dm22s1

Topic 01 : Module Overview

Part 04 : Review

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Outline

- Selected questions

DM pipeline and Roles

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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 - advantages

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    - fraud detection, textual stream classification

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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

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  - groups of people
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    - 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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  - role of feedback loops
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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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  - Connectionists
    - Feedforward artificial neural network

Regression versus Classification

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    - 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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  - time series data is serially correlated (earlier data predicts later)

ARM and Recommendation Systems

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  - association rules mining (ARM)
  - recommender systems

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    - online dating