

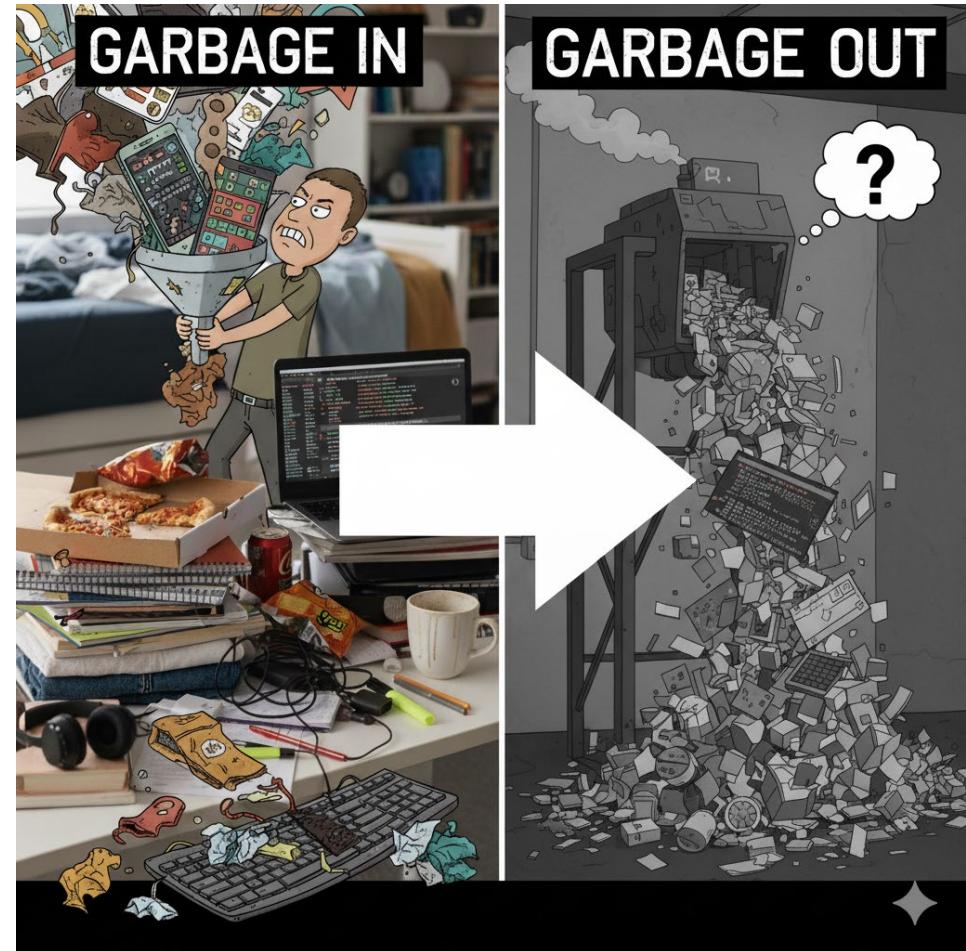


FROM MESS TO MODEL: MASTERING DATA PREPARATION

CS 180 Introduction to Data Science

WHY IS DATA PREPARATION SO IMPORTANT?

- Garbage IN – Garbage OUT
- Impacts model accuracy and reliability.
- A model is only as good as the data it learns from.
- Ensures trust in insights
- Data scientists spend ~70-80% of their time cleaning and preparing data



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LEARNING OBJECTIVES

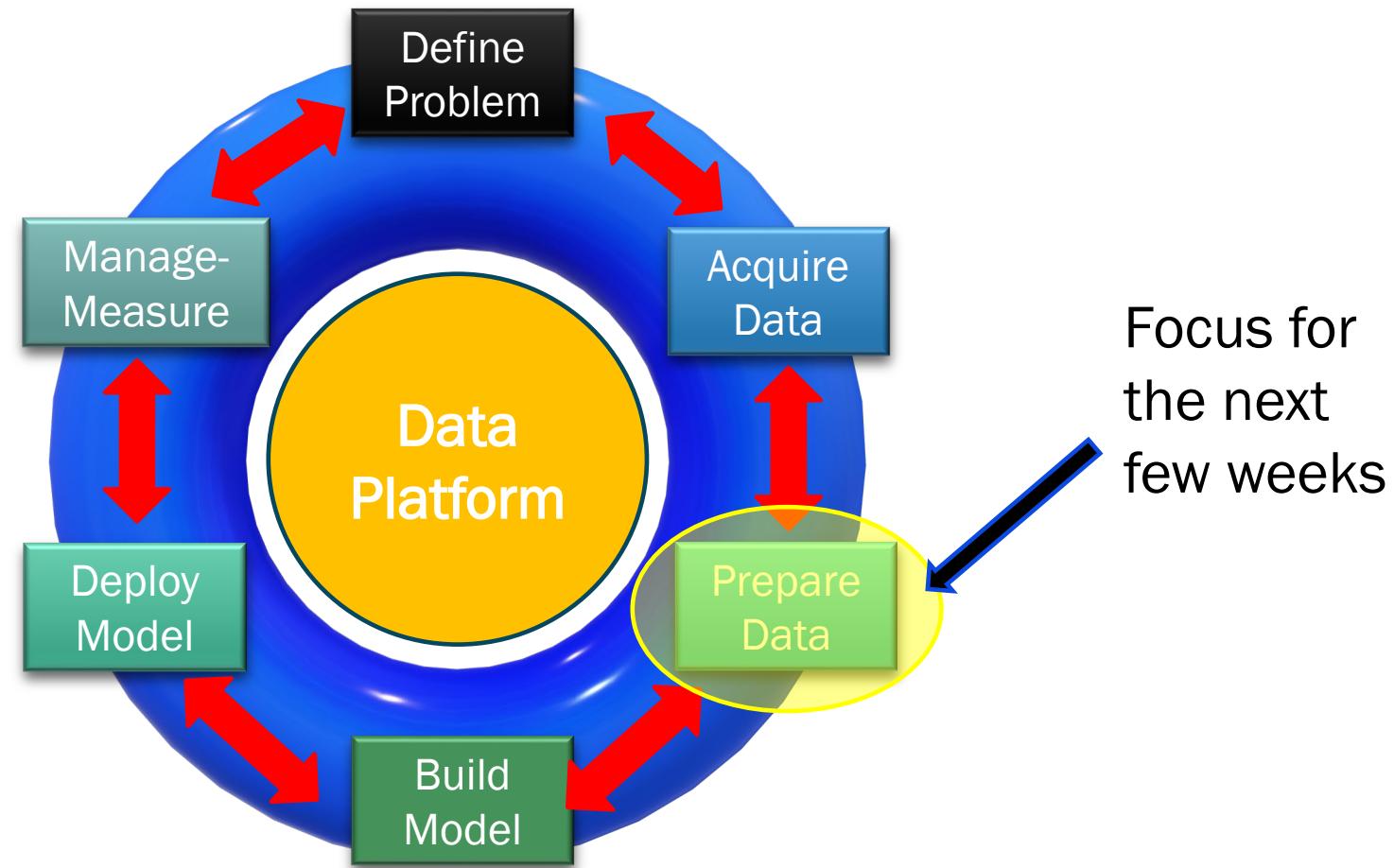
By the end of this lesson, students will be able to:

- Understand the importance of data preparation in the overall data science lifecycle.
- Explain why data preparation is critical to successful data science projects.
- Identify and apply standard techniques for cleaning datasets.
- Learn key data transformation and feature engineering techniques using Python.

DATA PREPARATION CONCEPTS FOR TODAY

- Data Profiling
- Data Cleaning
 - Missing Values
 - Inconsistencies
 - Duplicates
 - Outliers
- Data Transformation
 - Standardization
 - Normalization
 - Aggregation (e.g., Groupby)
 - Pivot Table
 - Contingency Table or Crosstab

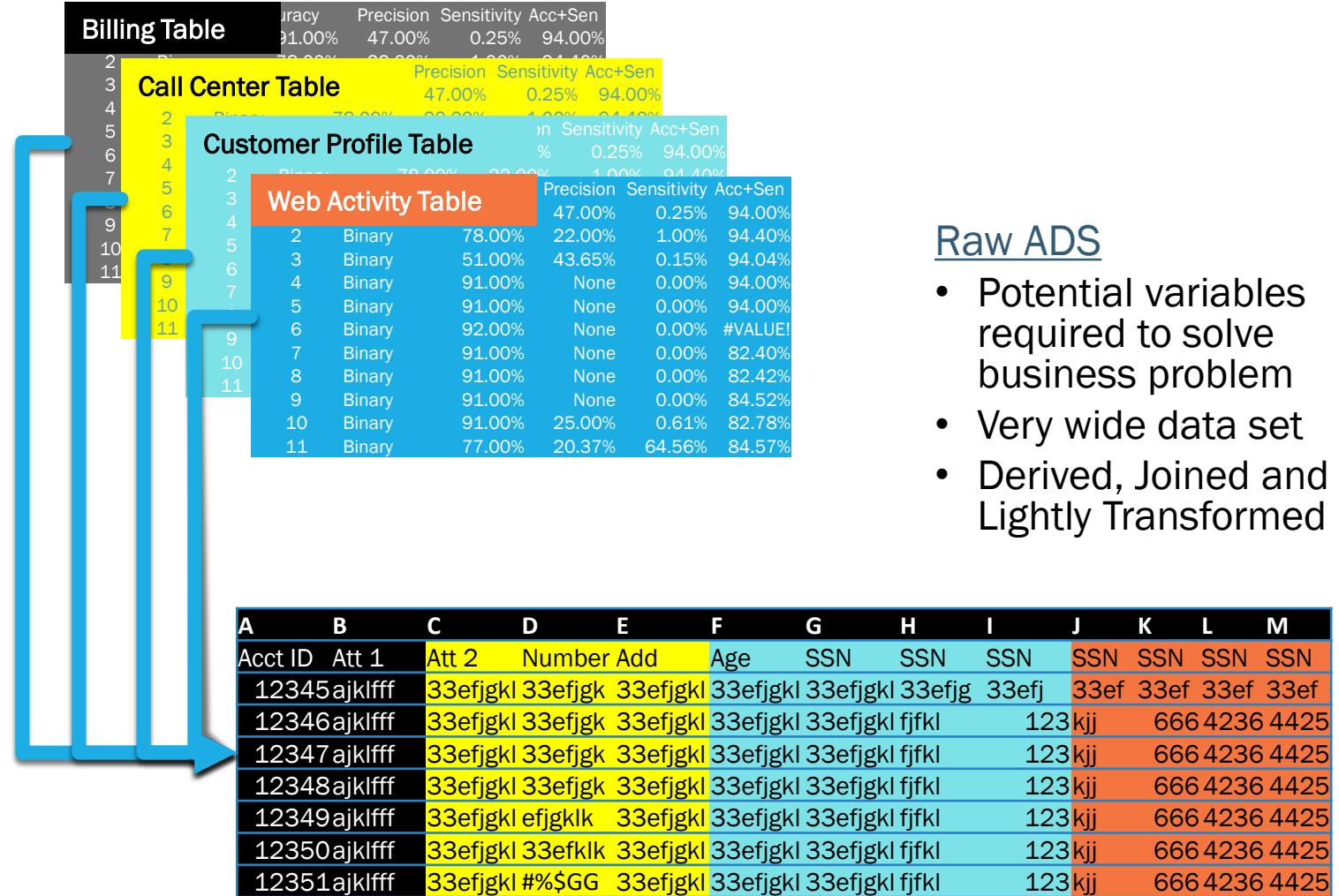
REVIEW: THE 6S5P DATA SCIENCE LIFECYCLE



2. IDENTIFY AND ACQUIRE THE DATA

Source Data

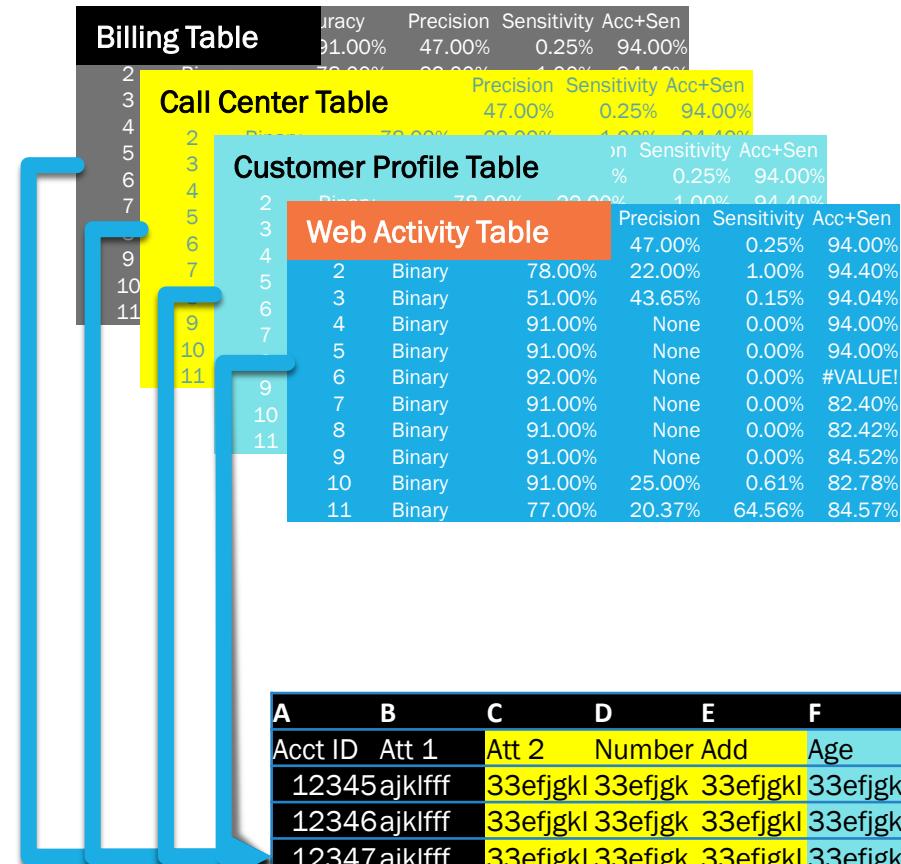
- Leverage Data Catalog to ID relevant data
- Use ETL# tools, processes
- Join data sources (often using SQL)
- Data Type checking
- Schema Matching
- Output: Raw Analytic Data Set or View





3. UNDERSTAND AND PREPARE THE DATA

- Profile Data
- Clean Data (missing / corrupted values)
- Outlier Analysis
- Transform Data
- Generate New Features
- Visualize Data
- Analyze Data (*EDA)
- Create Analytic Data Set (ADS)



A	B	C	D	E	F	G	H	I	J	K	L	M
Acct ID	Att 1	Att 2	Number Add		Age	SSN	SSN	SSN	SSN	SSN	SSN	SSN
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12351ajklfff	33efjgkl	%\$GG	33efjgkl	33efjgkl	33efjgkl	fjfkl	123	kjj	666	4236	4425	

Modeling Ready ADS

A	C	E	F	K	M
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12351	33efjgkl	33efjgkl	33efjgkl	666	4425
12345	Fjlk	Jlkjf	Fjfjf	345	0123



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PANDAS DATA PROFILING

Function	Purpose	Best For	Output
df.info()	Provides a technical summary of the DataFrame.	Quickly checking data types and finding columns with missing values.	A text summary of columns, non-null counts, and data types.
df.describe()	Generates descriptive statistics for numerical columns.	Understanding the distribution, scale, and potential outliers of numerical data.	A table of statistics (mean, median, min, max, etc.).
df.isnull().sum()	Counts the exact number of missing (NaN) values in each column.	Quantifying the severity of missing data for each feature.	A Series showing each column name and its null count.
df['col'].value_counts()	Counts the unique values in a categorical column.	Analyzing the distribution of categories and spotting inconsistencies.	A Series of unique values and their frequencies.
df.duplicated().sum()	Counts the total number of duplicate rows.	Checking for data redundancy and integrity issues.	A single integer representing the number of duplicate rows.

THE ZYBOOK DATA PREPARATION PROCESS

Table 3.1.1: Steps of data wrangling.

Step	Description
Step 1: Discovering	Discovery, also called data exploration, familiarizes the data scientist with source data in preparation for subsequent steps.
Step 2: Structuring	Structuring data transforms features to uniform formats, units, and scales.
Step 3: Cleaning	Cleaning data removes or replaces missing and outlier data.
Step 4: Enriching	Enriching data derives new features from existing features and applies domain knowledge.
Step 5: Validating	Validating data verifies that the dataset is internally consistent and accurate.
Step 6: Publishing	Publishing data makes the dataset available to other data scientists by storing data in a database, uploading data to the cloud, or distributing data files.

THE UPDATED DATA PREPARATION PROCESS

Step	Description
Step 1: Profiling	Data Profiling, also called data exploration, familiarizes the data scientist with source data in preparation for subsequent steps.
Step 2: Cleaning	Cleaning data removes or replaces missing and outlier data.
Step 3: Feature Gen	Enriching data derives new features from existing features and appends new data from external sources.
Step 4: Transform	Structuring data transforms to uniform formats, units, and scales.
Step 5: Validating	Validating data verifies that the dataset is internally consistent and accurate.
Step 6: Publishing	Publishing data makes the dataset available to other data scientists by storing data in a database, uploading data to the cloud, or distributing data files.

This is an iterative process. As new features/data are received, cycle through each step again.

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DATA CLEANING

- Missing Values
 - Code snippet with `fillna()`.
 - Visual: Table before/after missing value imputation.
- Inconsistencies
 - Example: “CA” vs “California.”
 - Visual: Table showing cleaned categories.
- Duplicates
 - Code: `drop_duplicates()`.
 - Visual: Highlight duplicate rows.
- Outliers
 - Z-score detection.
 - Visual: Boxplot before/after removing outliers.

DATA TRANSFORMATION & FEATURE ENGINEERING

- Feature Scaling: Normalization vs Standardization
 - Code: MinMaxScaler vs StandardScaler.
- Aggregation
 - Example: Sales per month.
- Feature Engineering
 - Example: “DayOfWeek” from timestamp.

FEATURE SCALING: NORMALIZATION VS. STANDARDIZATION

- A dataset's numeric features often have different scales, and in some datasets, scales may differ by orders of magnitude.
- This incongruity may bias some algorithms by giving more weight to larger numbers.
- *Feature scaling* converts numeric features to uniform ranges. Two of the most common feature scaling methods are standardization and normalization.

NORMALIZATION (AKA MIN-MAX SCALING)

- There are many types of data “normalization”
- Min-Max Normalization scales values between [0, 1] using the following formula:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

```
# Manually normalize each column to [0, 1] range
# Sample data
data = {'feature1': [1, 2, 3, 4, 5],
        'feature2': [10, 15, 20, 25, 30]}
df = pd.DataFrame(data)

df_normalized_manual = (df - df.min()) / (df.max() - df.min())
print(df_normalized_manual)
```

	feature1	feature2
0	0.00	0.00
1	0.25	0.25
2	0.50	0.50
3	0.75	0.75
4	1.00	1.00

STANDARDIZATION (AKA Z-SCORE NORMALIZATION)

- Rescales value to have a mean of 0 and standard deviation of 1:

$$x' = \frac{x - \mu}{\sigma}$$

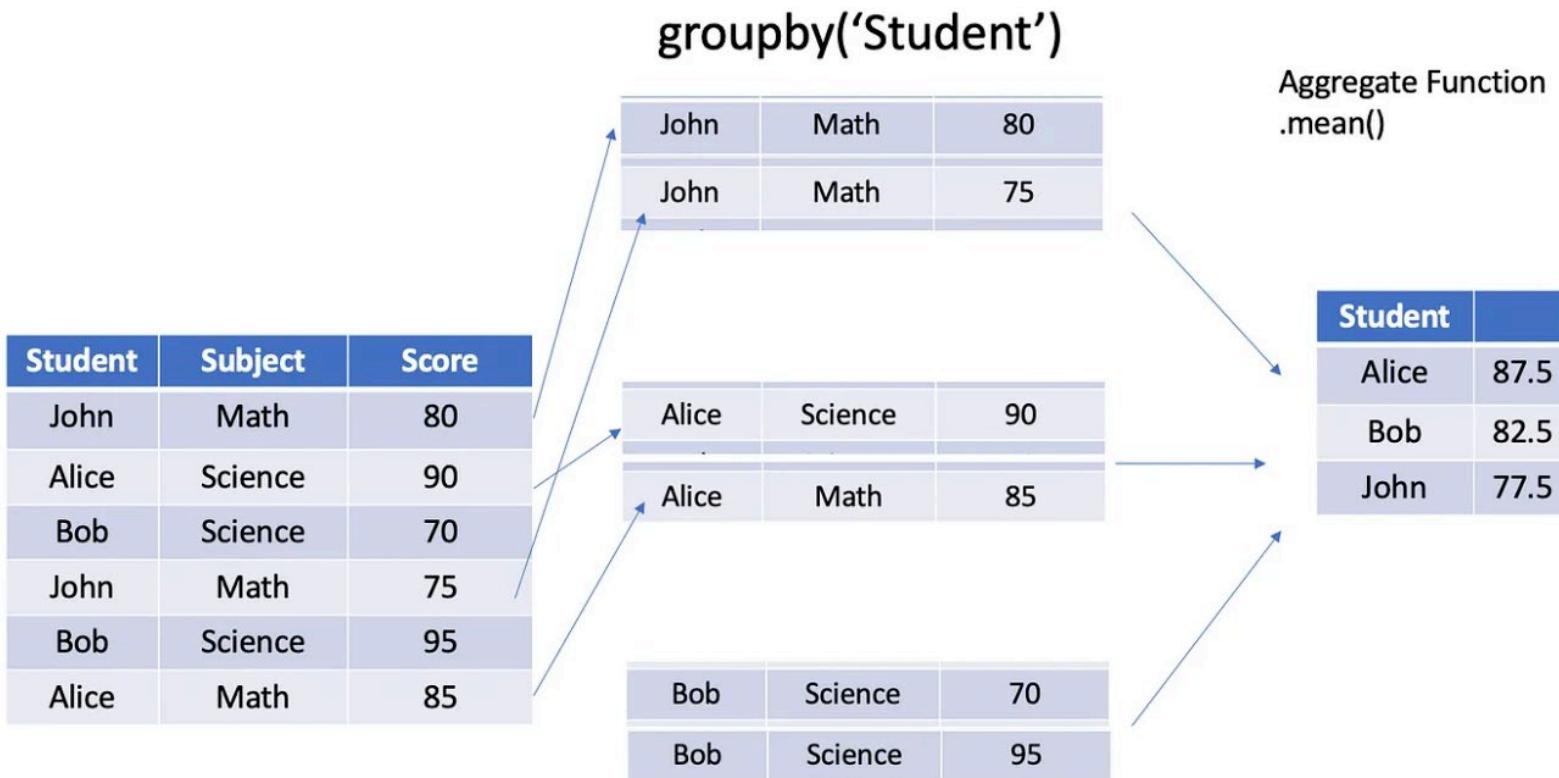
```
# Standardize the data (Z-score normalization)
df_standardized = (df - df.mean()) / df.std()
```

```
print(df_standardized)
```

	feature1	feature2
0	-1.264911	-1.264911
1	-0.632456	-0.632456
2	0.000000	0.000000
3	0.632456	0.632456
4	1.264911	1.264911

GROUPBY

- The groupby() function in pandas is one of the most powerful and frequently used tools for data analysis.
- The process is best understood by the term **"Split-Apply-Combine."**
- Split:** The data is split into groups based on some criteria (e.g., all rows with the same student).
- Apply:** A function is applied to each group independently (e.g., mean score for each student).
- Combine:** The results of these operations are combined into a new DataFrame or Series.



PIVOT TABLE

- `df.pivot_table()` takes several parameters.
- **value** specifies the values in the pivot table's elements.
- The feature in the pivot table's rows is specified using **index** and the feature in the pivot table's columns is **columns**.
- **aggfunc** specifies a function to apply to the values in each row/column combination within the pivot table.
- The default aggregate function is `np.mean`. Other functions include: `sum`, `count`, `min`, `max`, `median`, `mode`, `var` (variance), `first`, `last`, **size**, custom functions (e.g., `aggfunc=lambda x: x.max() - x.min()`)
- You can also apply multiple aggregation functions by passing them as a list: `pd.pivot_table(df, values='Sales', index='Region', aggfunc=['mean', 'sum', 'count'])`

CROSSTAB / CONTINGENCY / FREQUENCY TABLE

- **Purpose:** Primarily used to calculate the frequency (or other statistics) between two or more categorical variables.
- **Default Output:** Crosstabs typically result in contingency tables, where each row and column represents a different category, and the cells show the frequency of their co-occurrence.
- **Common Use:** It is most commonly used for counting and can also apply some basic aggregation functions.
- **Crosstab** is more limited and generally used for frequency counts, while **pivot tables** provide more flexibility, allowing for various types of aggregations (mean, sum, etc.).
- Crosstabs are usually used for two categorical variables, whereas pivot tables can handle both categorical and numerical data with multiple levels of summarization.