dm22s1

Topic 01 : Module Overview

Part 04 : Review

Dr Bernard Butler
Department of Computing and Mathematics, WIT.
(bernard.butler@setu.ie)

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Outline

- Selected questions

DM pipeline and Roles

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DM terms

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  3. Knowledge discovery and its potential to solve evolving problems

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    - Where data comes from
        - Transaction systems, to Unstructured web/social data
    - How the data is processed
        - In-database + Offline extracts, to pipelined streaming engines
    - How the results of that processing are used
        - operations and reporting, to knowledge discovery and integrated controls
    - Describe the technological trends in your answer.
        - see notes

Batch versus Streaming

- Compare batch and streaming approaches to data mining, giving 2 advantages and 1 disadvantage of each.
  - batch
  - streaming

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    - fraud detection, textual stream classification

Expertise and Roles

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- What is the role of *citizen data scientists* in Data Science teams?
  - original proposed to replace, now seen as adding to the data science team, with mentoring from senior data scientists

DM disadvantages

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  - individuals
  - groups of people
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  - the planet
    - energy usage in data centres
    - use of overly simplified models to represent complex systems

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    - Will the output be used to benefit the data processor at the expense of the data subjects or the wider community?

DIKW chain

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- see the lecture notes. Use examples for each phase and transformation.

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  - motivation
  - role of feedback loops
  - integration with software engineering processes more generally

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    - CRISP-DM: bridge waterfall and agile (particularlyfeature-oriented cyclical development) practices
    - TDSP: full agiles, integrates particularly with devops - resulting in *mlops*.

ML Tribes - Classification

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    - Logistic Regression (and variants)
  - Connectionists
    - Feedforward artificial neural network

Regression versus Classification

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  - How are they similar (at least 2 ways)?
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  - How are they different (2 ways)?
    - Target is numeric for regression and categorical for classification
    - Classification has a richer set of algorithms
    - Results analysis for classification is more complicated

Classification versus Clustering

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  - Clustering is more often used for data exploration rather than prediction

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  - desirable anomalies: discovering new medical treatments or subatomic particles (leading to new theories)

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ARM and Recommendation Systems

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  - recommender systems

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    - online dating