dm25s1

Topic 02 : Motivating Example

Part 02 : Introduction to Data Operations

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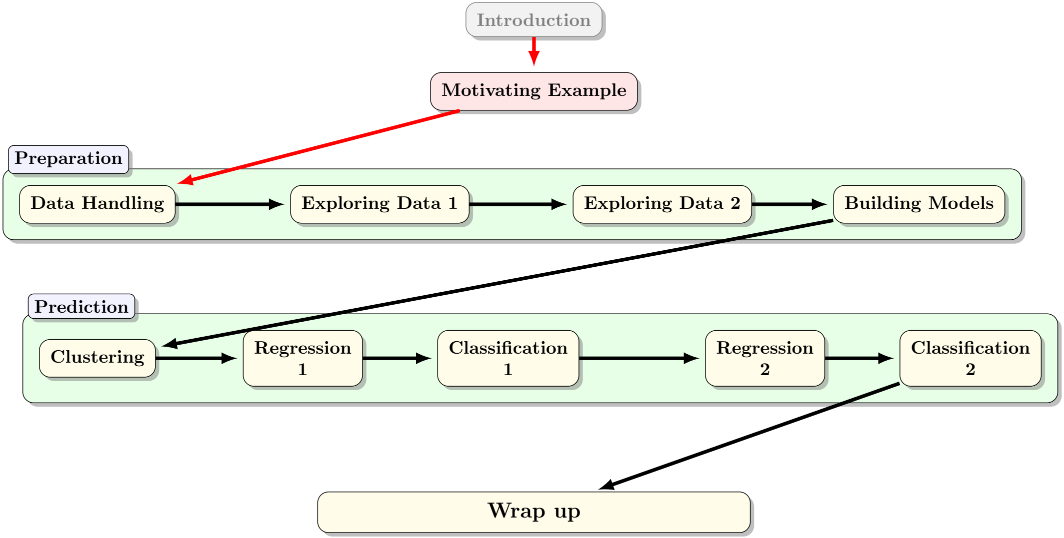
Outline

- 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, Postgresql, ...	SQL	Maps to dataframe
Flat	Key + Value	Caches	Redis, memcached, ...	DBMS-Specific	Not rich enough
Document	Serialised objects	Tweets	Mongodb, Cassandra. ...	MQL, CQL	Too rich
Graph	Nodes and edges	Social relationships	Neo4j, Dgraph, ...	Gremlin, Cypher, DQL, ...	Specialised analyses
Columnar	DataSet	Logs	HBase, Spark DataSet	Hive QL, Spark SQL	Maps to dataframe

Generally, rich flat data representations are best suited to machine learning

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
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11	15	8	390	190	3850	8.5	70	1	amc ambassador dpl
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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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    2. Banding - reduce the cardinality of a column
    3. Grouped Aggregation - roll up by level, aggregating as needed

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- 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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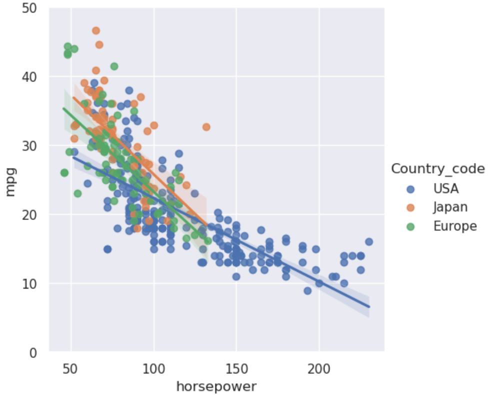

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- . . . Take a set of values, compute an aggregate value
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- . . . Example: average mpg per country of manufacture

```
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.