dm24s1

Topic 02 : Motivating Example

Part 02 : Introduction to Data Operations

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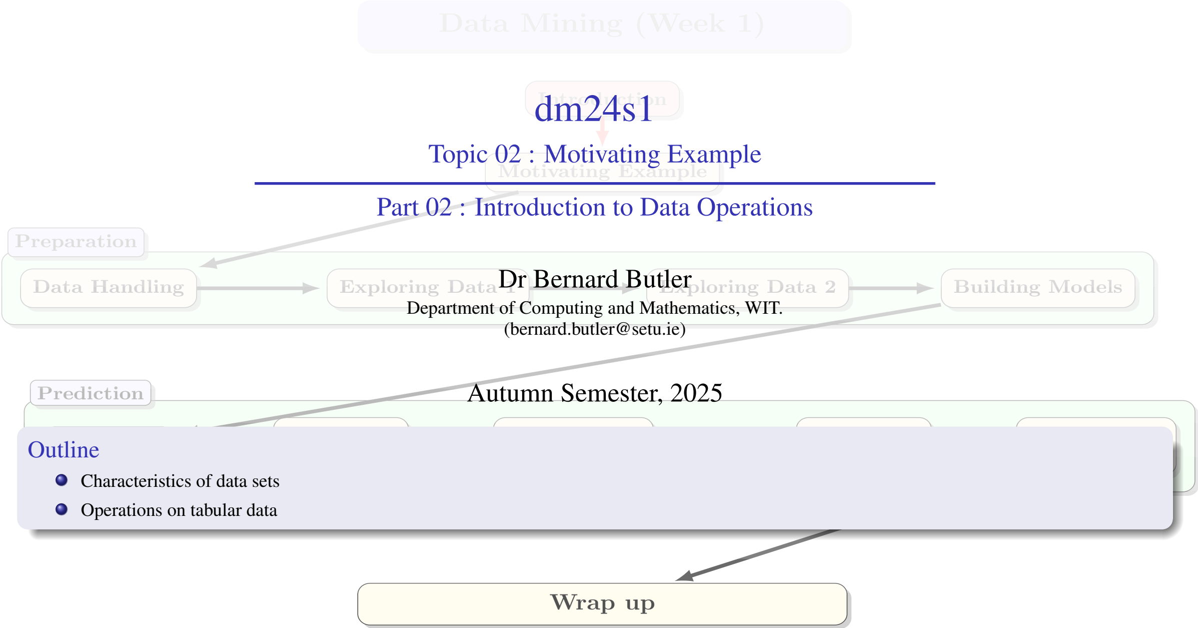
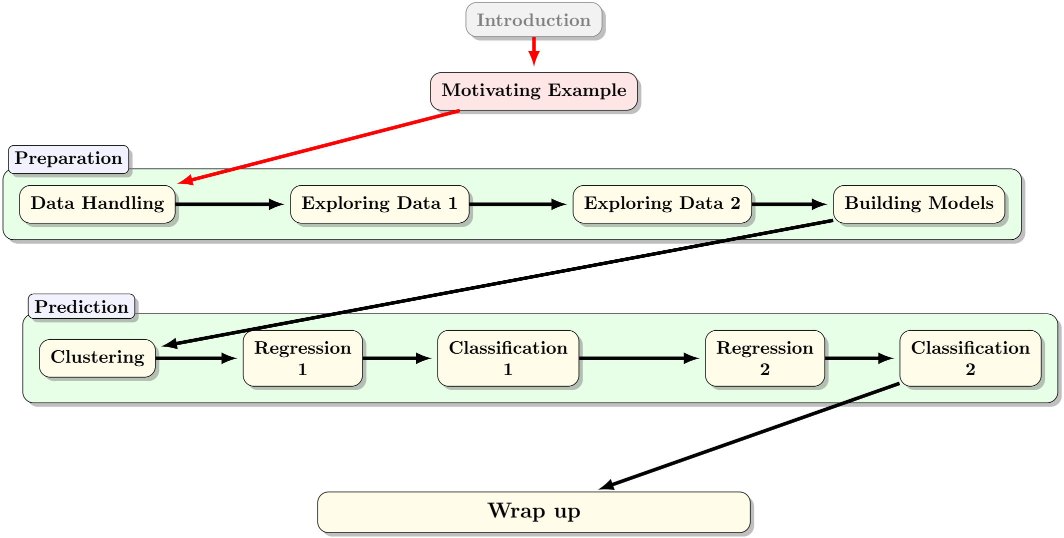
Autumn Semester, 2025



Outline

- Characteristics of data sets
- Operations on tabular data

Data Mining (Week 2)



Outline

Data sources

Type	Format	Example	DBMS	Language	Readiness for ML
Relational	Table	Transactions	MySQL, Post-gresql, ...	SQL	Maps to dataframe
Flat	Key + Value	Caches	Redis, mem-cached, ...	DBMS-Specific	Not rich enough
Document	Serialised objects	Tweets	Mongodb, Cassan-dra. ...	MQL, CQL	Too rich
Graph	Nodes and edges	Social relation-ships	Neo4j, Dgraph, ...	Gremlin, Cypher, DQL, ...	Specialised analyses
Columnar	DataSet	Logs	HBase, Spark DataSet	Hive QL, Spark SQL	Maps to dataframe

Preparing data

Data Preparation is the first step in data mining

In practice, data can be

- structured or unstructured,
- consolidated or scattered,
- consistent or inconsistent,
- clean or with error.

ML prefers structured, consolidated, consistent data, as clean as possible.

The `auto_mpg.csv` dataset already has these characteristics.

Outline

The auto-mpg dataset

1	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
2	18	8	307	130	3504	12	70	1	chevrolet chevelle malibu
3	15	8	350	165	3693	11.5	70	1	buick skylark 320
4	18	8	318	150	3436	11	70	1	plymouth satellite
5	16	8	304	150	3433	12	70	1	amc rebel sst
6	17	8	302	140	3449	10.5	70	1	ford torino
7	15	8	429	198	4341	10	70	1	ford galaxie 500
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3. Each column stores a *variable*. Other terms include attributes and targets.
4. Machine learning uses combinations of these columns to build models.

Understanding the `auto-mpg` dataset: Column Sufficiency

Learning

- Given a collection of columns (a *projection* of the full dataset), how does this help the machine to learn?

Applied to `auto-mpg`

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- What other learning can be derived from the chosen column collection?

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- …We can use *selection* (also known as *restriction*) - but how do we choose which rows to keep?

Example

```
SELECT displacement, horsepower, weight, mpg
FROM auto_mpg
WHERE horsepower > 79;
```

- SELECT clause: projection (restricting columns: column sufficiency)
- WHERE clause: selection (restricting rows: row sufficiency)

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- Can generate summaries in three ways
    1. Sampling - reduce/remove row duplication
    2. Banding - reduce the cardinality of a column
    3. Grouped Aggregation - roll up by level, aggregating as needed

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- Number of rows to keep in the sample is a compromise
- Can reduce runtime while allowing estimates of the uncertainty in a predictive model
- However, an aggregated column might be a better choice

```sql
-- Return a random sample of 3 Japanese cars
SELECT *
FROM AutoMpg
WHERE originID = 3
ORDER BY RANDOM()
LIMIT 3;
```

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   WHEN horsepower < 130 THEN 'low'
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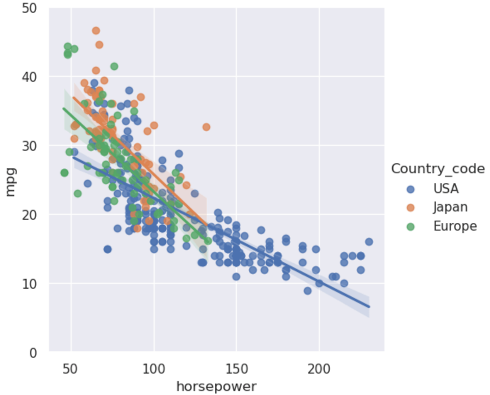

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- ...Take a set of values, compute an aggregate value
- Sets can be partitioned by grouping variable, aggregate applied to each partition
- ...Example: average mpg per country of manufacture

```
SELECT originID, AVG(mpg)
FROM AutoMpg
GROUP BY originID;
```

Outline

Summary

- Semantically rich, flat data is preferred for machine learning
- Ideally, this data would also be structured, consolidated, consistent and clean
- Several data operations were described, using the AutoMpg dataset as an example data source
  - Projection
  - Selection
  - Summarising: Sampling, Banding, Grouped Aggregation

Your task is to apply this to datasets using the python toolchain.