Analyse et manipulation des données

*DigitalLab@LaPlataforme_*

What is it about?

Problematic situation

Problematic situation → **data collection**

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data collection

Analysis and exploration

- What **random variables are available**?
- What **distribution** do they have?

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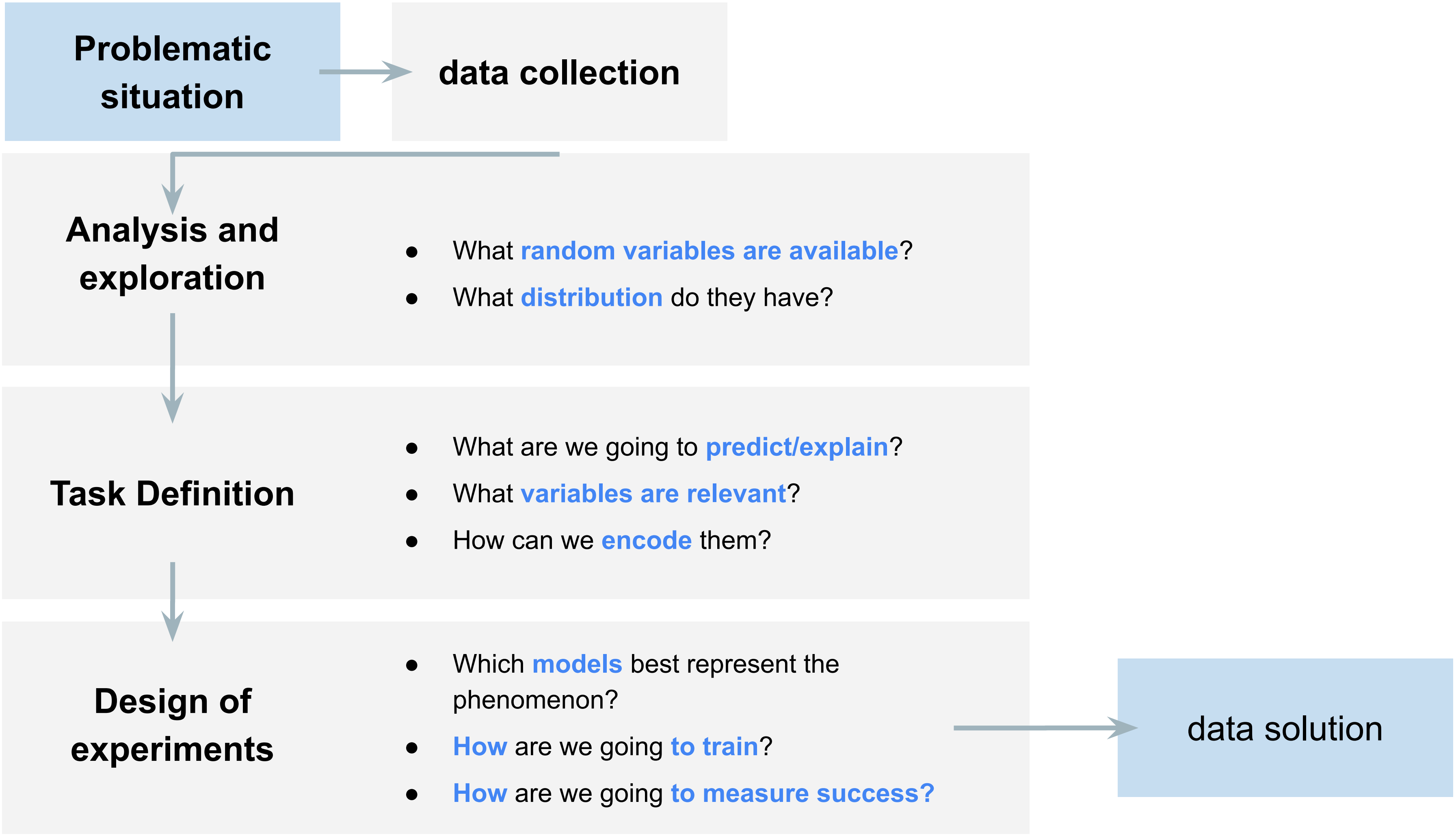
Design of experiments

- Which **models** best represent the phenomenon?
- **How** are we going **to train**?
- **How** are we going **to measure success**?



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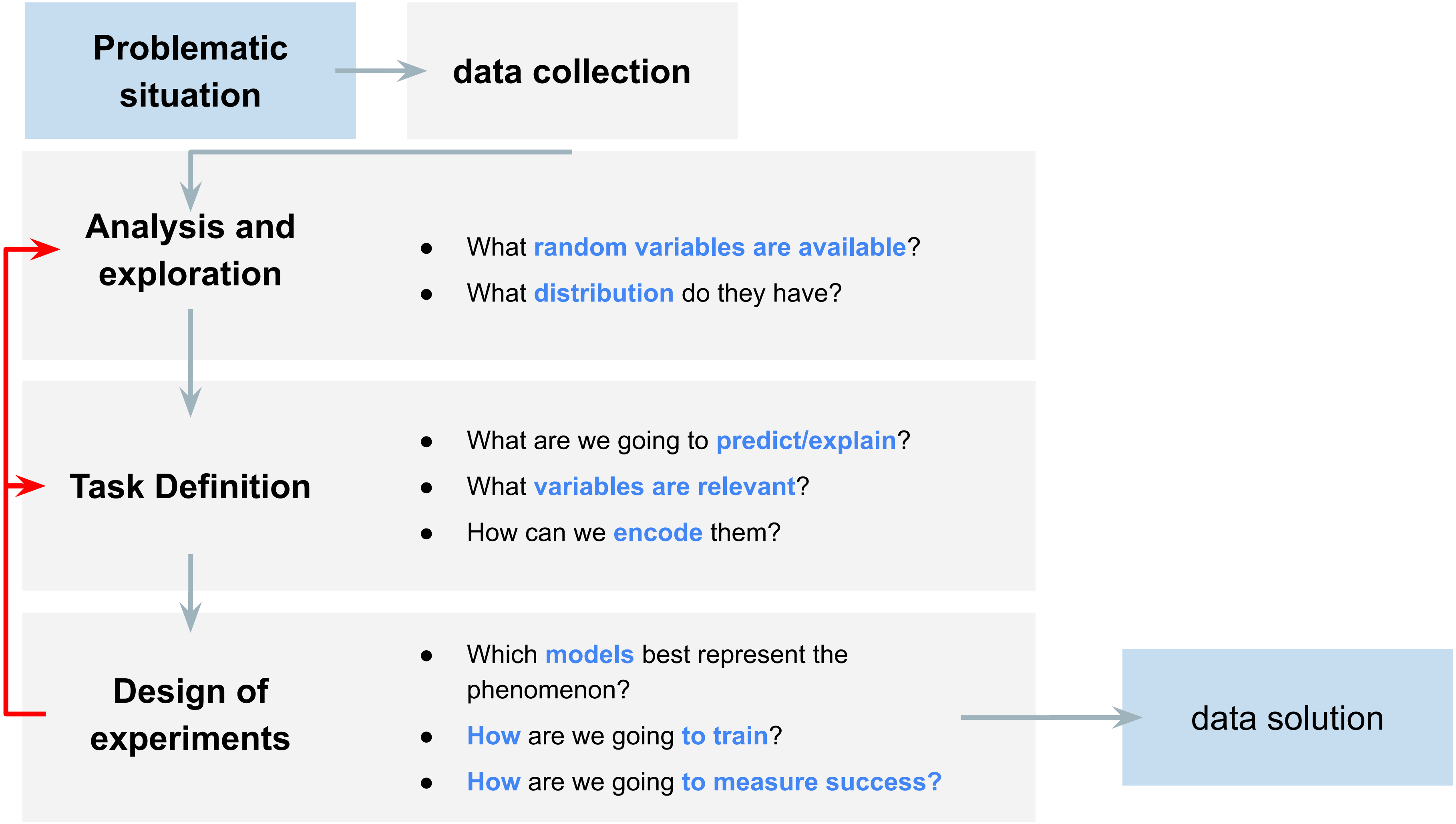
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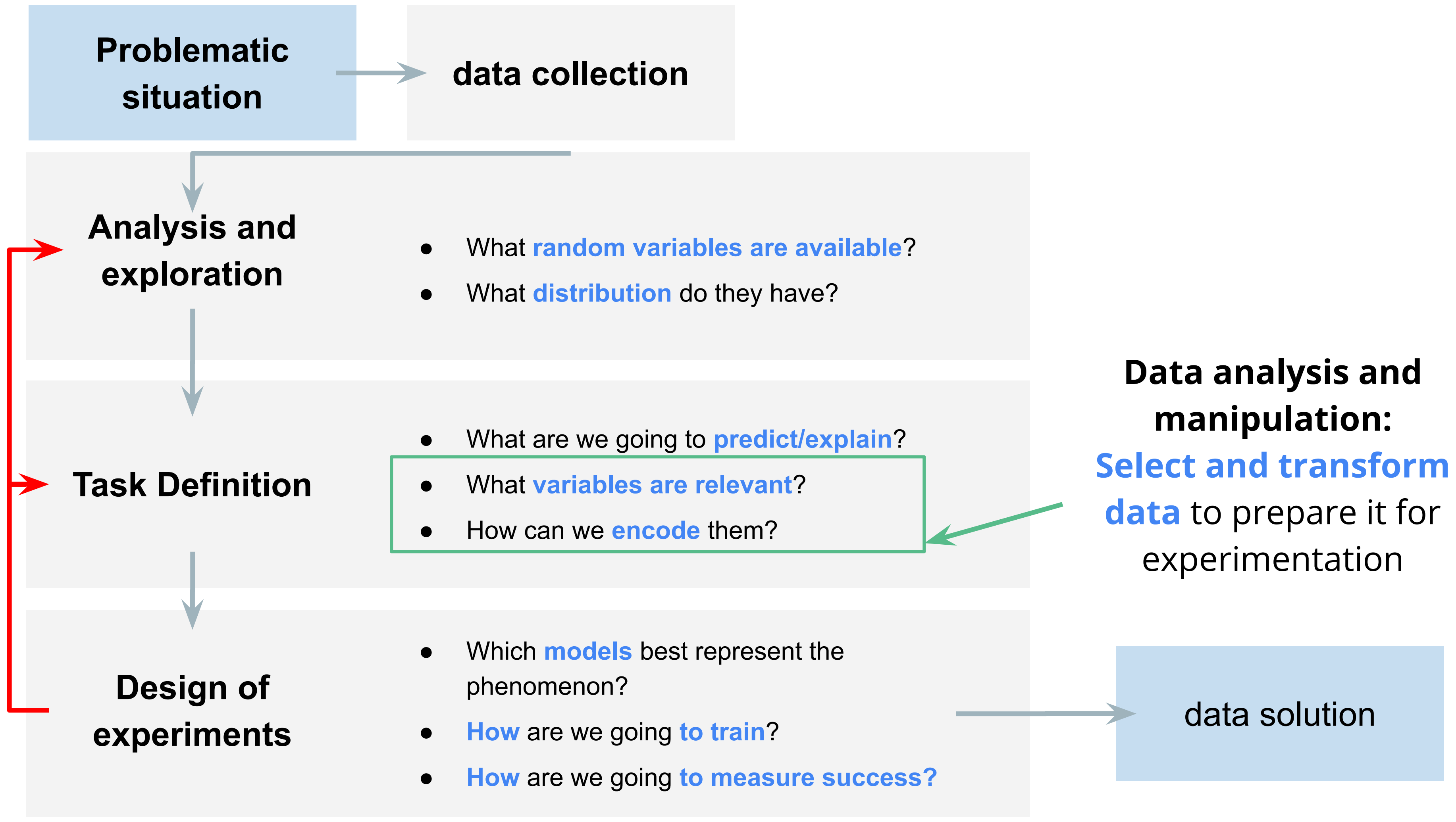
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Data analysis and manipulation:
Select and transform data to prepare it for experimentation
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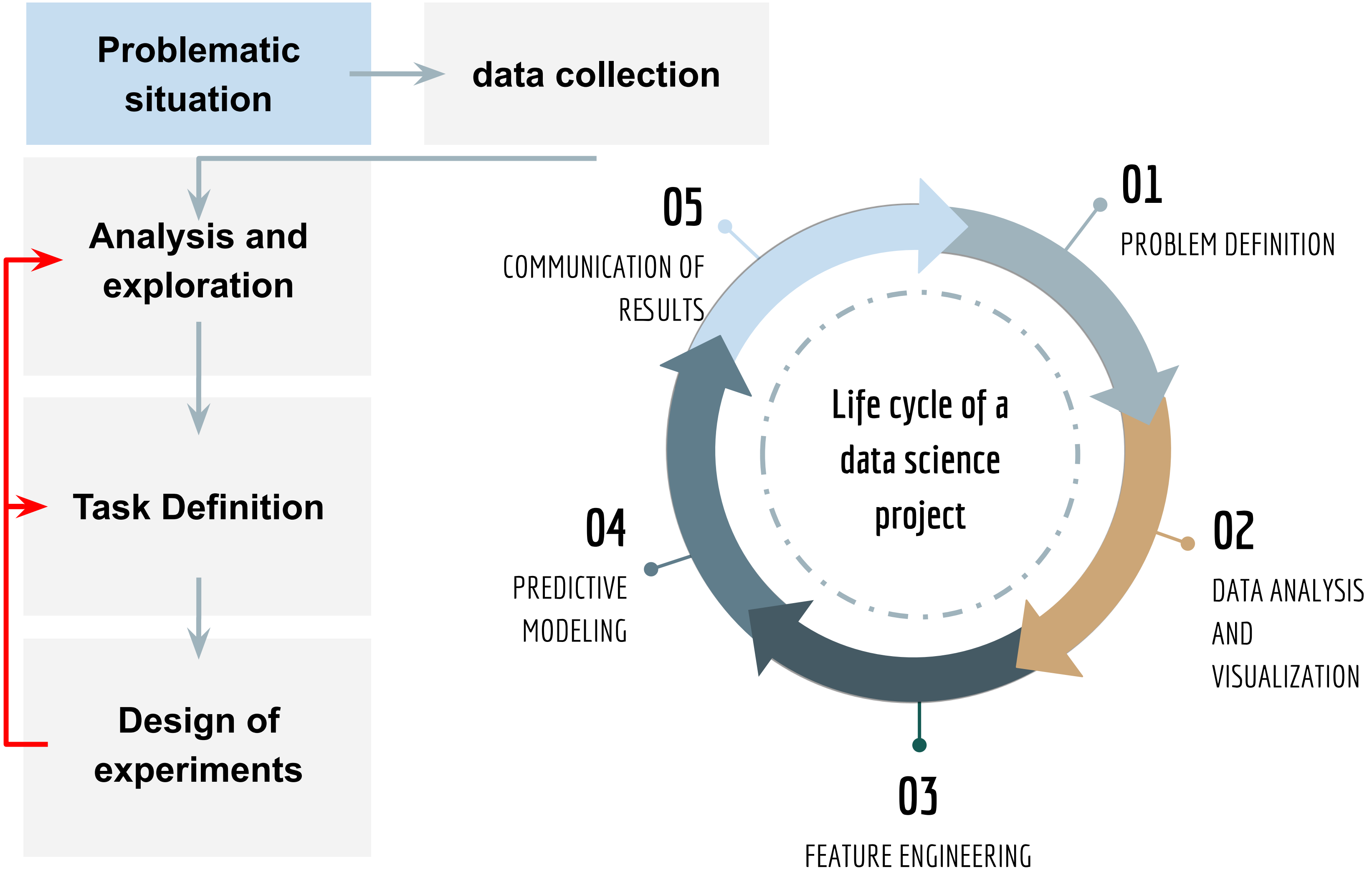
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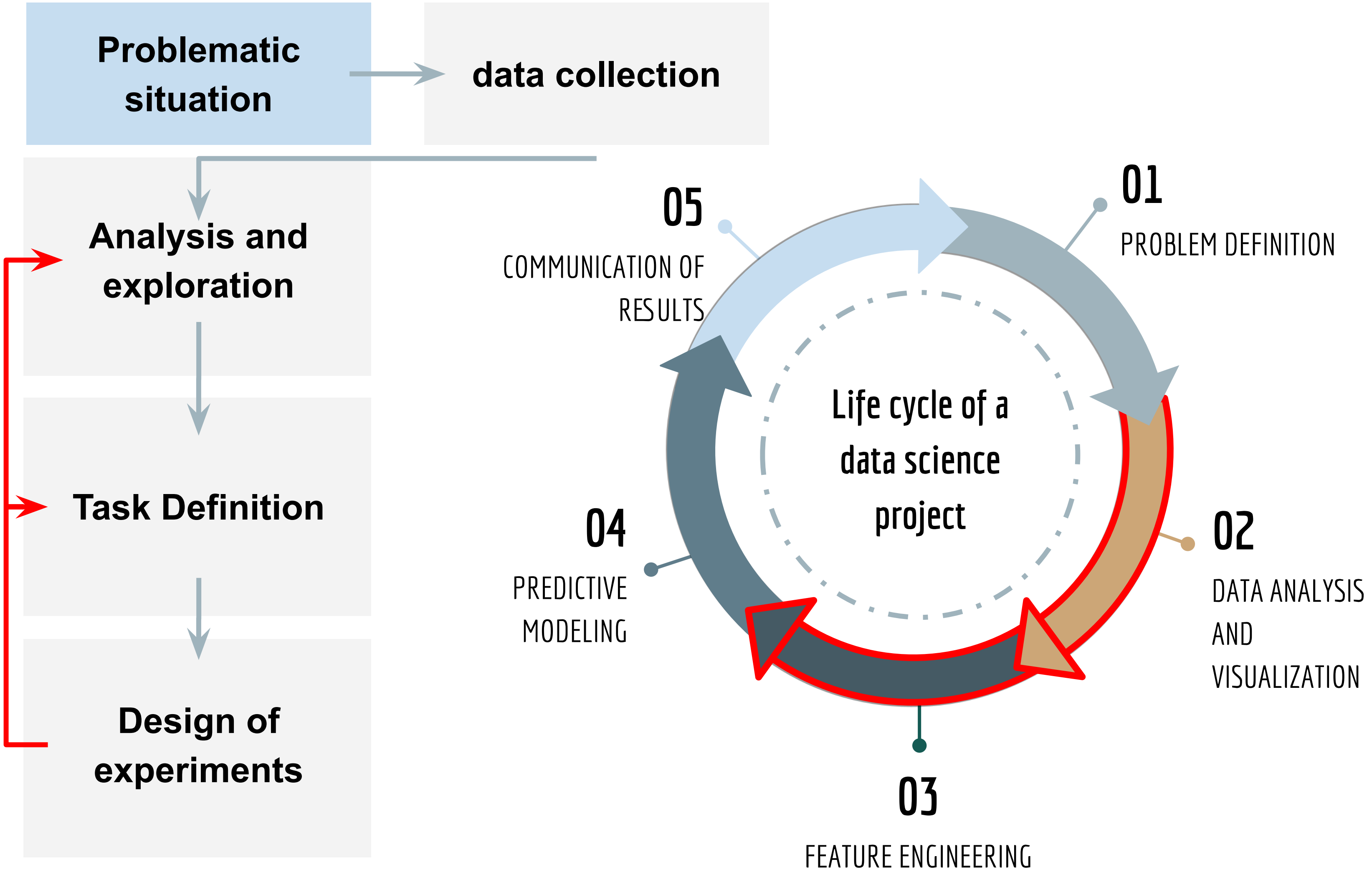
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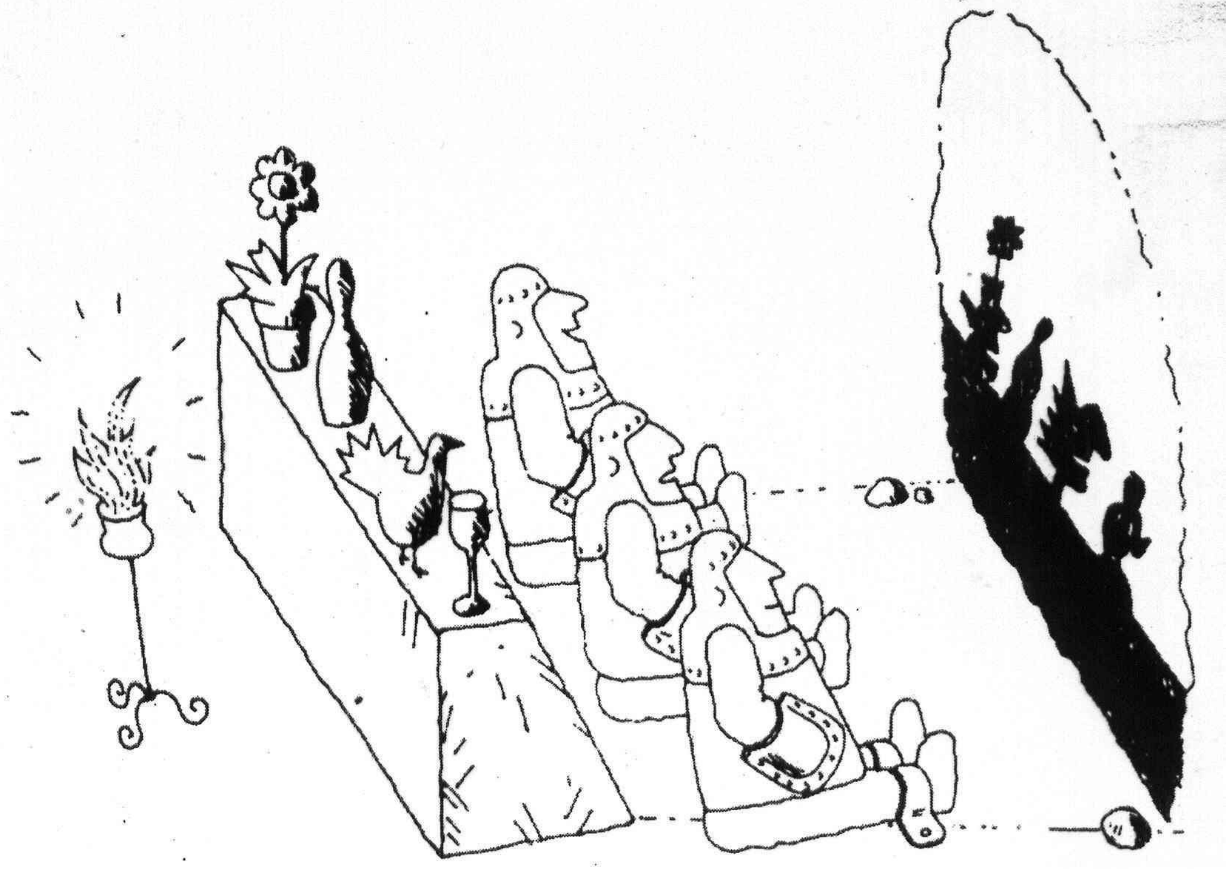
We want to bring out the **important features** for a given task

Data science is like

Plato's cave allegory

The data is a **projection** that shows us only **certain aspects of the phenomenon** we are studying.



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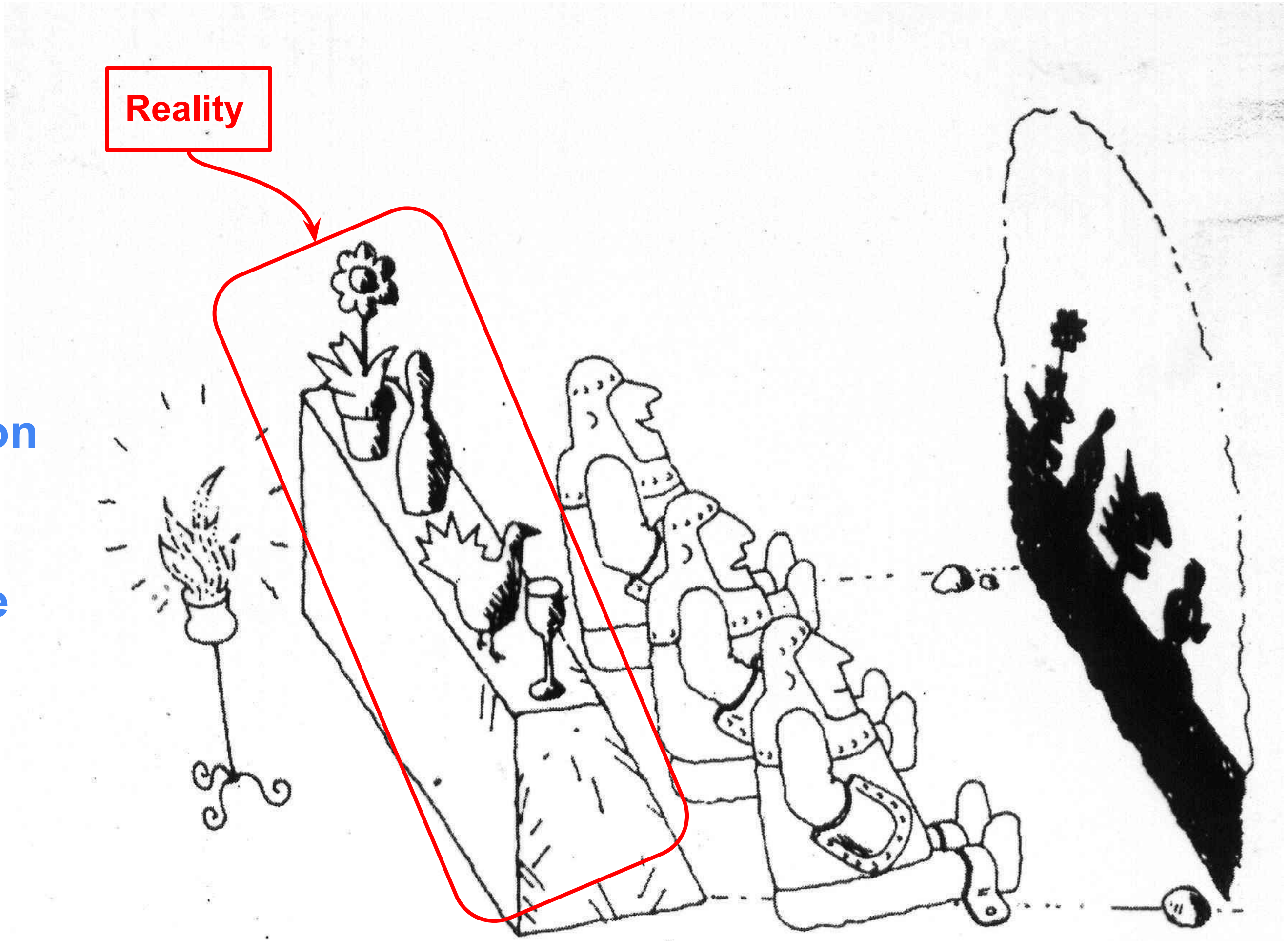

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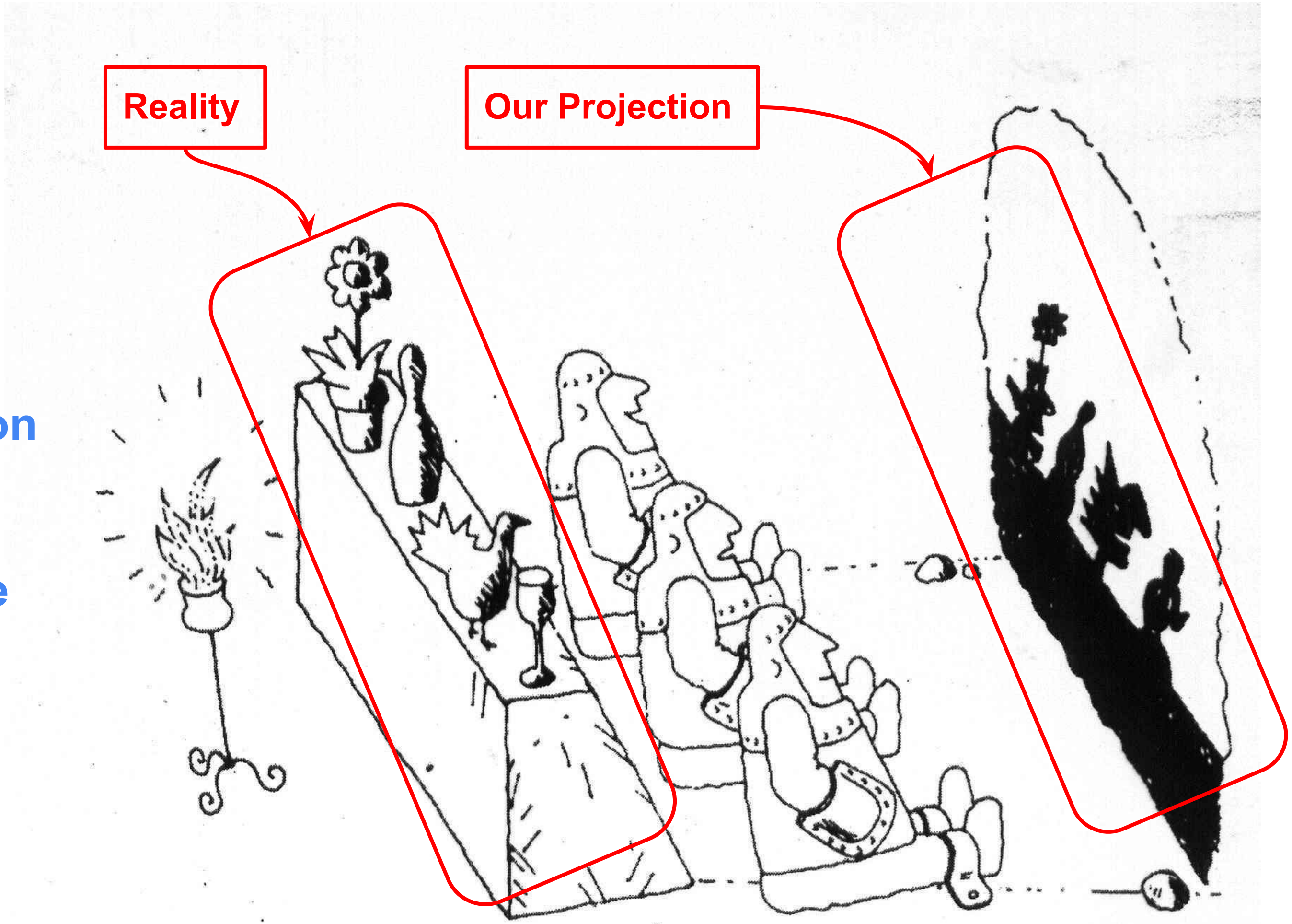

Demo notebook

01_exploration.ipynb

Filtering, Projecting and Curating

Conceptual aspects:

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Conceptual aspects:

- Outlier Treatment
- Bias Detection
- Value Imputation

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Practical Aspects:

Filtering, Projecting and Curating

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- Bias Detection
- Value Imputation

Practical Aspects:

- Reading and Cleaning
- Aggregation and Transformation
- Reproducibility
- Partitioning and Sampling

Filtering, Projecting and Curating

To decide on the manipulation processes, we have to **understand our data** as a whole. This includes:

Filtering, Projecting and Curating

To decide on the manipulation processes, we have to **understand our data** as a whole. This includes:

- All the analytics tools we've seen in **data visualization**.
- More complex techniques for data analysis that allow **multiple variables to be related**.
- Tradeoff: **filtering/curating** our dataset VS **limiting our dataset** too much.

Some Examples

Problematic situation	**Data**	**Curation decisions**
Predict programmers salaries in Argentina in 2020		

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Predict the price of a property	Government database with records of real house transactions. It has price, date and location.	➔ Delete day and month of the transaction. ➔ *Scrape* buying/selling sites to extract additional information about each property. ➔ **Impute missing values** using estimates based on similar examples.

The curse of the categories

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The **categories** give me information because they **group different examples**.

The **fewer examples** they group together, the **less informative** they are.

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Possible approaches with categories with fewer instances:

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Possible approaches with categories with fewer instances:

- **Delete the variable**.
- **Combine it** with another variable.
  - Ex: We only use the zipcode for neighborhoods that have more than one postal code.
- **Create new categories**:
  - Group similar categories.
  - Create an “other” category for categories that don't have many examples.

Data Enrichment

Combining different datasets

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Another common preprocessing strategy is **scrapping new information from other sources** and **merging it** with your current dataset. This helps to:

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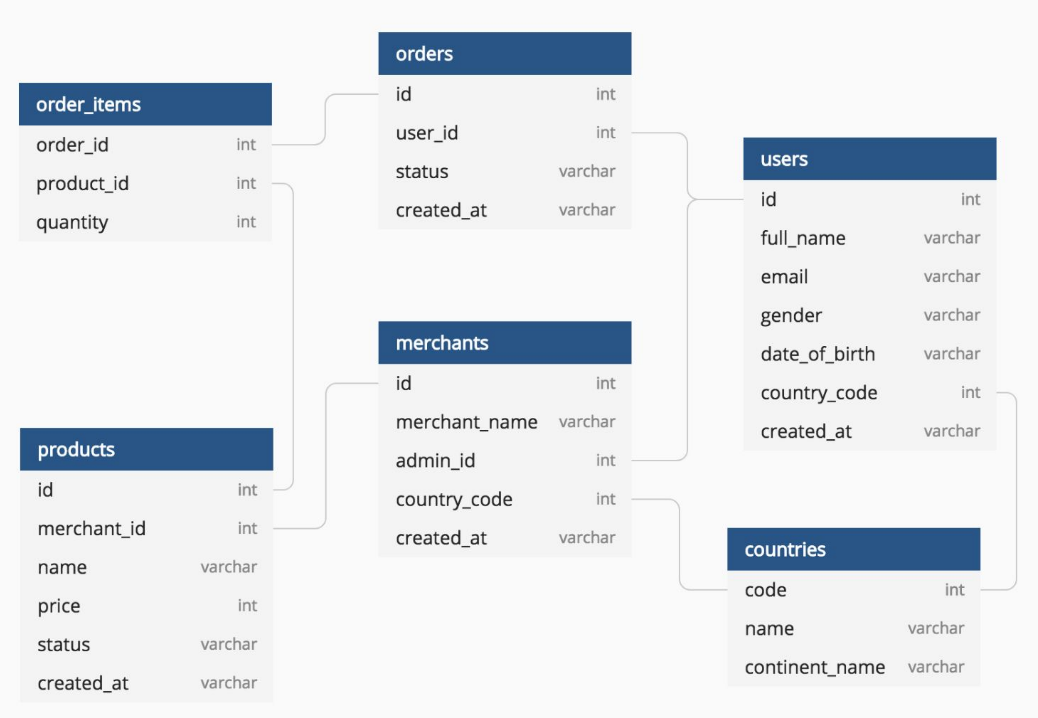
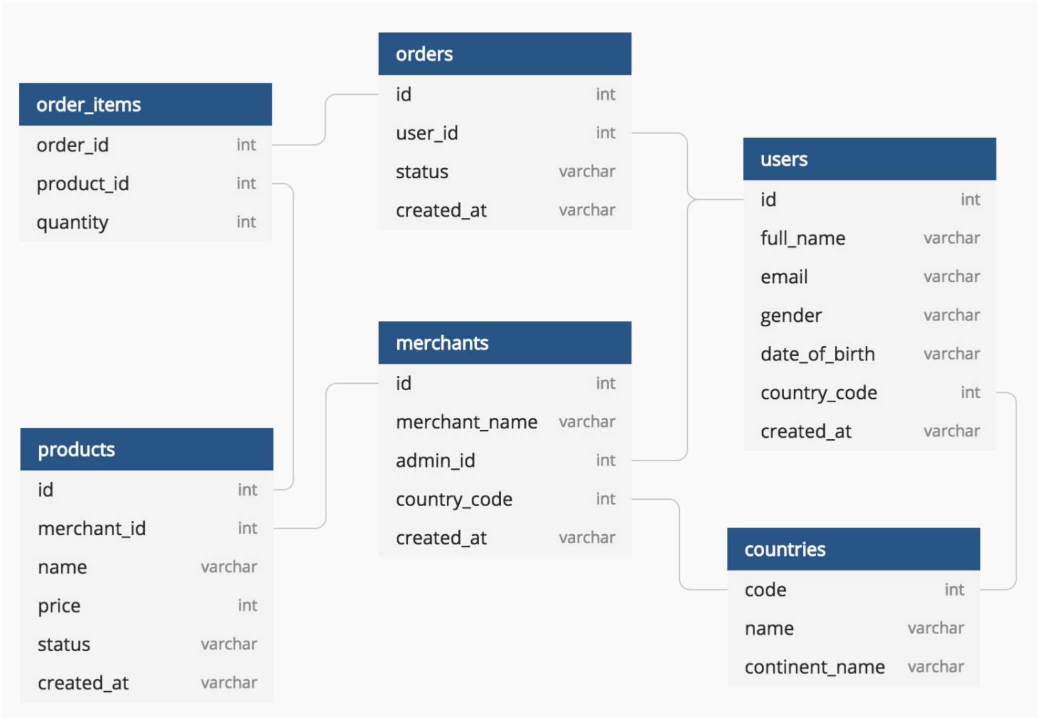
- Add new random variables that might help to improve get better performance in your task.
- Curate missing values.
- The data structure is not the same as the type of database.

Relational Data



Relational Data

- All **records** in a table **have the same characteristics**.



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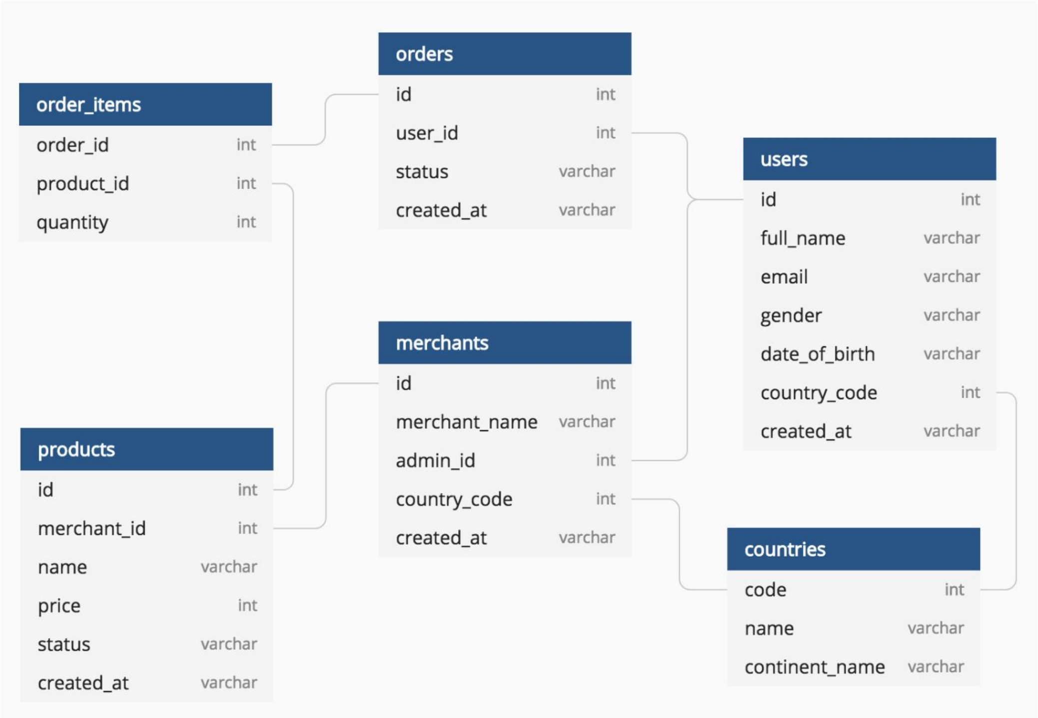

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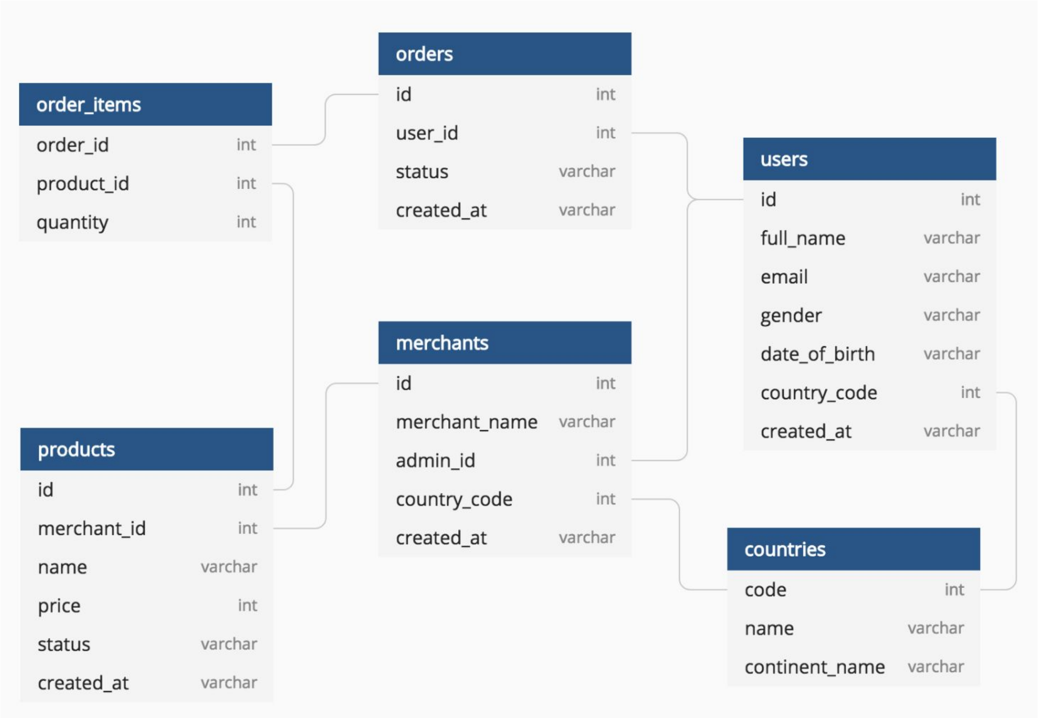

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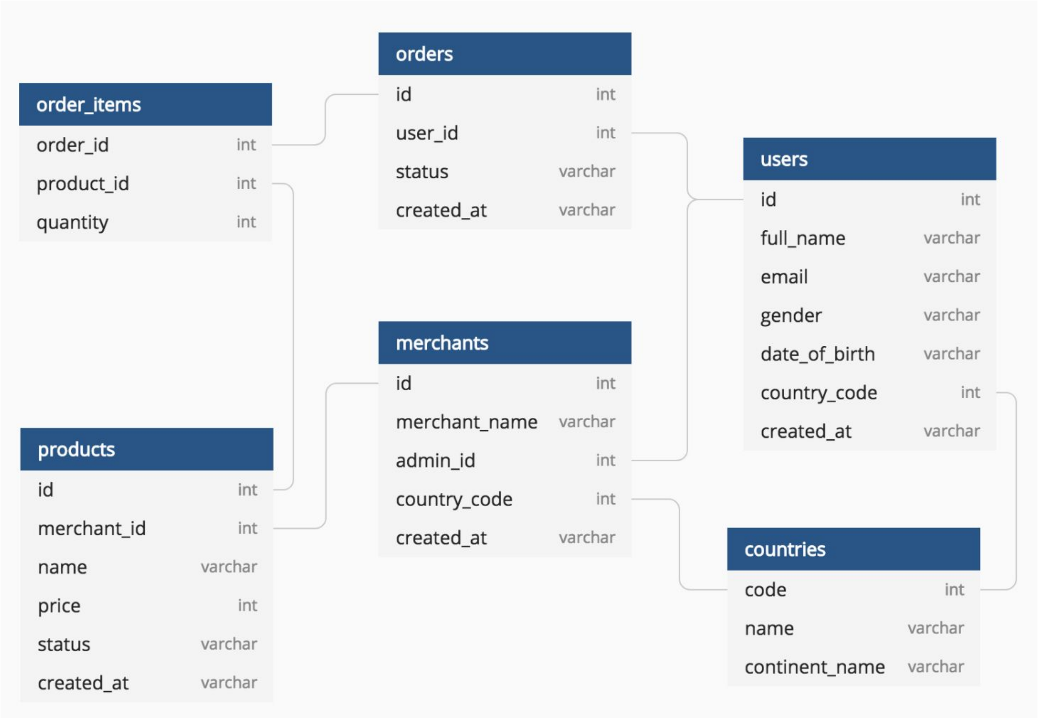

- Files in CSV format, parquet, etc.
- Relational databases like MySQL, Postgres

Semi-structured data

- Each record has a **different set of characteristics**


```json
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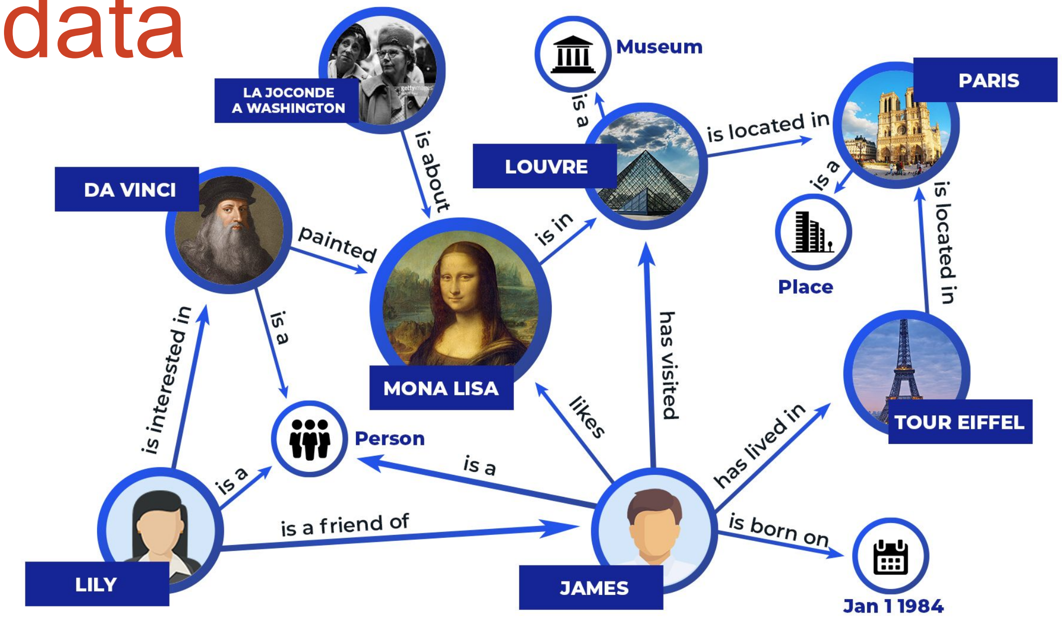
- Files in JSON format
- Non-relational databases like MongoDB

Semi-structured data

- Records can have complex relationships
  - Hierarchies
  - Graph Structure (Twitter)
  - Graph-oriented databases



Unstructured data

- Collections of different types:
  - Text documents
  - Images
  - Audio

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- Collections of different types:
  - Text documents
  - Images
  - Audio
- May or may not have associated metadata

Grouping and Aggregation

- groupby:
  - Takes a series of columns ***A***, ***B***, ***C***
  - For each combination of column values ***(a, b, c)***, group the rows that have those values.

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- agg:
  - Takes a function ***F***
  - For each group of rows, apply the function ***F*** to each column.

Grouping and Aggregation

	species	sepal_length	sepal_width	petal_length	petal_width
0	setosa	5.1	3.5	1.4	0.2
1	setosa	4.9	3.0	1.4	0.2
2	setosa	4.7	3.2	1.3	0.2
3	setosa	4.6	3.1	1.5	0.2
4	setosa	5.0	3.6	1.4	0.2
50	versicolor	7.0	3.2	4.7	1.4
51	versicolor	6.4	3.2	4.5	1.5
52	versicolor	6.9	3.1	4.9	1.5
53	versicolor	5.5	2.3	4.0	1.3
54	versicolor	6.5	2.8	4.6	1.5
100	virginica	6.3	3.3	6.0	2.5
101	virginica	5.8	2.7	5.1	1.9
102	virginica	7.1	3.0	5.9	2.1
103	virginica	6.3	2.9	5.6	1.8
104	virginica	6.5	3.0	5.8	2.2

df.groupby('species').agg('sum')

SUM

species	sepal_length	sepal_width	petal_length	petal_width
setosa	24.3	16.4	7.0	1.0
versicolor	32.3	14.6	22.7	7.2
virginica	32.0	14.9	28.4	10.5

SUM

SUM

https://towardsdatascience.com/how-to-use-the-split-apply-combine-strategy-in-pandas-groupby-29e0eb44b62e

Join and Merge

- df1.join(df2, how='outer')
    - Horizontally join the DataFrames and match the rows where the index value is the same

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K1	A1	B1	NaN	NaN
K2	A2	B2	C2	D2
K3	NaN	NaN	C3	D3

Join and Merge

- df1.merge(df2, on='key')
  - Same as join, but instead of comparing indexes, it compares a set of columns.

left

	key	A	B
0	K0	A0	B0
1	K1	A1	B1
2	K2	A2	B2
3	K3	A3	B3

right

	key	C	D
0	K0	C0	D0
1	K1	C1	D1
2	K2	C2	D2
3	K3	C3	D3

Result

	key	A	B	C	D
0	K0	A0	B0	C0	D0
1	K1	A1	B1	C1	D1
2	K2	A2	B2	C2	D2
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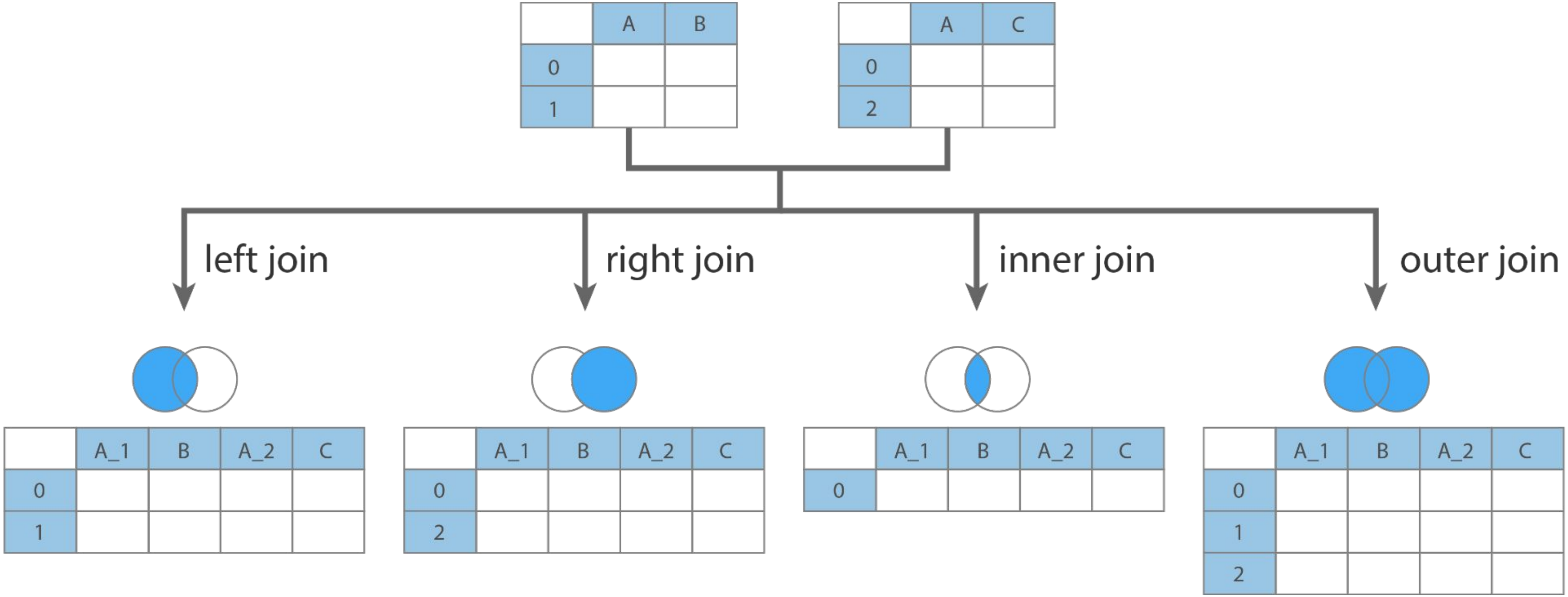

https://towardsdatascience.com/python-pandas-dataframe-join-merge-and-concatenate-84985c29ef78

Unexpected Duplicates!

df1

Product	Sales
R22	45
J14	10
R5	58
P17	24

df2

Product	Category
R22	T-shirt
J14	Jean
J14	Trousers
R5	T-shirt
P17	Trousers

```
all_sales = df1.merge(
    df2, on=’Product’)
```

Product	Category	Sales
R22	T-shirt	45
J14	Jean	10
J14	Trousers	10
R5	T-shirt	58
P17	Trousers	24

```
cat_sales = all_sales\
.groupby(Category).sum()
```

Category	Sales
T-shirt	103
Jean	10
Trousers	34

```
total_sales =
    all_sales.Sales.sum()
```

Demo notebook

02_combining_datasets.ipynb