

## Working with Missing Data in Pandas

In Pandas, missing data occurs when some values are missing or not collected properly and these missing values are represented as:

- **None:** A Python object used to represent missing values in object-type arrays.
- **NaN:** A special floating-point value from NumPy which is recognized by all systems that use IEEE floating-point standards.

In this article we see how to detect, handle and fill missing values in a DataFrame to keep the data clean and ready for analysis.

### Methods for Identifying Missing Data

Detecting and managing missing data is important for data analysis. Let's see some useful functions for detecting, removing and replacing null values in Pandas DataFrame.

Functions	Descriptions
<code>.isnull()</code>	Detect missing values
<code>.notnull()</code>	Detect non-missing values
<code>.info()</code>	Summary with missing counts
<code>.isna()</code>	Same as <code>isnull()</code> .
<code>dropna()</code>	Remove missing rows/columns
<code>fillna()</code>	Fill missing values
<code>replace()</code>	Replace specific values
<code>drop_duplicates()</code>	Remove duplicate rows
<code>unique()</code>	Get unique values in a Series/DataFrame

## Checking Missing Values in Pandas

You can download the csv file from [here](#)

Pandas provides two important functions which help in detecting whether a value is NaN helpful in making data cleaning and preprocessing easier in a DataFrame or Series are given below :

### 1. Using isnull()

[isnull\(\)](#) returns a DataFrame of Boolean value where True represents missing data (NaN). This is simple if we want to find and fill missing data in a dataset.

### Example 1: Finding Missing Values in a DataFrame

We will be using [Numpy](#) and [Pandas](#) libraries for this implementation.

```
import pandas as pd
```

```
import numpy as np
```

```
d = {'First Score': [100, 90, np.nan, 95],  
     'Second Score': [30, 45, 56, np.nan],  
     'Third Score': [np.nan, 40, 80, 98]}
```

```
df = pd.DataFrame(d)
```

```
mv = df.isnull()
```

```
print(mv)
```

	First Score	Second Score	Third Score
0	False	False	True
1	False	False	False
2	True	False	False
3	False	True	False

**Output:**

### Example 2: Filtering Data Based on Missing Values

Here we used random Employee dataset. The isnull() function is used over the "Gender" column in order to filter and print out rows containing missing gender data.

```
import pandas as pd
```

```
d = pd.read_csv("/content/employees.csv")
```

```
bool_series = pd.isnull(d["Gender"])
```

```
missing_gender_data = d[bool_series]
```

```
print(missing_gender_data)
```

**Output:**

	First Name	Gender	Start Date	Last Login Time	Salary	Bonus %	Senior Management	Team
20	Lois	NaN	4/22/1995	7:18 PM	64714	4.934	True	Legal
22	Joshua	NaN	3/8/2012	1:58 AM	90816	18.816	True	Client Services
27	Scott	NaN	7/11/1991	6:58 PM	122367	5.218	False	Legal
31	Joyce	NaN	2/20/2005	2:40 PM	88657	12.752	False	Product
41	Christine	NaN	6/28/2015	1:08 AM	66582	11.308	True	Business Development
49	Chris	NaN	1/24/1980	12:13 PM	113590	3.055	False	Sales
51	NaN	NaN	12/17/2011	8:29 AM	41126	14.009	NaN	Sales
53	Alan	NaN	3/3/2014	1:28 PM	40341	17.578	True	Finance
60	Paula	NaN	11/23/2005	2:01 PM	48866	4.271	False	Distribution
64	Kathleen	NaN	4/11/1990	6:46 PM	77834	18.771	False	Business Development
69	Irene	NaN	7/14/2015	4:31 PM	100863	4.382	True	Finance
70	Todd	NaN	6/10/2003	2:26 PM	84692	6.617	False	Client Services
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
939	Ralph	NaN	7/28/1995	6:53 PM	70635	2.147	False	Client Services
945	Gerald	NaN	4/15/1989	12:44 PM	93712	17.426	True	Distribution
961	Antonio	NaN	6/18/1989	9:37 PM	103050	3.050	False	Legal
972	Victor	NaN	7/28/2006	2:49 PM	76381	11.159	True	Sales
985	Stephen	NaN	7/10/1983	8:10 PM	85668	1.909	False	Legal
989	Justin	NaN	2/10/1991	4:58 PM	38344	3.794	False	Legal
995	Henry	NaN	11/23/2014	6:09 AM	132483	16.655	False	Distribution

145 rows × 8 columns

## 2. Using isna()

[`isna\(\)`](#) returns a DataFrame of Boolean values where True indicates missing data (NaN). It is used to detect missing values just like `isnull()`.

Example: Finding Missing Values in a DataFrame

```
import pandas as pd
```

```
import numpy as np
```

```
data = {'Name': ['Amit', 'Sita', np.nan, 'Raj'],  
        'Age': [25, np.nan, 22, 28]}
```

```
df = pd.DataFrame(data)
```

```
# Check for missing values using isna()  
print(df.isna())
```

**Output:**

	Name	Age
0	False	False
1	False	True
2	True	False
3	False	False

Using isna()

### 3. Checking for Non-Missing Values Using notnull()

[notnull\(\)](#) function returns a DataFrame with Boolean values where True indicates non-missing (valid) data. This function is useful when we want to focus only on the rows that have valid, non-missing values.

#### Example 1: Identifying Non-Missing Values in a DataFrame

```
import pandas as pd  
import numpy as np
```

```
d = {'First Score': [100, 90, np.nan, 95],  
     'Second Score': [30, 45, 56, np.nan],  
     'Third Score': [np.nan, 40, 80, 98]}
```

```
df = pd.DataFrame(d)
```

```
nmv = df.notnull()
```

```
print(nmv)
```

**Output:**

	First Score	Second Score	Third Score
0	True	True	False
1	True	True	True
2	False	True	True
3	True	False	True

## Example 2: Filtering Data with Non-Missing Values

notnull() function is used over the "Gender" column in order to filter and print out rows containing missing gender data.

```
import pandas as pd
```

```
d = pd.read_csv("/content/employees.csv")
```

```
nmg = pd.notnull(d["Gender"])
```

```
nmgd= d[nmg]
```

```
display(nmgd)
```

**Output:**

	First Name	Gender	Start Date	Last Login Time	Salary	Bonus %	Senior Management	Team
0	Douglas	Male	8/6/1993	12:42 PM	97308	6.945	True	Marketing
1	Thomas	Male	3/31/1996	6:53 AM	61933	4.170	True	NaN
2	Maria	Female	4/23/1993	11:17 AM	130590	11.858	False	Finance
3	Jerry	Male	3/4/2005	1:00 PM	138705	9.340	True	Finance
4	Larry	Male	1/24/1998	4:47 PM	101004	1.389	True	Client Services
5	Dennis	Male	4/18/1987	1:35 AM	115163	10.125	False	Legal
6	Ruby	Female	8/17/1987	4:20 PM	65476	10.012	True	Product
7	NaN	Female	7/20/2015	10:43 AM	45906	11.598	NaN	Finance
8	Angela	Female	11/22/2005	6:29 AM	95570	18.523	True	Engineering
9	Frances	Female	8/8/2002	6:51 AM	139852	7.524	True	Business Development
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
994	George	Male	6/21/2013	5:47 PM	98874	4.479	True	Marketing
996	Phillip	Male	1/31/1984	6:30 AM	42392	19.675	False	Finance
997	Russell	Male	5/20/2013	12:39 PM	96914	1.421	False	Product
998	Larry	Male	4/20/2013	4:45 PM	60500	11.985	False	Business Development
999	Albert	Male	5/15/2012	6:24 PM	129949	10.169	True	Sales

855 rows × 8 columns

## Filling Missing Values in Pandas

Following functions allow us to replace missing values with a specified value or use interpolation methods to find the missing data.

### 1. Using fillna()

[fillna\(\)](#) used to replace missing values (NaN) with a given value. Lets see various example for this.

#### Example 1: Fill Missing Values with Zero

```
import pandas as pd
```

```
import numpy as np
```

```
d = {'First Score': [100, 90, np.nan, 95],
      'Second Score': [30, 45, 56, np.nan],
      'Third Score': [np.nan, 40, 80, 98]}
```

```
df = pd.DataFrame(d)
```

```
df.fillna(0)
```

**Output:**

	First Score	Second Score	Third Score
0	100.0	30.0	0.0
1	90.0	45.0	40.0
2	0.0	56.0	80.0
3	95.0	0.0	98.0

**Example 2: Fill with Previous Value (Forward Fill)**

The pad method is used to fill missing values with the previous value.

```
df.fillna(method='pad')
```

**Output:**

	First Score	Second Score	Third Score
0	100.0	30.0	NaN
1	90.0	45.0	40.0
2	90.0	56.0	80.0
3	95.0	56.0	98.0

**Example 3: Fill with Next Value (Backward Fill)**

The bfill function is used to fill it with the next value.

```
df.fillna(method='bfill')
```

**Output:**

	First Score	Second Score	Third Score
0	100.0	30.0	40.0
1	90.0	45.0	40.0
2	95.0	56.0	80.0
3	95.0	NaN	98.0

**Example 4: Fill NaN Values with 'No Gender'**

```
import pandas as pd
```

```
import numpy as np
```

```
d = pd.read_csv("/content/employees.csv")
```

```
d[10:25]
```

## Output:

	First Name	Gender	Start Date	Last Login Time	Salary	Bonus %	Senior Management	Team
10	Louise	Female	8/12/1980	9:01 AM	63241	15.132	True	NaN
11	Julie	Female	10/26/1997	3:19 PM	102508	12.637	True	Legal
12	Brandon	Male	12/1/1980	1:08 AM	112807	17.492	True	Human Resources
13	Gary	Male	1/27/2008	11:40 PM	109831	5.831	False	Sales
14	Kimberly	Female	1/14/1999	7:13 AM	41426	14.543	True	Finance
15	Lillian	Female	6/5/2016	6:09 AM	59414	1.256	False	Product
16	Jeremy	Male	9/21/2010	5:56 AM	90370	7.369	False	Human Resources
17	Shawn	Male	12/7/1986	7:45 PM	111737	6.414	False	Product
18	Diana	Female	10/23/1981	10:27 AM	132940	19.082	False	Client Services
19	Donna	Female	7/22/2010	3:48 AM	81014	1.894	False	Product
20	Lois	NaN	4/22/1995	7:18 PM	64714	4.934	True	Legal
21	Matthew	Male	9/5/1995	2:12 AM	100612	13.645	False	Marketing
22	Joshua	NaN	3/8/2012	1:58 AM	90816	18.816	True	Client Services
23	NaN	Male	6/14/2012	4:19 PM	125792	5.042	NaN	NaN
24	John	Male	7/1/1992	10:08 PM	97950	13.873	False	Client Services

Now we are going to fill all the null values in Gender column with "No Gender"

```
d["Gender"].fillna('No Gender', inplace = True)
```

```
d[10:25]
```

## Output:

10	Louise	Female	8/12/1980	9:01 AM	63241	15.132	True	NaN
11	Julie	Female	10/26/1997	3:19 PM	102508	12.637	True	Legal
12	Brandon	Male	12/1/1980	1:08 AM	112807	17.492	True	Human Resources
13	Gary	Male	1/27/2008	11:40 PM	109831	5.831	False	Sales
14	Kimberly	Female	1/14/1999	7:13 AM	41426	14.543	True	Finance
15	Lillian	Female	6/5/2016	6:09 AM	59414	1.256	False	Product
16	Jeremy	Male	9/21/2010	5:56 AM	90370	7.369	False	Human Resources
17	Shawn	Male	12/7/1986	7:45 PM	111737	6.414	False	Product
18	Diana	Female	10/23/1981	10:27 AM	132940	19.082	False	Client Services
19	Donna	Female	7/22/2010	3:48 AM	81014	1.894	False	Product
20	Lois	No Gender	4/22/1995	7:18 PM	64714	4.934	True	Legal
21	Matthew	Male	9/5/1995	2:12 AM	100612	13.645	False	Marketing
22	Joshua	No Gender	3/8/2012	1:58 AM	90816	18.816	True	Client Services
23	NaN	Male	6/14/2012	4:19 PM	125792	5.042	NaN	NaN
24	John	Male	7/1/1992	10:08 PM	97950	13.873	False	Client Services

## 2. Using replace()

Use [replace\(\)](#) function to replace NaN values with a specific value.



## Example

```
import pandas as pd
```

```
import numpy as np
```

```
data = pd.read_csv("/content/employees.csv")
```

```
data[10:25]
```

## Output:

	First Name	Gender	Start Date	Last Login Time	Salary	Bonus %	Senior Management	Team
10	Louise	Female	8/12/1980	9:01 AM	63241	15.132	True	NaN
11	Julie	Female	10/26/1997	3:19 PM	102508	12.637	True	Legal
12	Brandon	Male	12/1/1980	1:08 AM	112807	17.492	True	Human Resources
13	Gary	Male	1/27/2008	11:40 PM	109831	5.831	False	Sales
14	Kimberly	Female	1/14/1999	7:13 AM	41426	14.543	True	Finance
15	Lillian	Female	6/5/2016	6:09 AM	59414	1.256	False	Product
16	Jeremy	Male	9/21/2010	5:56 AM	90370	7.369	False	Human Resources
17	Shawn	Male	12/7/1986	7:45 PM	111737	6.414	False	Product
18	Diana	Female	10/23/1981	10:27 AM	132940	19.082	False	Client Services
19	Donna	Female	7/22/2010	3:48 AM	81014	1.894	False	Product
20	Lois	NaN	4/22/1995	7:18 PM	64714	4.934	True	Legal
21	Matthew	Male	9/5/1995	2:12 AM	100612	13.645	False	Marketing
22	Joshua	NaN	3/8/2012	1:58 AM	90816	18.816	True	Client Services
23	NaN	Male	6/14/2012	4:19 PM	125792	5.042	NaN	NaN

Now, we are going to replace the all NaN value in the data frame with -99 value.

```
data = data.replace(to_replace=np.nan, value=-99)
```

```
print(data[10:25])
```

## Output:

10	Louise	Female	8/12/1980	9:01 AM	63241	15.132	True	-99
11	Julie	Female	10/26/1997	3:19 PM	102508	12.637	True	Legal
12	Brandon	Male	12/1/1980	1:08 AM	112807	17.492	True	Human Resources
13	Gary	Male	1/27/2008	11:40 PM	109831	5.831	False	Sales
14	Kimberly	Female	1/14/1999	7:13 AM	41426	14.543	True	Finance
15	Lillian	Female	6/5/2016	6:09 AM	59414	1.256	False	Product
16	Jeremy	Male	9/21/2010	5:56 AM	90370	7.369	False	Human Resources
17	Shawn	Male	12/7/1986	7:45 PM	111737	6.414	False	Product
18	Diana	Female	10/23/1981	10:27 AM	132940	19.082	False	Client Services
19	Donna	Female	7/22/2010	3:48 AM	81014	1.894	False	Product
20	Lois	-99	4/22/1995	7:18 PM	64714	4.934	True	Legal
21	Matthew	Male	9/5/1995	2:12 AM	100612	13.645	False	Marketing
22	Joshua	-99	3/8/2012	1:58 AM	90816	18.816	True	Client Services
23	-99	Male	6/14/2012	4:19 PM	125792	5.042	-99	-99
24	John	Male	7/1/1992	10:08 PM	97950	13.873	False	Client Services

### 3. Using interpolate()

The [interpolate\(\)](#) function fills missing values using interpolation techniques such as the linear method.

#### Example

**import pandas as pd**

```
df = pd.DataFrame({"A": [12, 4, 5, None, 1],
                  "B": [None, 2, 54, 3, None],
                  "C": [20, 16, None, 3, 8],
                  "D": [14, 3, None, None, 6]})
```

**print(df)**

**Output:**

	A	B	C	D
0	12.0	NaN	20.0	14.0
1	4.0	2.0	16.0	3.0
2	5.0	54.0	NaN	NaN
3	NaN	3.0	3.0	NaN
4	1.0	NaN	8.0	6.0

Let's interpolate the missing values using Linear method. This method ignore the index and consider the values as equally spaced.

```
df.interpolate(method='linear', limit_direction='forward')
```

**Output:**

	A	B	C	D
0	12.0	NaN	20.0	14.0
1	4.0	2.0	16.0	3.0
2	5.0	54.0	9.5	4.0
3	3.0	3.0	3.0	5.0
4	1.0	3.0	8.0	6.0

## Dropping Missing Values in Pandas

The [`dropna\(\)`](#) function is used to remove rows or columns with NaN values. It can be used to drop data based on different conditions.

### 1. Dropping Rows with At Least One Null Value

Remove rows that contain at least one missing value.

**Example**

```
import pandas as pd
```

```
import numpy as np
```

```
dict = {'First Score': [100, 90, np.nan, 95],  
        'Second Score': [30, np.nan, 45, 56],  
        'Third Score': [52, 40, 80, 98],  
        'Fourth Score': [np.nan, np.nan, np.nan, 65]}
```

```
df = pd.DataFrame(dict)
```

```
df.dropna()
```

	First Score	Second Score	Third Score	Fourth Score
3	95.0	56.0	98	65.0

**Output:**

### 2. Dropping Rows with All Null Values

We can drop rows where all values are missing using `dropna(how='all')`.

**Example**

```
dict = {'First Score': [100, np.nan, np.nan, 95],
        'Second Score': [30, np.nan, 45, 56],
        'Third Score': [52, np.nan, 80, 98],
        'Fourth Score': [np.nan, np.nan, np.nan, 65]}
df = pd.DataFrame(dict)
```

```
df.dropna(how='all')
```

**Output:**

	First Score	Second Score	Third Score	Fourth Score
0	100.0	30.0	52.0	NaN
2	NaN	45.0	80.0	NaN
3	95.0	56.0	98.0	65.0

### 3. Dropping Columns with At Least One Null Value

To remove columns that contain at least one missing value we use `dropna(axis=1)`.

**Example**

```
dict = {'First Score': [100, np.nan, np.nan, 95],
        'Second Score': [30, np.nan, 45, 56],
        'Third Score': [52, np.nan, 80, 98],
        'Fourth Score': [60, 67, 68, 65]}
df = pd.DataFrame(dict)
```

```
df.dropna(axis=1)
```

**Output:**

	Fourth Score
0	60
1	67
2	68
3	65

### 4. Dropping Rows with Missing Values in CSV Files

When working with CSV files, we can drop rows with missing values using `dropna()`.

### **Example**

```
import pandas as pd
```

```
d = pd.read_csv("/content/employees.csv")
```

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

```
print("Old data frame length:", len(d))
```

```
print("New data frame length:", len(nd))
```

```
print("Rows with at least one missing value:", (len(d) - len(nd)))
```

### **Output:**

#### Drop Rows with NaN

Since the difference is 236, there were 236 rows which had at least 1 Null value in any column. By using these functions we can easily detect, handle and fill missing values.