DSA/ISE 5103 Intelligent Data Analytics

CRISP-DM and Project Understanding

Charles Nicholson, Ph.D. cnicholson@ou.edu

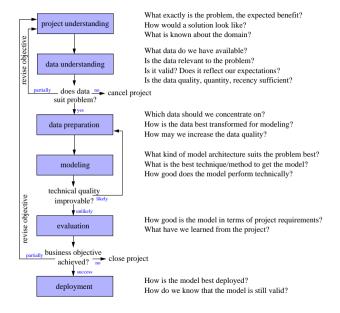
University of Oklahoma
Gallogly College of Engineering
School of Industrial and Systems Engineering

Outline

Process: CRISP-DM

Project Understanding

CRISP-DM Cross Industry Standard Process for Data Mining

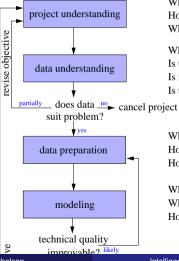


Outline

Process: CRISP-DM

Project Understanding

project understanding



What exactly is the problem, the expected benefit?

How would a solution look like?

What is known about the domain?

What data do we have available?

Is the data relevant to the problem?

Is it valid? Does it reflect our expectations?

Is the data quality, quantity, recency sufficient?

Which data should we concentrate on?

How is the data best transformed for modeling?

How may we increase the data quality?

What kind of model architecture suits the problem best?

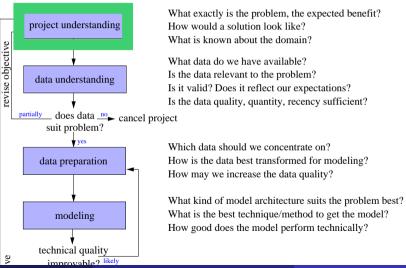
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What is the best technique/method to get the model?

How good does the model perform technically?

Charles Nicholson Intelligent Data Analytics University of Oklahoma

project understanding



project understanding

The 80-20 Rule!

- ► Average time spent for project and data understanding within the CRISP-DM model: 20%
- ► Importance for success: 80%

Determine business objectives

Pete Chapman, Julian Clinton, Randy Kerber, Thomas Khabaza, Thomas Reinartz, Colin Shearer, and Rüdiger Wirth (2000); CRISP-DM 1.0 Step-by-step data mining guides.

- Determine business objectives
- Assess situation

Pete Chapman, Julian Clinton, Randy Kerber, Thomas Khabaza, Thomas Reinartz, Colin Shearer, and Rüdiger Wirth (2000); CRISP-DM 1.0 Step-by-step data mining guides.

- Determine business objectives
- Assess situation
- Determine data mining goals

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- Determine business objectives
- Assess situation
- Determine data mining goals
- Produce project plan

Pete Chapman, Julian Clinton, Randy Kerber, Thomas Khabaza, Thomas Reinartz, Colin Shearer, and Rüdiger Wirth (2000); CRISP-DM 1.0 Step-by-step data mining guides.

Tasks:

- Understand problem from a business perspective
- Identify critical factors, competing objectives and constraints

- Background description
- Primary objectives
- Success criteria

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 - What could you do with a solution?

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What predictive analytics solutions could be proposed to help address this business problem?

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Payment prediction

- ▶ Model: predict the appropriate amount of money that should be paid
- Use: predicted amount used to offer settlement to members
- ▶ Benefit: limits the effort/expense of undergoing claim investigations

Each also has it downsides...

- Claim prediction: what if investigative team does not agree, e.g., the
 workload is too little, too much, too different
- Member prediction: if you issue a warning to a good customer, you may lose that customer
- Application prediction: how much future revenue are you giving up from good customers?
- Payment prediction: settlements might be too high

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- Criteria to measure the success of the project should be defined.

Poor examples...

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Increase sales

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- Model loyal customers to increase sales
- "I read something in Forbes magazine Walmart is doing something where they found that purchases of fishing tackle in late October is indicative of very profitable sales of decorative lamps in the Spring." Do that for us.

Good example...

objective: increase revenues (per customer) in direct mailing

campaigns by personalized offer and individual cus-

tomer selection

deliverable: application that automatically selects a pre-specified

number of customers from the database to whom the

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mailing shall be sent; runtime max: half-day

success criteria: improve purchase rate by 5% or total revenues by 5%,

measured within 4 weeks after mailing.

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Detailed fact-finding

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Outputs

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- Terminology
- Costs and benefits

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determine data mining goals

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Map the problem to a data analysis task

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- Data mining goals
- Data mining success criteria

determine data mining goals

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Task:

Describe and document plan

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Output:

Project plan

This is a *dynamic* document!

Initial assessment of tools and techniques

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project understanding

"A problem well stated is a problem half solved."

- Charles Kettering