MachineLearnAthon – Microlecture Data Preparation (for tabular data)

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MachineLearnAthon
A project Co-funded by the Erasmus+ programme of the European Union

Learning outcomes of today

After successfully completing this micro-lecture, you are able to….

- Identify the basic steps involved in data preparation
- Handle missing data in a dataset
- Understand different data types
- Perform data transformations

Agenda for today

- Missing data
- Data types
- Data transformation

Missing Data (I)

Product	Price	Country_Tax	Payment_Type	Country	Continent
1	1200	23.0	Diners	Ireland	NaN
1	1200	20.0	Mastercard	United Kingdom	Europe
2	3600	20.0	Visa	United Kingdom	Europe
NaN	NaN	NaN	NaN	Algeria	Africa

- Many data contain missing values
- In Python, missing values are represented with „NaN“, which stands for „Not a Number“
- It is important to check for missing values before applying ML methods to a dataframe
- Before deciding how to handle missing data, it is recommend to start counting the missing values

Count nan per column/row:

```
df_nan.isnull().apply(np.sum, axis=0/1)
```

	axis=0	axis=1	
Product	1	0	1
Price	1	1	0
Country_Tax	1	2	0
Payment_Type	1	3	4
Country	0		
Continent	1		

Bramer, M. (2007). *Principles of data mining*. Springer.

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Missing Data (II)

Product	Price	Country_Tax	Payment_Type	Country	Continent
1	1200	23.0	Diners	Ireland	NaN
1	1200	20.0	Mastercard	United Kingdom	Europe
2	3600	20.0	Visa	United Kingdom	Europe
NaN	NaN	NaN	NaN	Algeria	Africa

- Missing values can bias results or reduce the accuracy of data models
- If the proportion of missing values in a column or row is very high, it might be advisable to drop it
- Before dropping columns or rows, you should consider the entailed information loss
- Also consider the sparsity of your data
- Instead of dropping missing values, you could impute the data (replace the missing data with plausible data)

Bramer, M. (2007). *Principles of data mining*. Springer.

- Drop **rows with > 0 nan** values:

```
df.dropna(how='any', axis=0)
```

- Drop **all nan rows**:

```
df.dropna(how='all', axis=0)
```

- Use `axis=1` for dropping **columns** analogously
- **Replace nan** with value

```
df.fillna(value)
```

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Data Imputation

- Data imputation is „a class of procedures that aims to fill in the missing values with estimated ones”[1]
- Imputation techniques allow you to preserve as much data as possible, improving data integrity without discarding observations
- If possible, use other information available to fill missing values (e.g. in the data example below, the value of Continent in the first row is Europe)
- Common imputation techniques are the mean/ median/ mode imputation, which replace the missing values with either of these values
- More advanced methods include model-based imputation, which train a regressor to predict the missing value

Product	Price	Country_Tax	Payment_Type	Country	Continent
1	1200	23.0	Diners	Ireland	NaN
1	1200	20.0	Mastercard	United Kingdom	Europe
2	3600	20.0	Visa	United Kingdom	Europe
NaN	NaN	NaN	NaN	Algeria	Africa

[1] García, S., Luengo, J., & Herrera, F. (2015). *Data preprocessing in data mining* (Vol. 72, pp. 59-139). Cham, Switzerland: Springer International Publishing, p.60.

Data types

Tabular data may contain different data types. The most common data types are:

- Numerical data
  - Integer: Whole numbers (e.g. number of products)
  - Float: Decimal numbers (e.g. stock prices)
- Categorical data
  - Nominal: Categories without any order (e.g. countries)
  - Ordinal: Categories with an order (e.g. rating scales)
- Boolean data: Binary values (True/ False or 0/1)
- Text (string) data: Free-form text (e.g. names, addresses)
- Datetime data

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Importance of correct data types

The correct formatting of data…

- Ensures correct interpretation of the data and its meaning
- Impacts how data can be manipulated, filtered, or analyzed (e.g., mathematical operations for numerical data, grouping for categorical data)
- Data type errors can lead to inaccurate analysis, coding bugs, or model failures

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Datetime values

- There are different valid datestring formats (see on the right hand side)
- If formatted correctly, each element (day, month and year) of a date can be extracted and for example used to create another feature
- Mathematical operations can be performed on datatime values, such as adding a certain number of days to a date

Valid datestring formats:

- '27-11-2018'
- '2018-11-27'
- '27/11/2018,
- '27 11 2018,
- '27.11.2018
- '20181127,
- etc

Invalid datestring formats:

- '27112018
- '27\11\2018,
- etc

Source: https://docs.python.org/3/library/datetime.html

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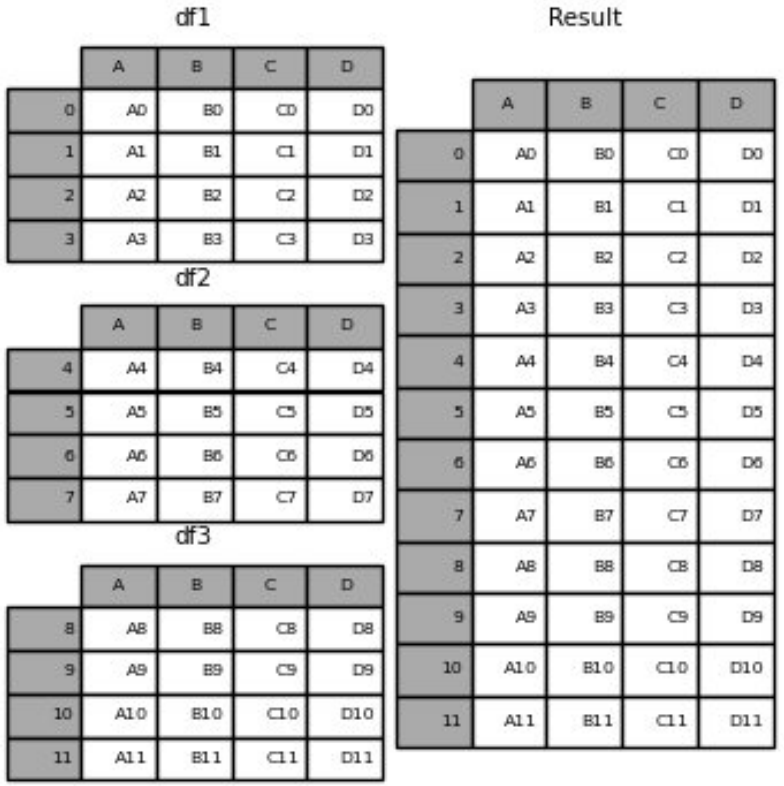
Combining datasets - concat

- There are different methods for combining multiple datasets
- If the datasets have the same variables, you can concat the data (see on the right hand side)
- The resulting dataframe will have the same numbers of columns but more rows



	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

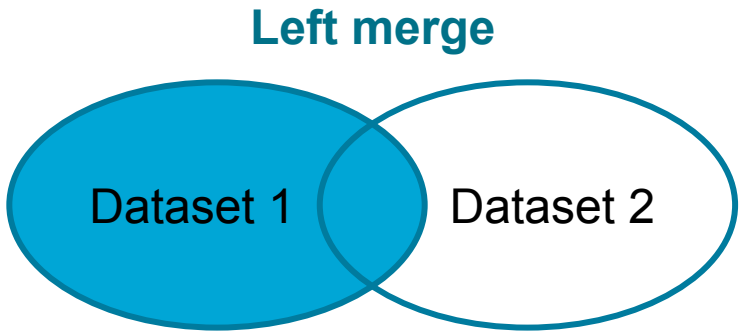
	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Source: https://pandas.pydata.org/docs/user_guide/merging.html

Combining datasets – merge (I)

- If the datasets have at least variable in column, they can be used as keys to join the datasets
- The merge can either be left, right, inner or outer
- In case of a left merge, only the keys from the left dataset are used
- This may result in missing values in the column from the right dataset



left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

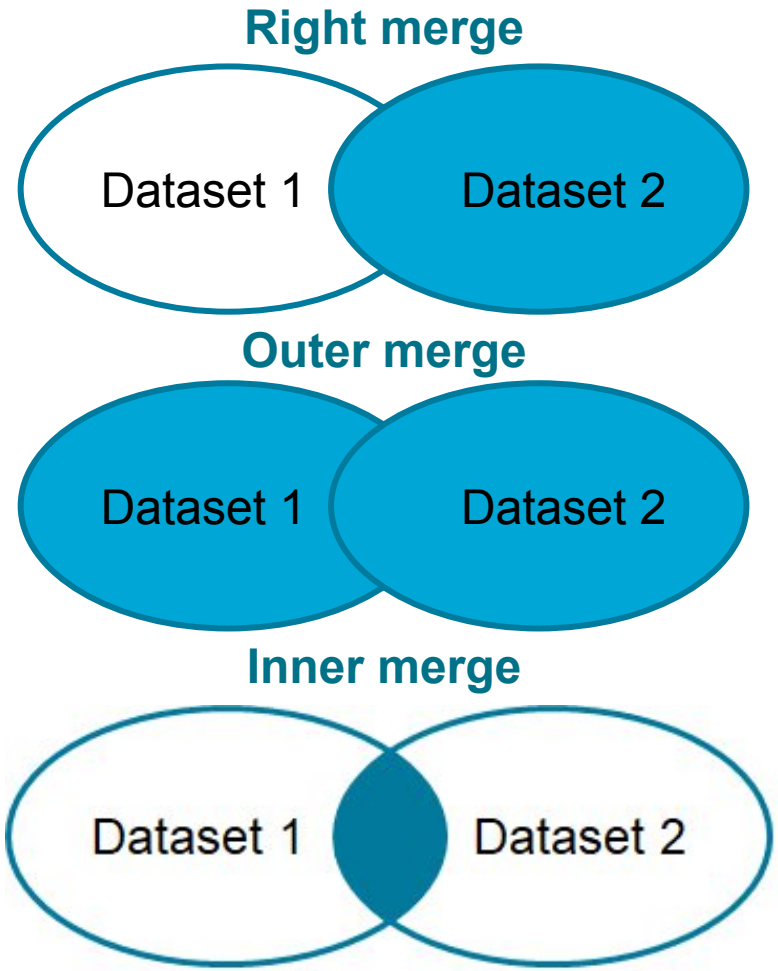
	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	C1	D1
3	K1	K0	A2	B2	C2	D2
4	K2	K1	A3	B3	NaN	NaN

Source: https://pandas.pydata.org/docs/user_guide/merging.html

Combining datasets – merge (II)



Source: https://pandas.pydata.org/docs/user_guide/merging.html

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2
3	K2	K0	NaN	NaN	C3	D3

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	C1	D1
3	K1	K0	A2	B2	C2	D2
4	K2	K0	NaN	NaN	C3	D3
5	K2	K1	A3	B3	NaN	NaN

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2

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Data normalization

- Data normalization is a technique used to rescale numerical data into a standardized range, typically between 0 and 1 or -1 and 1
- This ensures that all features contribute equally to analysis or modeling, regardless of their original scale
- The most commonly used normalization technique is the Min-Max Scaling

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

García et al. (2015): Data Preprocessing in Data Mining, p.46 f.

Further measures

- Delete data
- Delete duplicates
- One-hot encoding (Transforming categorical data into Boolean data)

Picture_id	Subject
1	Muffin
2	Chihuahua
3	Muffin
4	Chihuahua
5	Chihuahua

Picture_id	Muffin	Chihuahua
1	True	False
2	False	True
3	True	False
4	False	True
5	False	True

Source: https://www.freecodecamp.org/news/chihuahua-or-muffin-my-search-for-the-best-computer-vision-api-cbda4d6b425d/

Recap this lecture

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