In [40]: import numpy as np import pandas as pd In []: In [41]: # Import the dataset df = pd.read_csv("salary.csv") # Below is a sample of the missing data Out[41]: **ID Gender Salary Country Company** Male 15000.0 India Google 2 Female 45000.0 China NaN 3 Female 25000.0 2 India Google 3 4 NaN NaN Australia Google 5 Male NaN India Google Male 54000.0 6 NaN Alibaba 7 NaN 74000.0 6 China NaN Male 14000.0 Australia NaN 9 Female 15000.0 NaN NaN Male 33000.0 Australia NaN 1.detecting missing values:pandas provides the isna(), isnull() and notna() functions a) isna()/isnull() Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.NaN, gets mapped to True values. Both isna() and isnull() do the same thing • Svntax: dataframe.isna() In [42]: # check in individual column df["Company"].isna() False Out[42]: True 2 False 3 False False 4 5 False 6 True 7 True 8 True True Name: Company, dtype: bool In [43]: # You can also count the number of missing values present inside each column using isna().sum() df["Company"].isna().sum() # There are 5 NaN values in the "Company" column 5 Out[43]: in below example isna() returns a data frame consisting of true and false values. A true value indicates data is null or missing, while a false one indicates that data is not null and not missing. # Check in the whole DataFrame df.isna() Out[44]: **ID Gender Salary Country Company** O False False False False False False False False False True 2 False False False False False **3** False True True False False **4** False False True False False **5** False False False True False **6** False True False False True **7** False False False False True 8 False False False True True **9** False False False False True # Returns the number of missing values in each column. In [45]: Out[45]: Gender 2 Salary 2 Country 2 Company 5 dtype: int64 b) notna()

IOTA ACADEMY

Become Job Ready...

• Missing data is defined as the values or data that is not stored (or not present) for some variable/s in the given dataset.

• In many cases, however, the Python None will arise and we wish to also consider that "missing" or "not available" or "NA".

NaN is the default missing value marker for reasons of computational speed and convenience.

Missing Data

Detect existing (non-missing) values.

Syntax: DataFrame.notna()

Name: Salary, dtype: bool

df["Salary"].notna().sum()

For datetime64[ns] types, NaT represents missing values.

Salary Country Company

India

China

India

India

NaN

China

NaN

Australia

df1["Hiring Date"] = pd.Timestamp("20221009")

India

China

India

India

NaN

China

NaN

Salary Country Company

India

China

India

India

NaN

China

NaN

The fillna() method replaces the NULL values with a specified value.

• Syntax: dataframe.fillna(value, method, axis, inplace, limit, downcast)

Google

Google

Google

Google

Alibaba

NaN

NaN

NaN

NaN

Google

Google

Google

Google

Alibaba

Google

Google

Google

Google Alibaba

NaN

NaN

NaN

NaN

Google

missing

Google

Google

Google Alibaba

missing

missing

missing

missing

df["Salary"].fillna(df["Salary"].mean()) # fill with mean value

df["Company"].fillna("missing",inplace=True) # We can also make changes in any individual column too.

NaN

0

0

df # inplace = False, Changes will not appear in the original DataFrame.

0

All missing values are filled with zeros

NaN

Australia

Australia

Australia

Google

Google

Google

Google

Alibaba

NaN

NaN

NaN

NaN

Salary Country Company Hiring Date

Google

Google

Google

Google

Alibaba

NaN

NaN

NaN

NaN

Google

Google

Google

Google

Alibaba

NaN

NaN

NaN

NaN

NaN

NaN

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

Hiring Date

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

2022-10-09

The fillna() method returns a new DataFrame object unless the inplace parameter is set to True, in that case the fillna() method does

NaT

NaT

NaN

df["Salary"].notna()

True

True
True
False
False
True
True
True
True
True

Datetimes

dfl= df.copy()

Gender

Male

NaN

Male

Male

Male

Female

Gender

Male

NaN

Male

Male

NaN

Male

Female

ID Gender

Female 25000.0

Female

Female

15000.0

45000.0

NaN

NaN

54000.0

74000.0

14000.0

15000.0

15000.0

45000.0

NaN

NaN

54000.0

74000.0

15000.0

Inserting missing data

Male 15000.0

Female 45000.0

Female 25000.0

Male 54000.0

NaN 74000.0

15000.0

Male 33000.0 Australia

NaN

NaN

14000.0 Australia

2. Filling missing values:

the replacing in the original DataFrame instead.

Salary Country Company

India

China

India

India

NaN

China

NaN

Salary Country Company

India

China

India

India

China

Salary Country Company

India

China

India

India

NaN

China

NaN

Salary Country Company

India

China

India

India

NaN

China

NaN

Australia

Australia

Australia

Australia

NaN

Male

Male

Female

fillna()

ID Gender

Male

NaN

Male

Female 25000.0

Male 54000.0

NaN 74000.0

Female 15000.0

Male 15000.0

45000.0

25000.0

54000.0

74000.0

Male 14000.0 Australia

Male 33000.0 Australia

15000.0

45000.0

25000.0

NaN

NaN

54000.0

74000.0

15000.0

15000.0

45000.0

25000.0

NaN

NaN

54000.0

74000.0

15000.0

Male 33000.0 Australia

14000.0 Australia

Male 33000.0 Australia

14000.0 Australia

0.0

0.0

Female

15000.0

45000.0

NaN

NaN

Male 14000.0 Australia

Male 33000.0 Australia

Replace NA with a scalar value

df1.iloc[[0,4],[5]] = np.nan

Male 33000.0 Australia

14000.0 Australia

Male 33000.0 Australia

Female 25000.0

df1

ID

5

7

10

df1

3

ID

5

9

10

df1

0 1

3

5 6

6 7

3

4 5

9

10

In [46]:

Out[46]:

In [47]:

Out[47]:

In [48]:

Out[48]:

In [49]:

In [50]:

Out[50]:

In [51]:

Out[51]:

In [52]:

Out[52]:

In [53]:

Out[53]:

In [54]:

Out[54]:

In [55]:

In [56]:

Out[56]:

In [57]:

Out[57]:

df

0

2

3

5

6

2 3

3

5

10

ID Gender

Male

Female

Female

NaN

Male

Male

NaN

Male

Female

Gender

Male

Female

Female

NaN

Male

Male

NaN

Male

Female

15000.0

45000.0 25000.0

34375.0

15000.0 33000.0

Name: Salary, dtype: float64

Action

Salary

15000.0

45000.0

25000.0

NaN

NaN

74000.0

14000.0

15000.0

Male 33000.0 Australia

Salary

45000.0

25000.0

25000.0

25000.0

54000.0

74000.0

14000.0

15000.0

15000.0

45000.0

25000.0

54000.0

54000.0

54000.0

74000.0

14000.0

15000.0

Male 33000.0 Australia

df.fillna(method="bfill")

Male 33000.0 Australia

Salary Country

India

China

India

India

China

China

3. Dropping axis labels with missing data:

Syntax: dataframe.dropna(axis, how, thresh, subset, inplace)

In [61]: df = pd.DataFrame({"name": ['Alfred', 'Batman', 'Catwoman'],

born

NaT

NaT

default inplace = False

born

In [63]: # Drop the columns where at least one element is missing.

In [62]: # Drop the rows where at least one element is missing.

df.dropna() # default axis is 0 (rows)

pd.NaT] })

Australia

Australia

Fill values forward

Fill values backward

Country Company

Google

missing

Google

Google

Google

Alibaba

missing

missing

missing

missing

Google

missing

Google

Google

Google

Alibaba

missing

missing

missing

missing

Company

Google

missing

Google

Google

Google

Alibaba

missing

missing

missing

missing

- You may wish to simply exclude labels from a data set which refer to missing data. To do this, use

"toy": [np.nan, 'Batmobile', 'Bullwhip'],
"born": [pd.NaT, pd.Timestamp("1940-04-25"),

India

China

India

India

NaN

China

NaN

Country Company

India

China

India

India

India

China

Australia

Australia

Australia

Australia

Australia

Fill gaps forward or backward

3

5

10

6 7

3

4

6

8

In [58]: df

0 1

2 3

3

5

6 7

4 5

6

8

9

9 10

0

2 3

3

5

6 7

0

2 3

3

4

6

7

8

10

dropna()

dropna():

name

Alfred

2 Catwoman

name

df.dropna(axis=1)

name

Alfred

Batman

name

Alfred

Batman

df.dropna(how="all")

name

Alfred

df.dropna(thresh=2)

2 Catwoman

2 Catwoman

name

Great Job!

2 Catwoman

2 Catwoman

2 Catwoman

toy

NaN

Batman Batmobile 1940-04-25

Bullwhip

toy

1 Batman Batmobile 1940-04-25

df.dropna(axis="columns")

In [65]: # Drop the rows where all elements are missing.

In [66]: # Keep only the rows with at least 2 non-NA values.

In [67]: # Define in which columns to look for missing values.

born

NaT

NaT

born

NaT

toy

NaN

Batman Batmobile 1940-04-25

Bullwhip

Batman Batmobile 1940-04-25

df.dropna(subset=['name', 'toy'])

toy

Batman Batmobile 1940-04-25

Bullwhip

Bullwhip

df

Out[61]:

Out[62]:

Out[63]:

Out[64]:

Out[65]:

Out[66]:

Out[67]:

0

In [64]: # Example

0

0

5

8

9

10

Out[58]:

In [59]:

Out[59]:

Out[60]:

Method

pad / ffill -

bfill / backfill -

Gender

Male

Female

Female

NaN

Male

NaN

Male

Female

Gender

Female

Female

Female

Male

Male

Male

Male

Female

ID Gender

Male

Female

Female

Male

Male

Male

Male

Male 54000.0

df.fillna(method="ffill")

Male 15000.0

5

9

10

6

3

5

6

7

8

9

10

ID Gender

Female

Female

0

Male

Male

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True.

Let's show a few convenient methods to deal with Missing Data in pandas: