Database and Data Wrangling

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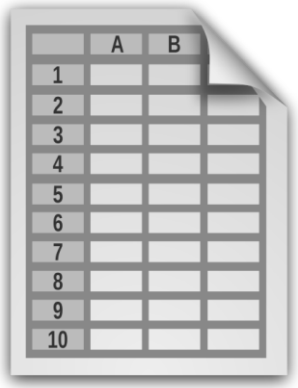
Growth
STARTUP
Success
idea

Taxonomy of the data

- Data is facts, observations and measurements that are used to make discoveries and to support decisions. A data point is a single unit of data with in a dataset
  - Datasets may come in different formats and structures, and will usually be classified based on its *source*
  - For example, a company's monthly earnings might be in a *spreadsheet* but hourly heart rate data from a smartwatch or simple personal information in a club may be in *JSON* format. It's common for data scientists to work with different types of data



JSON

```
{
    "firstName": "John",
    "lastName": "Doe",
    "age": "23",
    "hobbies": [
        { "type": "Sports", "value": "Golf" },
        { "type": "Leisure", "value": "Reading" },
        { "type": "Leisure", "value": "Guitar" }
    ]
}
```

https://docs.microsoft.com/en-us/learn/modules/choose-storage-approach-in-azure/2-classify-data

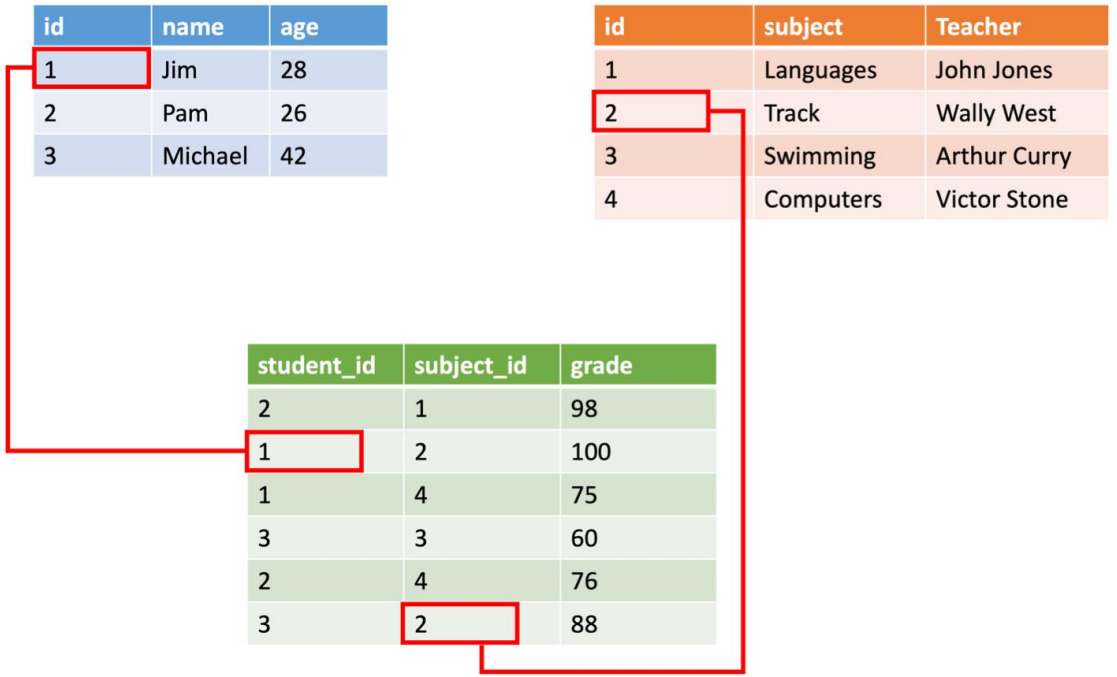
Database and data wrangling

- On the other hand, the data may live in *databases*, systems designed for efficiently storing and querying data. You will need to know how to read it and extract the data you want
  - The bulk of these are relational databases, such as SQLite, MySQL, and SQL Server, which store data in tables and are typically queried using Structured Query Language (SQL), a declarative language for manipulating data
  - https://leemeng.tw/why-you-need-to-learn-sql-as-a-data-scientist.html

- However, most flexible way of data processing is writing your own program to manipulate data
  - When more complex data processing is needed, it cannot be done easily using SQL
  - Data wrangling using Dataframe is a rescue

1. How data is Described?

- **Structured data** is data that is organized into rows and columns, where each row will have the same set of columns and it adheres to a strict *schema*
  - Columns will often have a *specific set of rules or restrictions on the values*, to ensure that the values accurately represent the column
    - \+ High efficiency and it can be organized in such a way that it can be *related* to other structured data
    - \- However, making changes to its overall structure can take a lot of effort to do
  - Examples of structured data: relational databases



id	name	age
1	Jim	28
2	Pam	26
3	Michael	42

id	subject	Teacher
1	Languages	John Jones
2	Track	Wally West
3	Swimming	Arthur Curry
4	Computers	Victor Stone

student_id	subject_id	grade
2	1	98
1	2	100
1	4	75
3	3	60
2	4	76
3	2	88

https://docs.microsoft.com/en-us/learn/modules/choose-storage-approach-in-azure/2-classify-data

2. Relational Database

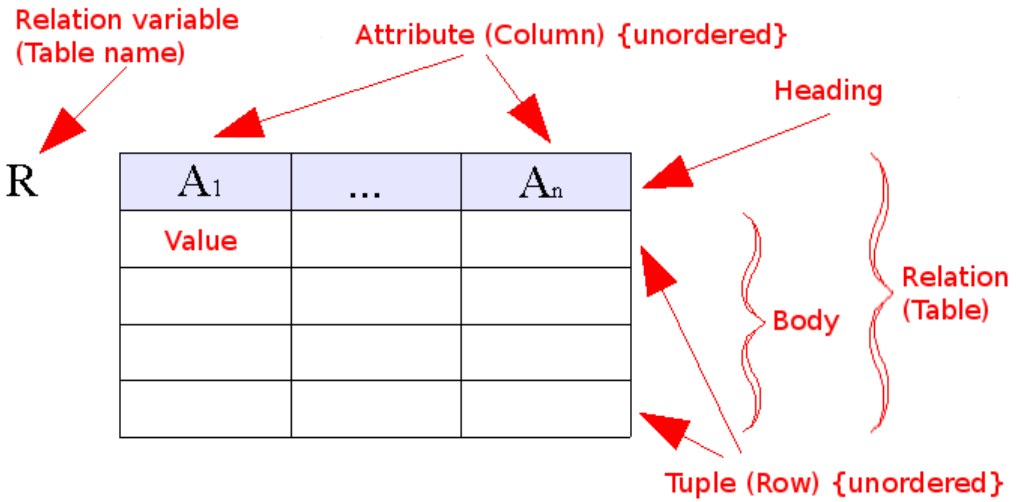
- Data scientists will usually already get data that has *passed a first round of cleaning and manipulation*
  - A *relational database* is built upon the core principle of columns (fields, attributes) and rows (records, tuples) in tables, allowing you to have information spread across multiple tables. This allows you to work with complex data, avoid duplication, and have flexibility
  - A *DataBase Management System* ***(DBMS)*** is software that allows applications to store and analyze information in a database
    - ACID (atomicity, consistency, isolation, durability) is a set of properties of database transactions intended to guarantee data validity despite errors, power failures, and other mishaps

Data Model

- Proposed in 1970 by Ted Codd
  - Database abstraction
    - Store database in simple data structures (relations)
    - Physical storage is left up to the DBMS implementation
    - Access data through a high-level language
- A data model is a collection of concepts for describing the data in a database
  - **Relational**
  - Key/Value
  - Graph
  - Document/object
  - Column-family
  - Array/Matrix

Relational model

- A relation is unordered set that contain the relationship of attributes that represent entities
  - A *tuple* is a set of attribute values in the relation
  - *n*-ary Relation = Table with *n* columns
  - A relation's *primary key* uniquely identifies a single tuple
  - A *foreign key* specifies that an attribute from one relation has to map to a tuple in another relation



https://en.wikipedia.org/wiki/Relational_model

Relational Algebra

- Fundamental operations to retrieve and manipulate tuples in a relation
  - Based on set algebra
  - Each operator takes one or more relations as its inputs and outputs a new relation
  - We can “chain” operators together to create more complex operations
- SQL provides hundreds of different ways to analyze and recombine data. We will only look at a handful of queries
  - When a user submits a SQL query to a database, the DBMS translates the query into a series of relational algebra operations that can be executed against the database
  - When we are using a database, we send queries to a database manager. The database manager does whatever lookups and calculations the query specifies, returning the results in a tabular form that we can then use as a starting point for further queries
  - Cheat sheet: https://www.mit.edu/~amidi/teaching/data-science-tools/study-guide/data-retrieval-with-sql/

Schema

- The structure of a table is called its **schema**. We need to understand a table's schema to effectively pull out the data we want
  - The database schema is its structure described in a formal language supported by the DBMS. The term "schema" refers to the organization of data as a blueprint of how the database is constructed (divided into database tables in the case of relational databases)

`pets_and_toys` table schema

```
SchemaField('ID', 'INTEGER', 'NULLABLE', None, ()),
SchemaField('Name', 'STRING', 'NULLABLE', None, ()),
SchemaField('Age', 'INTEGER', 'NULLABLE', None, ()),
SchemaField('Animal', 'STRING', 'NULLABLE', None, ()),
SchemaField('Toy', 'RECORD', 'NULLABLE', None, (
   SchemaField('Name', 'STRING', 'NULLABLE', None, ()),
   SchemaField('Type', 'STRING', 'NULLABLE', None, ())
))
```

https://www.kaggle.com/learn/intro-to-sql

Foundation of extraction – `SELECT, FROM, WHERE`

- The most basic SQL query selects a single column from a single table
  - Specify the column you want after the word `SELECT`, and then
  - Specify the table after the word `FROM`
- For instance, to select the `` `Name` `` column (from the `` `pets` `` table in the `` `pet_records` `` database), our query would appear as follows:

```
query = """
        SELECT Name
        FROM `bigquery-public-data.pet_records.pets`
        """
```

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

Foundation of extraction – `SELECT, FROM, WHERE`

- Datasets are usually very large, so you'll usually want to return only the rows meeting specific conditions. You can do this using the `WHERE` clause
  - The query below returns the entries from the `` `Name` `` column that are in rows where the `` `Animal` `` column has the text `` `Cat` ``

```
query = """
        SELECT Name
        FROM `bigquery-public-data.pet_records.pets`
        WHERE Animal = 'Cat'
        """
```

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

Get more interesting insights – `GROUP BY, HAVING, COUNT`

- This can help you answer questions like:
  - How many of each kind of fruit has our store sold?
  - How many species of animal has the vet office treated?
- `COUNT()` returns a count of things. If you pass it the name of a column, it will return the number of entries in that column
  - For instance, if we `SELECT` the `COUNT()` of the `` `ID` `` column in the `` `pets` `` table, it will return 4, because there are 4 ID's in the table
  - `COUNT()` is an example of an **aggregate function**, which takes many values and returns one. Other examples of aggregate functions include `SUM(), AVG(), MIN(),` and `MAX()`

```
query = """
        SELECT COUNT(ID)
        FROM `bigquery-public-data.pet_records.pets`
        """
```

f0_
4

Get more interesting insights – GROUP BY, HAVING, COUNT

- GROUP BY takes the name of one or more columns, and treats all rows with the same value in that column as a single group when you apply aggregate functions like COUNT()
  - We can use GROUP BY to group together rows that have the same value in the `Animal` column, while using COUNT() to find out how many ID's we have in each group If we want to know how many of each type of animal in the `pets` table

```
query = """
        SELECT Animal, COUNT(ID)
        FROM `bigquery-public-data.pet_records.pets`
        GROUP BY Animal
        """
```

Animal	f0_
Rabbit	1
Dog	1
Cat	2

Get more interesting insights – GROUP BY, HAVING, COUNT

- HAVING is used in combination with GROUP BY to ignore groups that don't meet certain criteria
  - HAVING clause behaves similarly to a WHERE clause, except that its filter is applied to the aggregates (whereas a WHERE would filter out rows before aggregation even took place)
  - So this query, for example, will only include groups that have more than one ID in them

```
query = """
        SELECT Animal, COUNT(ID)
        FROM `bigquery-public-data.pet_records.pets`
        GROUP BY Animal
        HAVING COUNT(ID) > 1
        """
```

Animal	f0_
Cat	2

Order results to focus on the most important data – `ORDER BY`

- You can change the order of results using the `ORDER BY` clause
  - `ORDER BY` is usually the **last clause** in your query, and it sorts the results returned by the rest of your query
  - Notice that the original rows are not ordered by the `ID` column. We can quickly remedy this with the query below

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
4	Tom	Cat
2	Moon	Dog
3	Ripley	Cat

```
query = """
        SELECT ID, Name, Animal
        FROM `bigquery-public-data.pet_records.pets`
        ORDER BY ID
        """
```

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

Order results to focus on the most important data – `ORDER BY`

- The `ORDER BY` clause also works for columns containing text, where the results show up in *alphabetical order*
  - You can reverse the order using the `DESC` argument (short for 'descending'). The following query sorts the table by the `Animal` column, where the values that are last in alphabetic order are returned first

```
query = """
        SELECT ID, Name, Animal
        FROM `bigquery-public-data.pet_records.pets`
        ORDER BY Animal DESC
        """
```

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

Look at interesting part - EXTRACT

- Often you'll want to look at part of a date. You can do this with EXTRACT
  - The query below returns two columns, where column `Day` contains the day corresponding to each entry the `Date` column from the `pets_with_date` table:

ID	Name	Animal	Date
1	Dr. Harris Bonkers	Rabbit	2019-04-18
4	Tom	Cat	2019-05-16
2	Moon	Dog	2019-01-07
3	Ripley	Cat	2019-02-23

```
query = """
        SELECT Name, EXTRACT(DAY from Date) AS Day
        FROM `bigquery-public-data.pet_records.pets_with_date`
        """
```

Name	Day
Dr. Harris Bonkers	18
Tom	16
Moon	7
Ripley	23

  - SQL is very smart about dates, and we can ask for information beyond just extracting part of the cell

```
query = """
        SELECT Name, EXTRACT(WEEK from Date) AS Week
        FROM `bigquery-public-data.pet_records.pets_with_date`
        """
```

Name	Week
Dr. Harris Bonkers	15
Tom	19
Moon	1
Ripley	7

Organize your query for better readability – `AS`, `WITH`

- With all that you've just learned, your SQL queries are getting pretty long, which can make them hard understand (and debug)
  - Use `AS` and `WITH` to tidy up your queries and make them easier to read
  - To use `AS` in SQL, insert it right after the column you select

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

```
query = """
        SELECT Animal, COUNT(ID)
        FROM `bigquery-public-data.pet_records.pets`
        GROUP BY Animal
        """
```

Animal	f0_
Rabbit	1
Dog	1
Cat	2

```
query = """
        SELECT Animal, COUNT(ID) AS Number
        FROM `bigquery-public-data.pet_records.pets`
        GROUP BY Animal
        """
```

Animal	Number
Rabbit	1
Dog	1
Cat	2

Organize your query for better readability – `AS`, `WITH`

- On its own, `AS` is a convenient way to clean up the data returned by your query. It's even more powerful when combined with `WITH` in what's called a ”common table expression” (or CTE)
  - CTE is a temporary table that you return within your query. CTEs are helpful for splitting your queries into readable chunks, and you can write queries against them

ID	Name	Animal	Years_old
1	Dr. Harris Bonkers	Rabbit	4.5
2	Moon	Dog	9.0
3	Ripley	Cat	1.5
4	Tom	Cat	7.8

```
query = """
        WITH Seniors AS
        (
            SELECT ID, Name
            FROM `bigquery-public-data.pet_records.pets`
            WHERE Years_old > 5
        )
        This query is incomplete. More coming soon!
        """
```

ID	Name
2	Moon
4	Tom

This is a **CTE** named `Seniors`.
(*It is not returned by the query.*)

Organize your query for better readability – `AS, WITH`

- While this incomplete query above won't return anything, it creates a CTE that we can then refer to (as `Seniors`) while writing the rest of the query
  - It's important to note that CTEs only exist inside the query where you create them, and you can't reference them in later queries. So, any query that uses a CTE is always broken into two parts: (1) first, we create the CTE, and then (2) we write a query that uses the CTE

ID	Name	Animal	Years_old
1	Dr. Harris Bonkers	Rabbit	4.5
2	Moon	Dog	9.0
3	Ripley	Cat	1.5
4	Tom	Cat	7.8

ID	Name
2	Moon
4	Tom

is is a **CTE** named `Seniors`.
is not returned by the query.)

```
query = """
        WITH Seniors AS
        (
            SELECT ID, Name
            FROM `bigquery-public-data.pet_records.pets`
            WHERE Years_old > 5
        )
        SELECT ID
        FROM Seniors
        """
```

ID
2
4

Combine data sources – `JOIN`, `UNION`

- You have the tools to obtain data from a single table in whatever format you want it. But what if the data you want is spread *across multiple tables*?
  - That's where `JOIN` comes in! `JOIN` is incredibly important in practical SQL workflows

`owners` table

ID	Name	Age	Pet_ID
1	Aubrey Little	20	1
2	Chett Crawfish	45	3
3	Jules Spinner	10	4
4	Magnus Burnsides	9	2
5	Veronica Dunn	8	**NULL**

`pets` table

ID	Name	Age	Animal
1	Dr. Harris Bonkers	1	Rabbit
2	Moon	9	Dog
3	Ripley	7	Cat
4	Tom	2	Cat
5	Maisie	10	Dog

Dr. Harris Bonkers is owned by **Aubrey Little**.

Moon is owned by **Magnus Burnsides**.

Ripley is owned by **Chett Crawfish**.

Tom is owned by **Jules Spinner**.

Veronica Dunn does not have a pet.
Maisie does not have an owner.

Combine data sources – `JOIN`, `UNION`

- Using `JOIN`, we can write a query to create a table with just two columns: the name of the `pet` and the name of the `owner`
  - We combine information from both tables by matching rows where the `ID` column in the `pets` table matches the `Pet_ID` column in the `owners` table
  - In the query, `ON` determines which column in each table to use to combine the tables. Note that we have to clarify which `ID` to use. We use `p.ID` to refer to the `ID` column from the `pets` table, and `o.Pet_ID` refers to the `Pet_ID` column from the `owners` table

```
query = """
        SELECT p.Name AS Pet_Name, o.Name AS Owner_Name
        FROM `bigquery-public-data.pet_records.pets` AS p
        INNER JOIN `bigquery-public-data.pet_records.owners` AS o
            ON p.ID = o.Pet_ID
        """
```

Pet_Name	Owner_Name
Dr. Harris Bonkers	Aubrey Little
Moon	Magnus Burnsides
Ripley	Chett Crawfish
Tom	Jules Spinner

Combine data sources – `JOIN`, `UNION`

- To create a table containing all rows from the owners table, we can use a `LEFT JOIN`. In this case, "left" refers to the table that appears before the `JOIN` in the query. ("Right" refers to the table that is after the `JOIN`.)

```
`bigquery-public-data.pet_records.owners` AS o INNER JOIN `bigquery-public-data.pet_records.pets` AS p
```

left table *right table*

Owner_Name	Pet_Name
Aubrey Little	Dr. Harris Bonkers
Magnus Burnsides	Moon
Chett Crawfish	Ripley
Jules Spinner	Tom

Owner_Name	Pet_Name
Aubrey Little	Dr. Harris Bonkers
Magnus Burnsides	Moon
Chett Crawfish	Ripley
Jules Spinner	Tom
Veronica Dunn	**NULL**

Combine data sources – `JOIN, UNION`

- If we instead use a `RIGHT JOIN`, we get the matching rows, along with all rows in the right table (whether there is a match or not)
- Finally, a `FULL JOIN` returns all rows from both tables. Note that in general, any row that does not have a match in both tables will have `NULL` entries for the missing values. You can see this in the image below

Owner_Name	Pet_Name
Aubrey Little	Dr. Harris Bonkers
Magnus Burnsides	Moon
Chett Crawfish	Ripley
Jules Spinner	Tom
Veronica Dunn	**NULL**
NULL	Maisie

Combine data sources – JOIN, UNION

- JOINs horizontally combine results from different tables. If you instead would like to *vertically concatenate columns*, you can do so with a UNION. The example query below combines the Age columns from both tables
  - Note that with a UNION, the data types of both columns must be the same, but the column names can be different
  - For instance, we cannot take the UNION of the Age column from the owners table and the Pet_Name column from the pets table!

```
query = """
        SELECT Age FROM `bigquery-public-data.pet_records.pets`
        UNION ALL
        SELECT Age FROM `bigquery-public-data.pet_records.owners`
        """
```

Age
20
45
10
9
8
1
9
7
2
10

Advance SQL - Nested data

- Consider a dataset containing information about `pets` and their `toys`. We could organize this information in two different tables. The `toys` table could contain a "`Pet_ID`" column that match each `toy` to the `pet` that owns it
- Another option is to organize all of the information in a single table, similar to the `pets_and_toys` table below
  - Nested columns have type `STRUCT` (or type `RECORD`). This is reflected in the table schema

`pets` table

ID	Name	Age	Animal
1	Moon	9	Dog
2	Ripley	7	Cat
3	Napoleon	1	Fish

`toys` table

ID	Name	Type	Pet_ID
1	McFly	Frisbee	1
2	Fluffy	Feather	2
3	Eddy	Castle	3

vs.

`pets_and_toys` table

ID	Name	Age	Animal	Toy
1	Moon	9	Dog	{**Name**: McFly, **Type**: Frisbee}
2	Ripley	7	Cat	{**Name**: Fluffy, **Type**: Feather}
3	Napoleon	1	Fish	{**Name**: Eddy, **Type**: Castle}

Advance SQL - Nested data

- To query a column with nested data, we need to identify each field in the context of the column that contains it:
  - `Toy.Name` refers to the "`Name`" field in the "`Toy`" column, and
  - `Toy.Type` refers to the "`Type`" field in the "`Toy`" column

`pets_and_toys` table

ID	Name	Age	Animal	Toy
1	Moon	9	Dog	{**Name**: McFly, **Type**: Frisbee}
2	Ripley	7	Cat	{**Name**: Fluffy, **Type**: Feather}
3	Napoleon	1	Fish	{**Name**: Eddy, **Type**: Castle}

```
query = """
        SELECT Name AS Pet_Name,
               Toy.Name AS Toy_Name,
               Toy.Type AS Toy_Type
        FROM `bigquery-public-data.pet_records.pets_and_toys`
        """
```

Pet_Name	Toy_Name	Toy_Type
Moon	McFly	Frisbee
Ripley	Fluffy	Feather
Napoleon	Eddy	Castle

Advance SQL - Nested data

- Now consider the case where each pet can have multiple toys. In this case, to collapse this information into a table, we need to leverage a *different datatype*
  - We say that the "`Toys`" column contains repeated data, because it permits more than one value for each row. This is reflected in the table schema below, where the mode of the "`Toys`" column appears as '`REPEATED`'

`pets` table

ID	Name	Age	Animal
1	Moon	9	Dog
2	Ripley	7	Cat
3	Napoleon	1	Fish

`toys_type` table

ID	Type	Pet_ID
1	Frisbee	1
2	Bone	1
3	Rope	1
4	Feather	2
5	Ball	2
6	Castle	3

vs.

`pets_and_toys_type` table

ID	Name	Age	Animal	Toys
1	Moon	9	Dog	[Frisbee, Bone, Rope]
2	Ripley	7	Cat	[Feather, Ball]
3	Napoleon	1	Fish	[Castle]

Advance SQL - Nested data

- When querying repeated data, we need to put the name of the column containing the repeated data inside an `UNNEST()` function

```
query = """
        SELECT Name AS Pet_Name,
               Toy_Type
        FROM `bigquery-public-data.pet_records.pets_and_toys_type`,
            UNNEST(Toys) AS Toy_Type
        """
```

Pet_Name	Toy_Type
Moon	Frisbee
Moon	Bone
Moon	Rope
Ripley	Feather
Ripley	Ball
Napoleon	Castle

  - This essentially flattens the repeated data (which is then appended to the right side of the table) so that we have one element on each row!

3. Data wrangling with Pandas

- When you have a lot of data, and it is contained in many different linked tables, it definitely makes sense to use SQL for working with it
  - However, there are many cases when we have a table of data, and we need to gain some **understanding** about this data, such as distribution, correlation between values, etc
  - In data science, there are a lot of cases when we need to perform some transformations of the original data, followed by visualization *in an interactive way*
- Pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with "relational" or "labeled" data
  - Most of the operations in SQL can be implemented with Pandas
  - Intelligent label-based slicing, fancy indexing, and subsetting of large datasets
  - Easy handling of missing data in floating point as well as non-floating point data

Data wrangling with Pandas

- In addition
  1. Flexible group by functionality to perform split-apply-combine operations on datasets, for both aggregating and transforming data. Intuitive merging and joining datasets
  2. Flexible reshaping and pivoting of datasets
  3. Robust IO tools for loading data from flat files (CSV and delimited), Excel files, databases
  4. Time series-specific functionality: date range generation and frequency conversion, moving window statistics, date shifting, and lagging

Data wrangling

- To see the important data wrangling techniques, refer to here
  - Creating `Dataframe`
  - Subset observations (rows), Subset variables (columns), Subsets (rows and columns)
  - Summarize data
  - Reshaping data (Change layout, sorting, dropping, renaming)
  - Handing missing value
  - Make new column
  - Plotting
  - Query (Filtering)
  - Group data
  - Combine data
  - Windows

Conclusion

- SQL is a pretty essential part of the data scientist's toolkit
  - When you have a lot of data, and it is contained in many different linked tables, it definitely makes sense to use SQL for working with it
- However, there are many cases when we have a table of data, and we need to gain some understanding or insights about this data
  - In data science, there are a lot of cases when we need to perform some transformations of the original data, followed by visualization. In these cases, the spreadsheet is helpful
- We now have basic tools for retrieving and manipulating data, we can go on to *cleaning and preparing* our data in the next lecture!

References

[1] Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 3rd Edition Chapter 1

[2] https://github.com/microsoft/Data-Science-For-Beginners/blob/main/2-Working-With-Data/05-relational-databases/README.md

[3] https://www.kaggle.com/learn/intro-to-sql

[4] https://www.kaggle.com/learn/advanced-sql

[5] Python for Data Analysis, 2nd Edition

[6] Data Science from scratch, 2nd Edition

Appendix

Resources and libraries

- SQL and Pandas
  - https://www.kaggle.com/learn/pandas
  - https://www.kaggle.com/learn/intro-to-sql
  - https://datawranglingpy.gagolewski.com/
- Theory about database
  - https://15445.courses.cs.cmu.edu/spring2023/schedule.html
- Create or update database
  - https://cloud.google.com/bigquery/docs/reference/standard-sql/data-manipulation-language
- Implementation of relational database
  - https://ucsbcarpentry.github.io/2020-01-31-UCSB-SQL/ (SQLite)
  - https://github.com/timescale/timescaledb (PostgreSQL)
  - https://cloud.google.com/sql (MySQL, SQL Server and PostgreSQL)

Resources and libraries

- Non-relational database
  - Introduction from microsoft
  - Cassandra
  - MongoDB
  - Hbase
- High-performance dataframe for large data
  - Various tools
  - Pandas use tips
  - Parquet
- In memory analytics and column-oriented database
  - Arrow
  - Click house

Resources and libraries

- Text to SQL
  - https://github.com/eosphoros-ai/Awesome-Text2SQL
  - https://github.com/Sinaptik-AI/pandas-ai/blob/main/examples/from_googlebigquery.py
  - https://github.com/vanna-ai/vanna
  - https://github.com/sqlchat/sqlchat
  - https://github.com/Dataherald/dataherald
- https://github.com/pola-rs/polars/

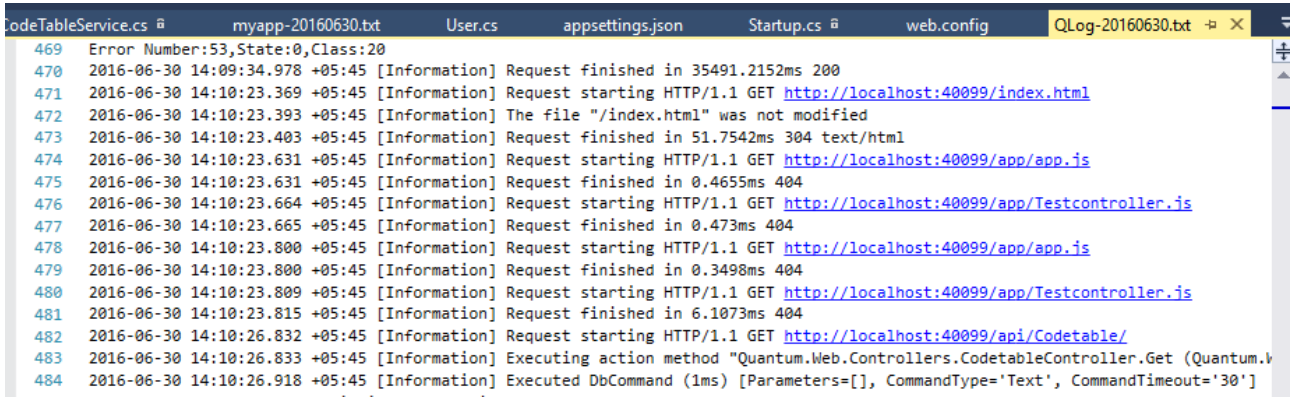
1. How data is Described?

- **Raw data** is data that has come from its source in its initial state and has not been analyzed or organized
  - In order to make sense of what is happening with a dataset, it needs to be organized into a format that can be understood by humans or can be analyze further

- The structure of a dataset describes how it's organized and can be classified as *structured*, *unstructured and semi-structured*. There are several options:
  1. *Text files* are easiest to create, and work well with version control, but then we would have to build search and analysis tools ourselves
  2. *Spreadsheets* are good for analysis, but they don't handle large or complex datasets well
  3. *Relational databases*, however, include powerful tools for search and simple analysis, and can handle large, complex datasets

1. How data is Described?

- **Unstructured data** typically cannot be categorized into rows or columns and doesn't contain a format or set of rules to follow
  - \+ Because unstructured data has fewer restrictions on its structure it's easier to add new information in comparison to a structured dataset
  - \- However, this may make analyzing or investigating this type of data take longer time
  - Examples of unstructured data
    - Office files, such as Word documents
    - Text files
    - Log files
    - Media files, such as photos, videos, and audio files (Binary files)



1. How data is Described?

- **Semi-structured data** has features that make it a combination of structured and unstructured data and it is not stored in a *relational format*
  - It doesn't typically conform to a format of rows and columns but is organized in a way that is considered structured and allows for easy integration of new data
  - *Metadata* is used that helps decide how the data is organized. Some common names for metadata are tags, elements, entities and attributes
    - For example, email message will have a subject, body and a set of recipients and can be organized by whom or when it was sent
  - Examples of semi-structured data: HTML, CSV files, JSON or NoSQL

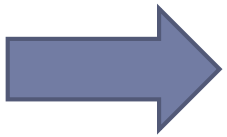
JSON

```
{
    "firstName": "John",
    "lastName": "Doe",
    "age": "23",
    "hobbies": [
        { "type": "Sports", "value": "Golf" },
        { "type": "Leisure", "value": "Reading" },
        { "type": "Leisure", "value": "Guitar" }
    ]
}
```

The shortcomings of a single table approach

- Begin our exploration by starting a table to store information about cities. We might start with their name and country
  - Let's start to add some additional data to our database - annual rainfall (in millimeters). We'll focus on the years 2018, 2019 and 2020. If we were to add it for Tokyo, it might look something like this
  - It could take up quite a bit of storage, and is largely unnecessary to have multiple copies

City	Country
Tokyo	Japan
Atlanta	United States
Auckland	New Zealand



City	Country	Year	Amount
Tokyo	Japan	2020	1690
Tokyo	Japan	2019	1874
Tokyo	Japan	2018	1445

The shortcomings of a single table approach

- Let's try something else. Let's add new columns for each year
  - While this avoids the row duplication, it adds a couple of other challenges. We would need to modify the structure of our table each time there's a new year. Additionally, as our data grows having our years as columns will make it trickier to retrieve and calculate values
  - This is why we need multiple tables and relationships. By breaking apart our data we can avoid duplication and have more flexibility in how we work with our data

City	Country	2018	2019	2020
Tokyo	Japan	1445	1874	1690
Atlanta	United States	1779	1111	1683
Auckland	New Zealand	1386	942	1176

The concepts of relationships

- Let's determine how we want to split things up. We know we want to store the name and country for our cities, so this will probably work best in one table
  - But before we create the next table, we need to figure out how to reference each city. We need some form of an identifier, ID or (in technical database terms) a *primary key*
  - A primary key is a value used to identify one specific row in a table. We don't want the id to ever change as it would break the relationship
  - With our cities table created, let's store the rainfall. **Rather than duplicating the full information about the city**, we can use the id. We should also ensure the newly created table has an id column as well, as all tables should have an id or primary key

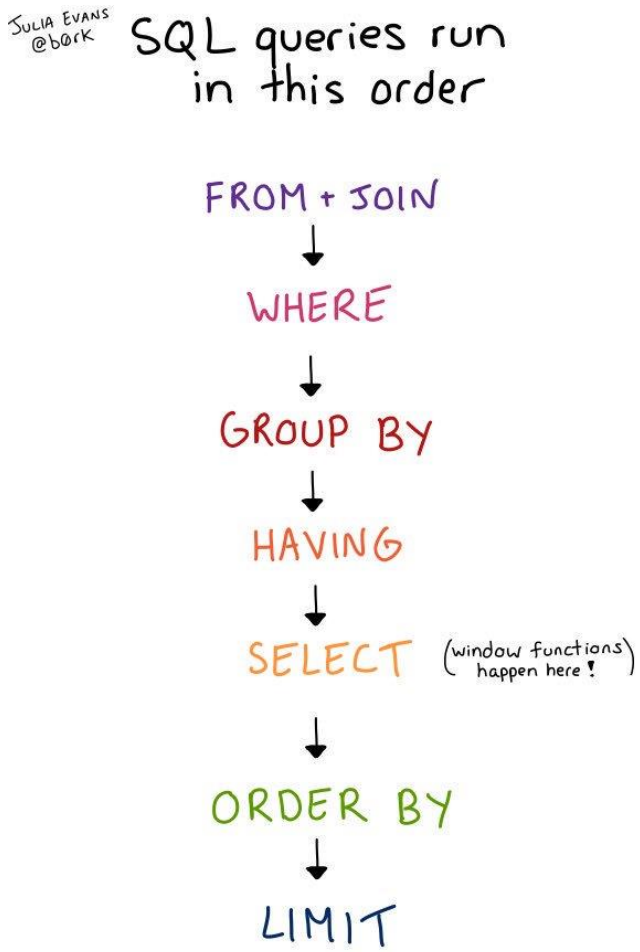
city_id	City	Country
1	Tokyo	Japan
2	Atlanta	United States
3	Auckland	New Zealand

The concepts of relationships

- Notice the *city_id* column inside the newly created rainfall table. This column contains values which reference the IDs in the cities table. In technical relational data terms, this is called a *foreign key*; it's a primary key from another table. You can just think of it as a reference or a pointer

rainfall_id	city_id	Year	Amount
1	1	2018	1445
2	1	2019	1874
3	1	2020	1690
4	2	2018	1779
5	2	2019	1111
6	2	2020	1683
7	3	2018	1386
8	3	2019	942
9	3	2020	1176

The precedence of SQL operators



https://jvns.ca/blog/2019/10/03/sql-queries-don-t-start-with-select/

Analytical functions

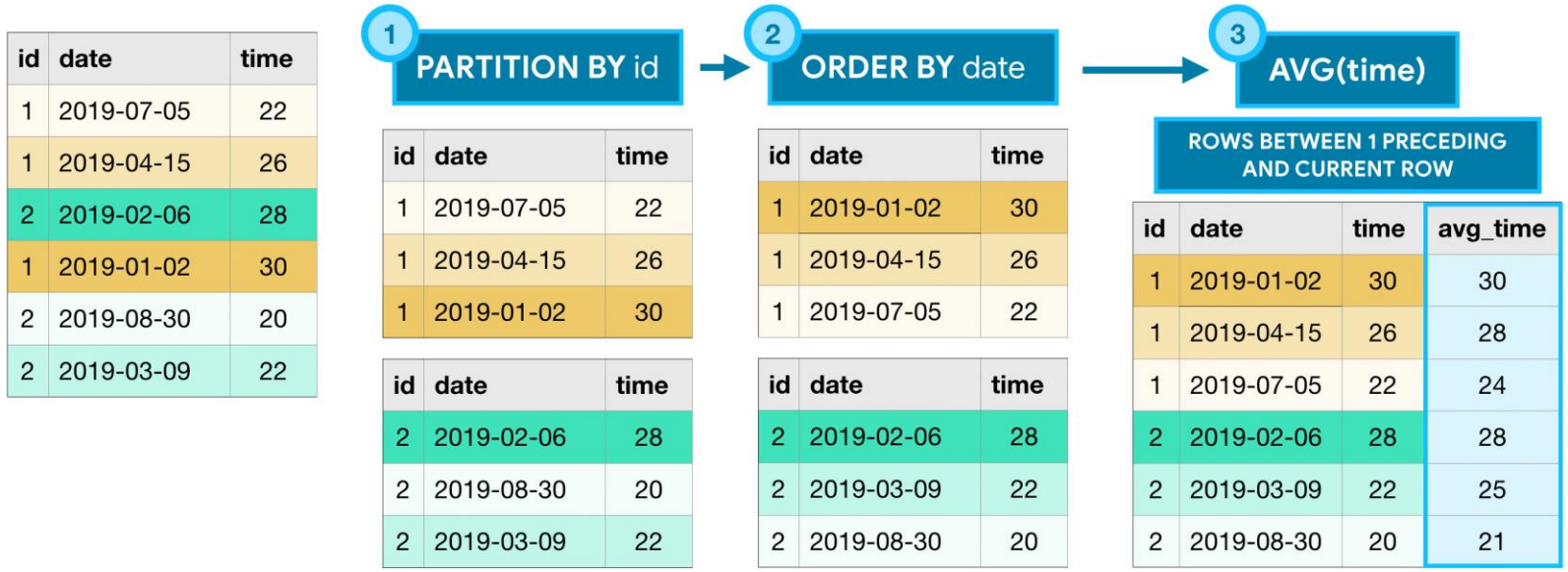
- Unlike aggregate functions, analytic functions return a value for each row in the original table
  - Analytic functions allow us to perform complex calculations with relatively straightforward syntax. For instance, we can quickly calculate moving averages and running totals, among other quantities
  - We'd like to calculate a moving average of the training times for each runner, where we always take the average of the current and previous training sessions. We can do this with the following query:

id	date	time
1	2019-07-05	22
1	2019-04-15	26
2	2019-02-06	28
1	2019-01-02	30
2	2019-08-30	20
2	2019-03-09	22

```
query = """
        SELECT *,
            AVG(time) OVER(
                                PARTITION BY id
                                ORDER BY date
                                ROWS BETWEEN 1 PRECEDING AND CURRENT ROW
                                ) as avg_time
        FROM `bigquery-public-data.runners.train_time`
        """
```

Analytical functions

- All analytic functions have an OVER clause, which defines the sets of rows used in each calculation. The OVER clause has three parts:
  - The PARTITION BY clause divides the rows of the table into different groups
  - The ORDER BY clause defines an ordering within each partition
  - The final clause known as a *window frame* clause. It identifies the set of rows used in each calculation. We can refer to this group of rows as a window



id	date	time
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1	2019-04-15	26
2	2019-02-06	28
1	2019-01-02	30
2	2019-08-30	20
2	2019-03-09	22

id	date	time
1	2019-07-05	22
1	2019-04-15	26
1	2019-01-02	30

id	date	time
2	2019-02-06	28
2	2019-08-30	20
2	2019-03-09	22

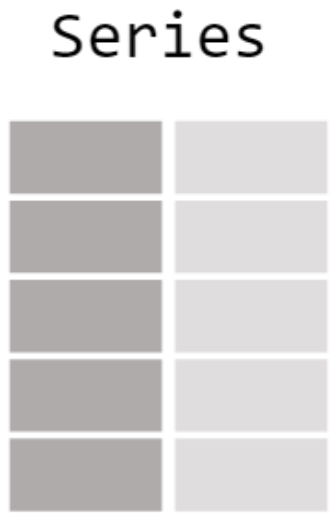
id	date	time
1	2019-01-02	30
1	2019-04-15	26
1	2019-07-05	22

id	date	time
2	2019-02-06	28
2	2019-03-09	22
2	2019-08-30	20

id	date	time	avg_time
1	2019-01-02	30	30
1	2019-04-15	26	28
1	2019-07-05	22	24
2	2019-02-06	28	28
2	2019-03-09	22	25
2	2019-08-30	20	21

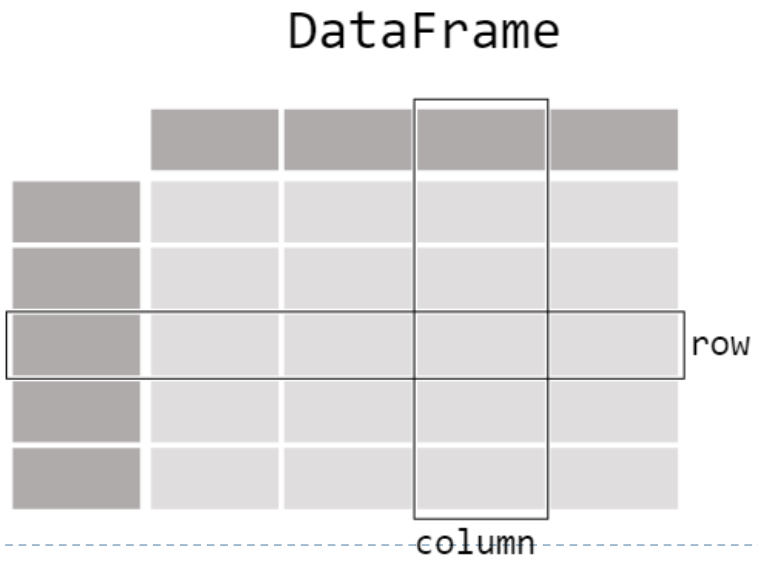
Working with data - `Series`

- `Series` is a sequence of values, similar to a list or `Numpy` array. The main difference is that series also has an index, and when we operate on series (eg., add them), the index is taken into account. `Index` can be as simple as integer row number (it is the index used by default when creating a series from list or array), or it can have a complex structure, such as date interval
  - A `DataFrame` is essentially a collection of `series` with the same `index`. We can combine several series together into a `DataFrame`

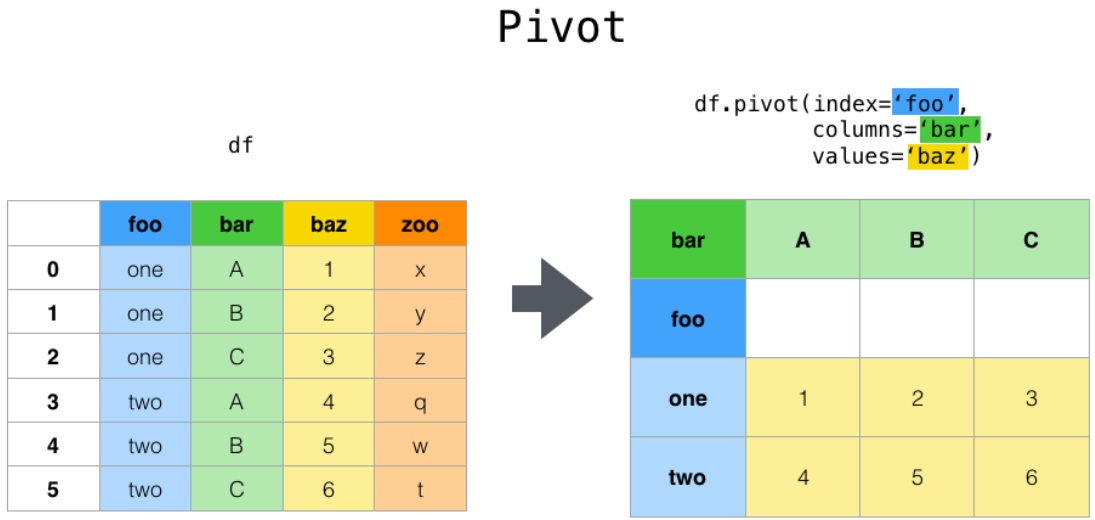


DataFrame

- It is a 2-dimensional data structure that can store data of different types (including characters, integers, floating-point values, categorical data and more) in columns
  - It is similar to a spreadsheet, a SQL table or the `data.frame` in R.
    - https://pandas.pydata.org/docs/getting_started/index.html
  - Rows indicating records (samples) and columns indicating fields (features)



Pivot



	foo	bar	baz	zoo
0	one	A	1	x
1	one	B	2	y
2	one	C	3	z
3	two	A	4	q
4	two	B	5	w
5	two	C	6	t

bar	A	B	C
foo			
one	1	2	3
two	4	5	6

https://pandas.pydata.org/docs/user_guide/reshaping.html