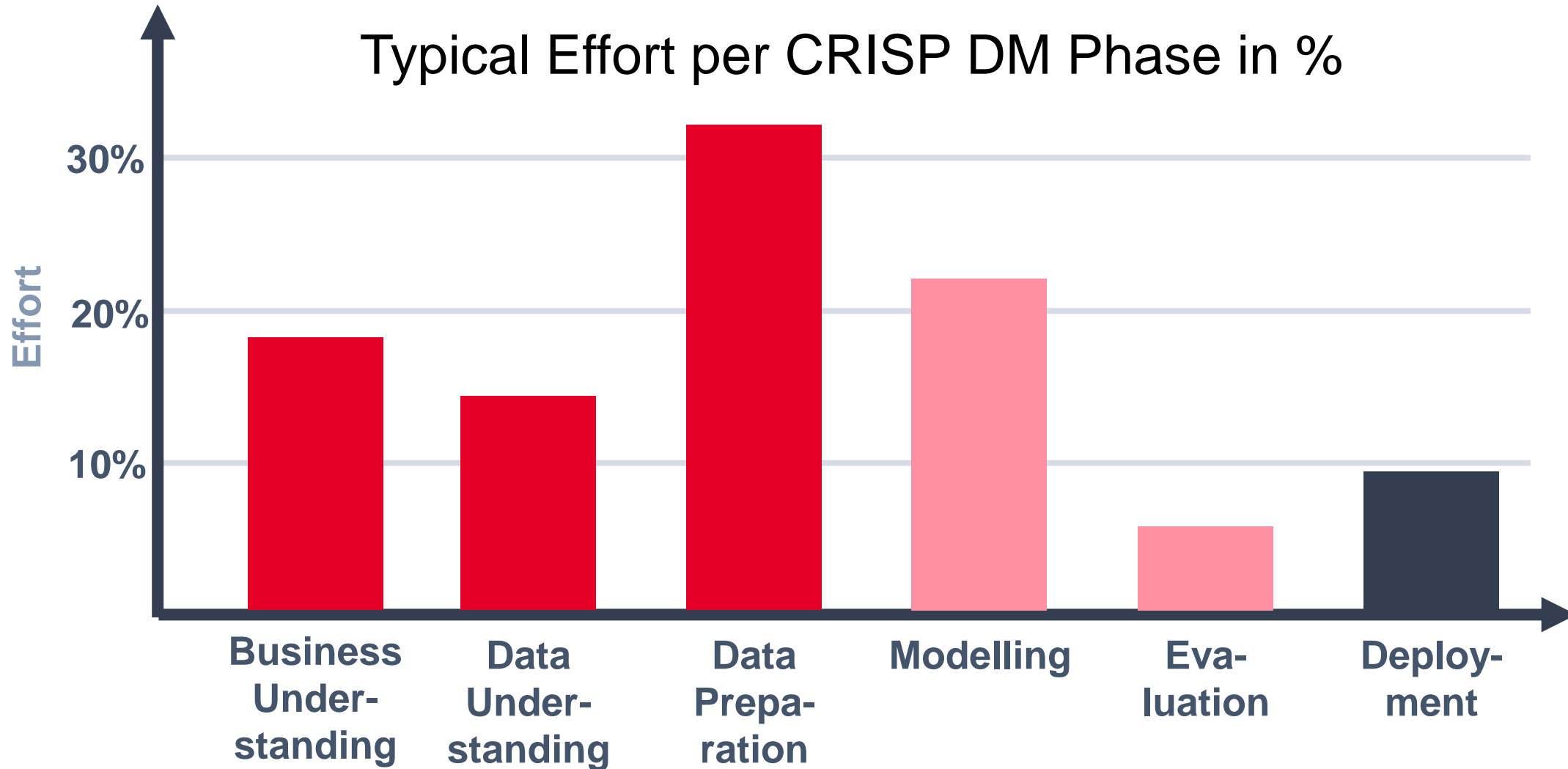
Final Report.  
Final Presentation.

### Review Project

Experience  
Documentation.

# CRISP DM – Objectives and Benefits

Typical Effort per CRISP DM Phase in %



# CRISP DM – 1 Business Understanding

## 1.1 Determine Business Objectives

Background.

Business Objectives.

Business Success Criteria.

## 1.2 Assess Situation

Inventory of Resources, Requirements, Assumptions and Constraints.

Risks and Contingencies Terminology.

Costs and Benefits.

## 1.3 Determine Data Mining Goals

Data Mining Goals.

Data Mining Success Criteria.

## 1.4 Produce Project Plan

Project Plan.

Initial Assessment of Tools and Techniques.





# CRISP DM – 2 Data Understanding

## 2.1 Collect Initial Data

Initial Data Collection Report.

## 2.2 Describe Data

Data Description Report.

## 2.3 Explore Data

Data Exploration Report.

## 2.4 Verify Data Quality

Data Quality Report.



# CRISP DM – 3 Data Preparation

## 3.1 Select Data

Rationale for Inclusion / Exclusion.

## 3.2 Clean Data

Data Cleaning Report.

## 3.3 Construct Data

Derived Attributes.  
Generated Records.

## 3.4 Integrate Data

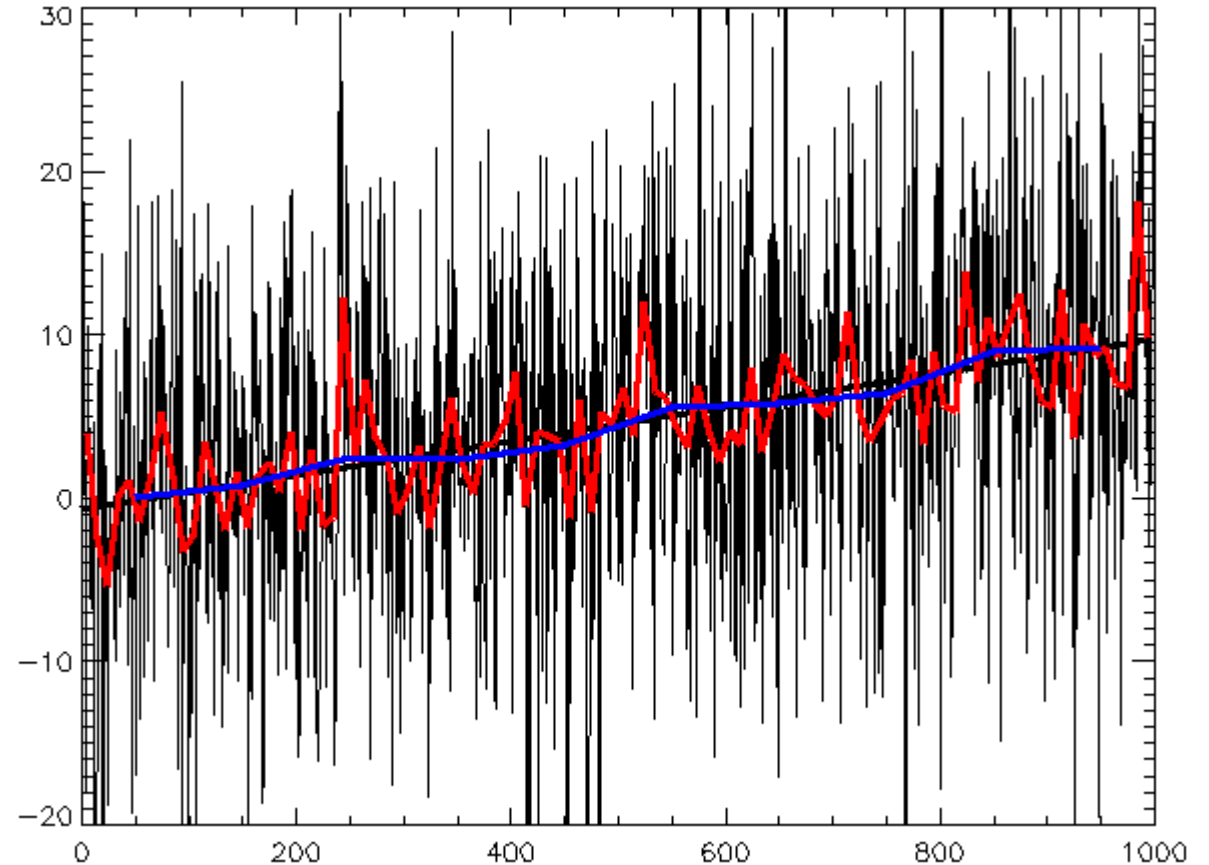
Merged Data.

## 3.5 Format Data

Reformatted Data.

## 3.6 Dataset

Dataset Description.



# CRISP DM – 4 Modelling

## 4.1 Select Modelling Technique

Modelling Technique.  
Modelling Assumptions.

## 4.2 Generate Test Design

Test Design.

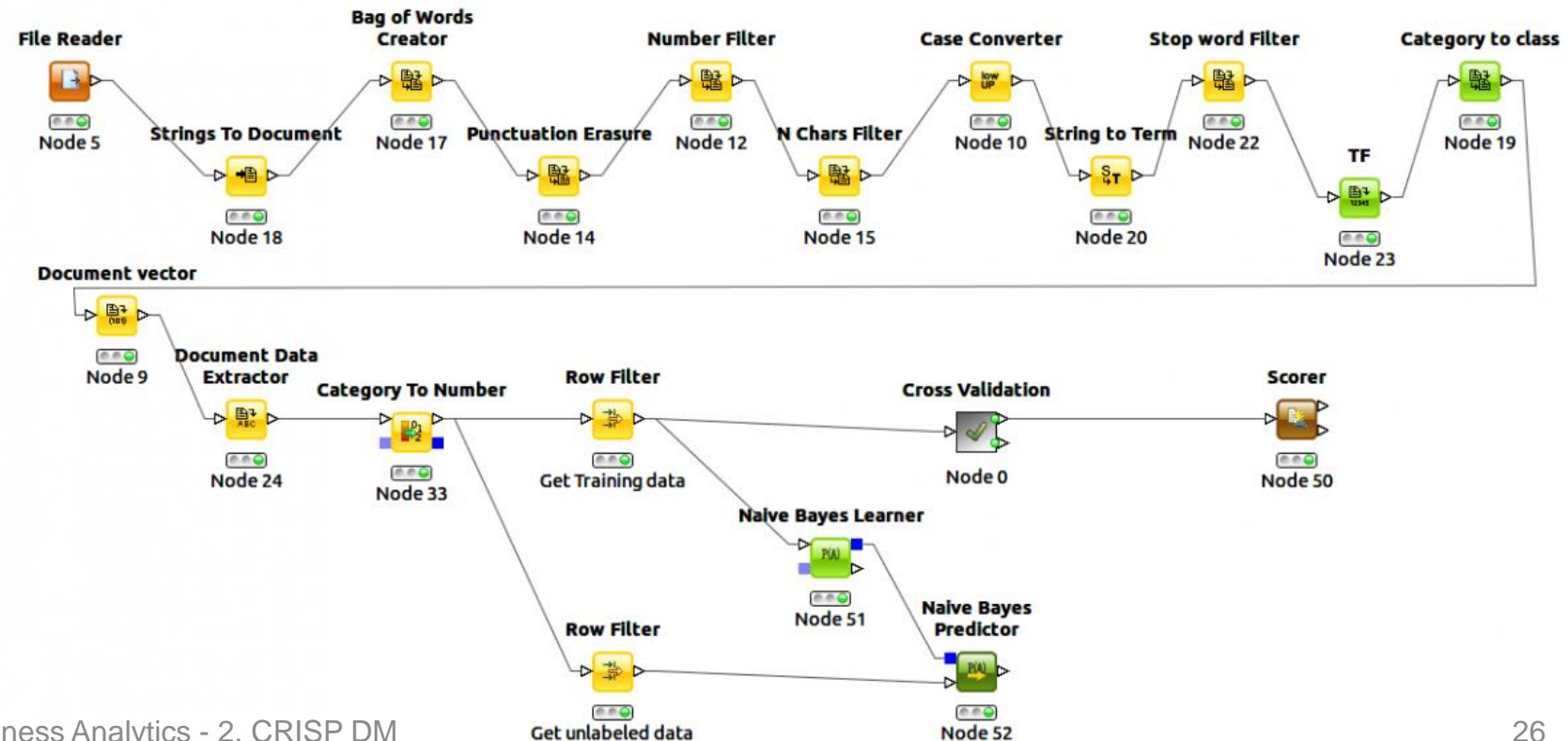
## 4.3 Build Model

Parameter Settings Models.  
Model Description.

## 4.4 Assess Model

Model Assessment.  
Revised Parameter Settings.

Data Mining Context				
Dimension	Application Domain	Data Mining Problem Type	Technical Aspect	Tool and Technique
Examples	Response Modeling	Description and Summarization	Missing Values	Clementine
	Churn Prediction	Segmentation	Outliers	MineSet
	...	Concept Description	...	Decision Tree
		Classification		...
		Prediction		
	Dependency Analysis			



# CRISP DM – 5 Evaluation

## 5.1 Evaluate Results

Assessment of Data.

Mining Results with respect to Business Success Criteria.

Approved Models.

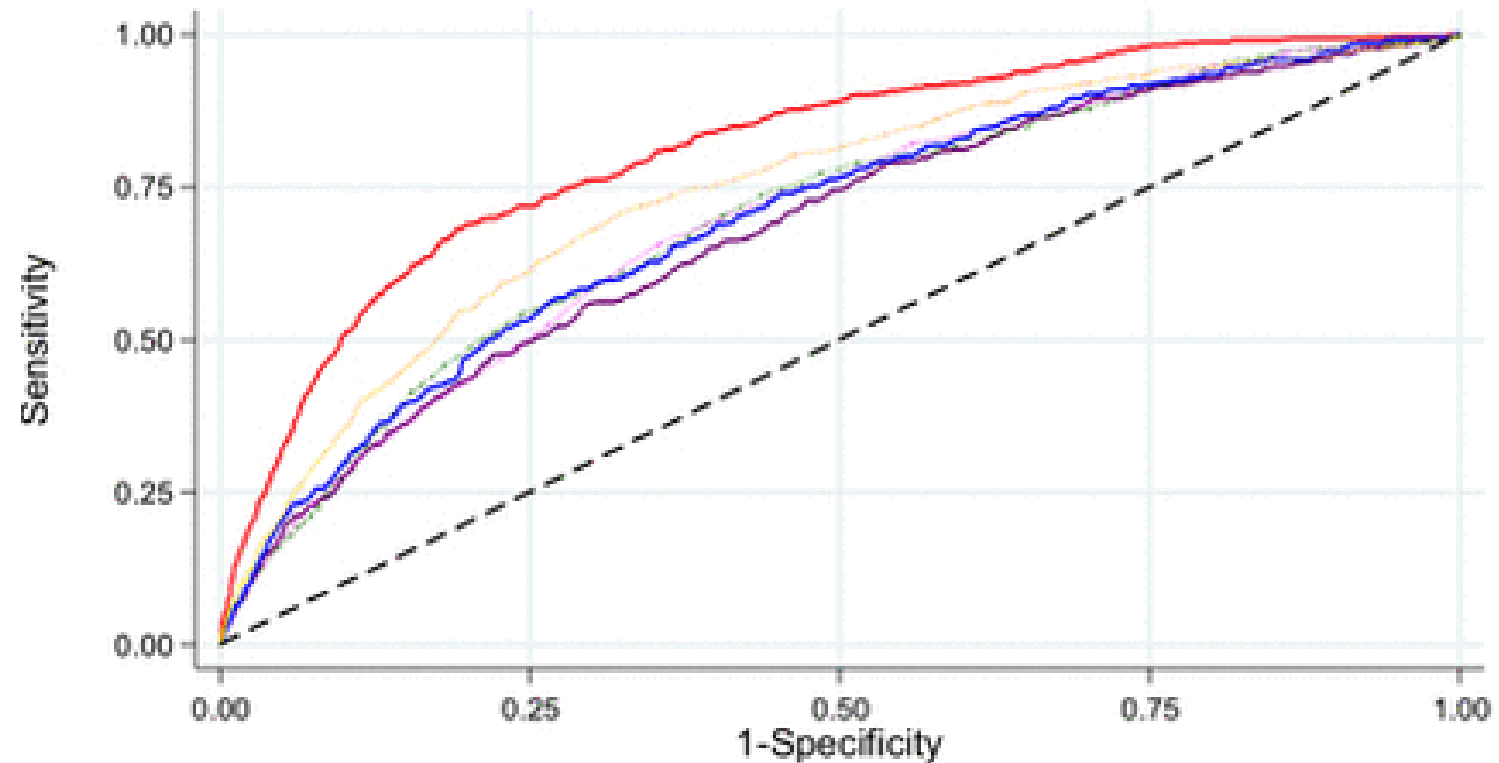
## 5.2 Review Process

Review of Process.

## 5.3 Determine Next Steps

List of Possible Actions.

Decision.





# CRISP DM – 6 Deployment

## 6.1 Plan Deployment

Deployment Plan.

## 6.2 Plan Monitoring and Maintenance

Monitoring and Maintenance Plan.

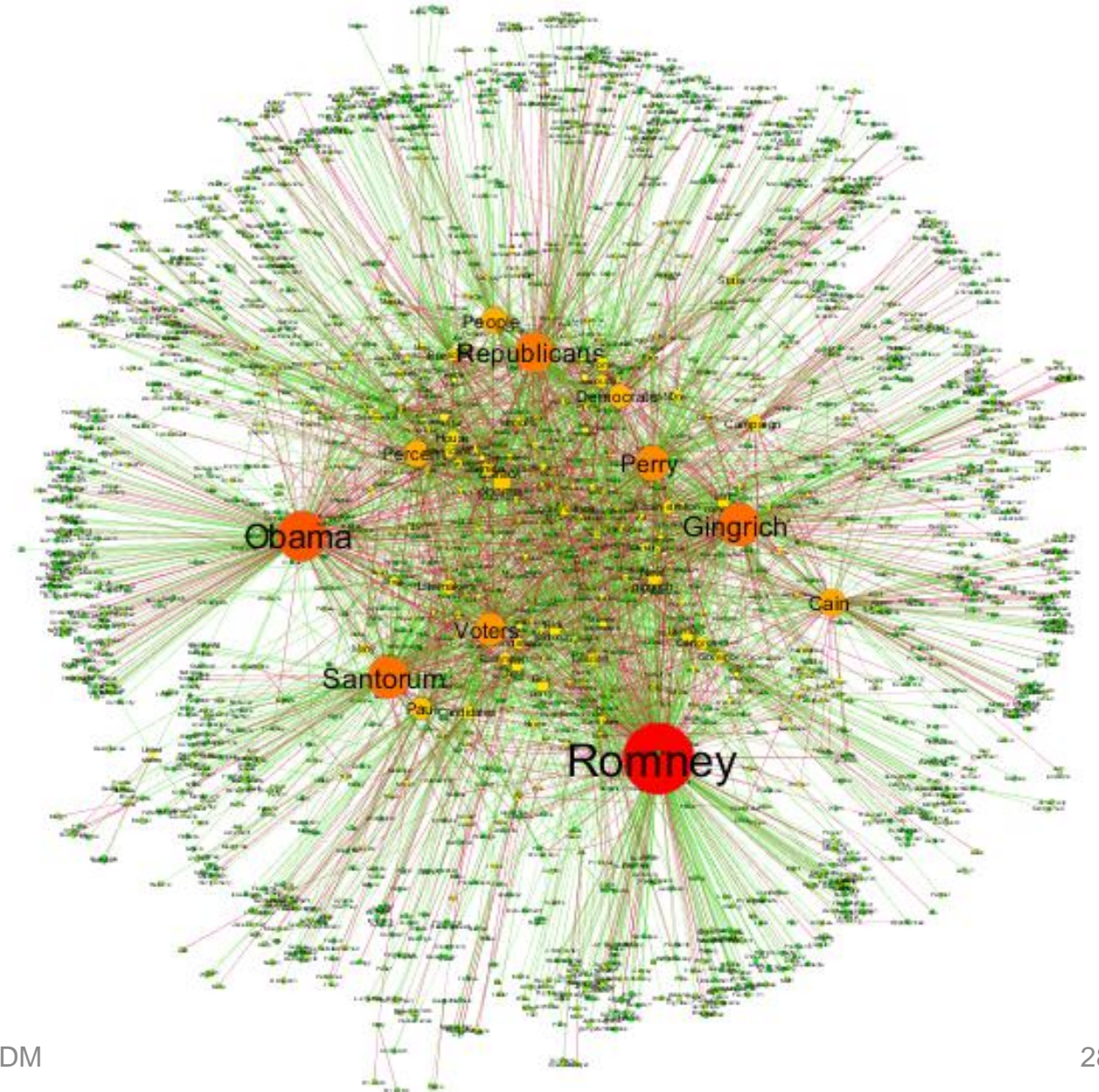
## 6.3 Produce Final Report

Final Report.

Final Presentation.

## 6.4 Review Project

Experience Documentation.





# Lessons Learned

- CRISP DM is a highly adopted and standardized process for data mining projects.
- Ex-ante definition of success criteria is essential for successful projects.
- Data understanding and preparation are typically the most costly and time-consuming (~80%) phases in CRISP DM.
- CRISP DM is an iterative approach. Certain phases are likely to be passed multiple times (modelling and evaluation).

# Resources

## CRISP DM 1.0 Document

<https://www.the-modeling-agency.com/crisp-dm.pdf>

## From Data Mining to Knowledge Discovery in Databases

<http://www.kdnuggets.com/gpspubs/aimag-kdd-overview-1996-Fayyad.pdf>

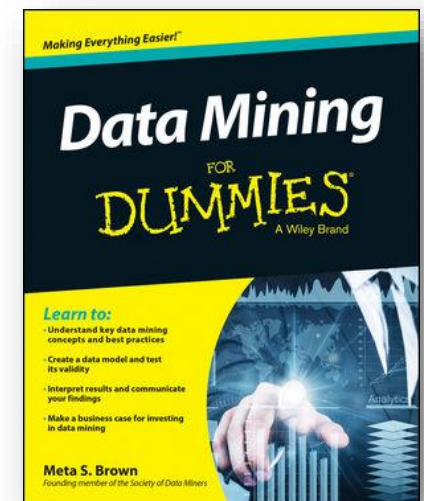
## IBM ASUM DM

<https://developer.ibm.com/predictive-analytics/2015/10/16/have-you-seen-asum-dm/>

## Data Mining Curriculum, ACM

[http://www.kdd.org/exploration\\_files/CURMay06.pdf](http://www.kdd.org/exploration_files/CURMay06.pdf)

*I do not recommend this, but it's great.*



# Get Prepared (Homework)

- Read the KDD article by Usama Fayyad

<http://www.kdnuggets.com/gpspubs/aimag-kdd-overview-1996-Fayyad.pdf>

- Read the CRISP DM 1.0 Document

<https://www.the-modeling-agency.com/crisp-dm.pdf>

- Read the Data Mining Curriculum

[http://www.kdd.org/exploration\\_files/CURMay06.pdf](http://www.kdd.org/exploration_files/CURMay06.pdf)

# Any Questions?

