Reference guide: Data cleaning in Python

This reference guide contains common functions and methods that data professionals use to clean data. The reference guide contains three different tables of useful tools, each grouped by cleaning category: missing data, outliers, and label encoding. standard

Missing data

The following pandas functions and methods are helpful when dealing with missing data.

df.info()

- **Description:** A DataFrame method that returns a concise summary of the dataframe, including a 'non-null count,' which helps you know the number of missing values

Example input:

```
print(df)
print()
df.info()
```

Example output:

```
    planet  radius_km  moons
0  Mercury       2440      0
1    Venus       6052      0
2    Earth       6371      1
3     Mars       3390      2
4  Jupiter      69911     80
5   Saturn      58232     83
6   Uranus      25362     27
7  Neptune      24622     14

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8 entries, 0 to 7
Data columns (total 3 columns):
planet       8 non-null object
radius_km    8 non-null int64
moons        8 non-null int64
dtypes: int64(2), object(1)
memory usage: 272.0+ bytes
```

df.isna() / isnull()

- **Description:** A pandas function that returns a same-sized Boolean array indicating whether each value is null (you can also use `pd.isnull()` as an alias). Note that this function also exists as a `DataFrame` method.

Example input:

```
print(df)
print('\n After pd.isnull(): \n')

pd.isnull(df)
```

Example output:

```
    Planet  radius_km  moons
0  Mercury       2440    NaN
1    Venus       6052    NaN
2    Earth       6371    1.0
3     Mars       3390    NaN
4  Jupiter      69911   80.0
5   Saturn      58232   83.0
6   Uranus      25362   27.0
7  Neptune      24622   14.0

 After pd.isnull():

  Planet radius_km  moons
0  False     False   True
1  False     False   True
2  False     False  False
3  False     False   True
4  False     False  False
5  False     False  False
6  False     False  False
7  False     False  False
```

pd.notna() / notnull()

- **Description:** A pandas function that returns a same-sized Boolean array indicating whether each value is NOT null (you can also use `pd.notnull()` as an alias). Note that this function also exists as a `DataFrame` method.

Example input:

```
print(df)
print('\n After notnull(): \n')
pd.notnull(df)
```

Example output:

```
    Planet  radius_km  moons
0  Mercury       2440    NaN
1    Venus       6052    NaN
2    Earth       6371    1.0
3     Mars       3390    NaN
4  Jupiter      69911   80.0
5   Saturn      58232   83.0
6   Uranus      25362   27.0
7  Neptune      24622   14.0

 After notnull():

  Planet radius_km  moons
0   True      True  False
1   True      True  False
2   True      True   True
3   True      True  False
4   True      True   True
5   True      True   True
6   True      True   True
7   True      True   True
```

df.fillna()

- **Description:** A DataFrame method that fills in missing values using specified method

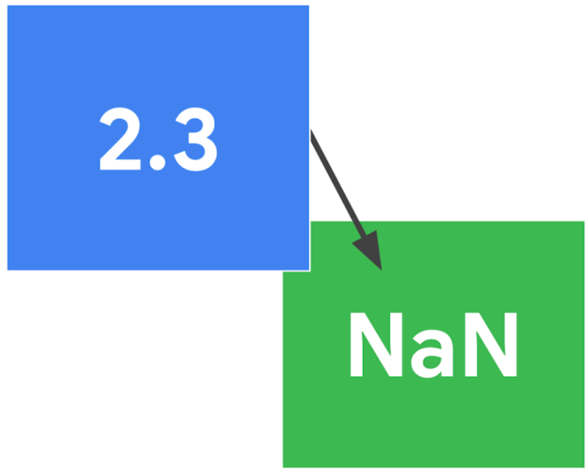
Example input:

```
print(df)
print('\n After fillna(): \n')

df.fillna(2)
```

Example output:

```
    animal     class  color  legs
0  cardinal      Aves    red   NaN
1     gecko  Reptilia  green   4.0
2     raven      Aves  black   NaN

 After fillna():

     animal     class  color   legs
0  cardinal      Aves    red   2.0
1     gecko  Reptilia  green   4.0
2     raven      Aves  black   2.0
```

The following image shows a value of 2.3 replacing a NaN in a data cell.



df.replace()

- **Description:** A DataFrame method that replaces specified values with other specified values. Can also be applied to pandas Series.

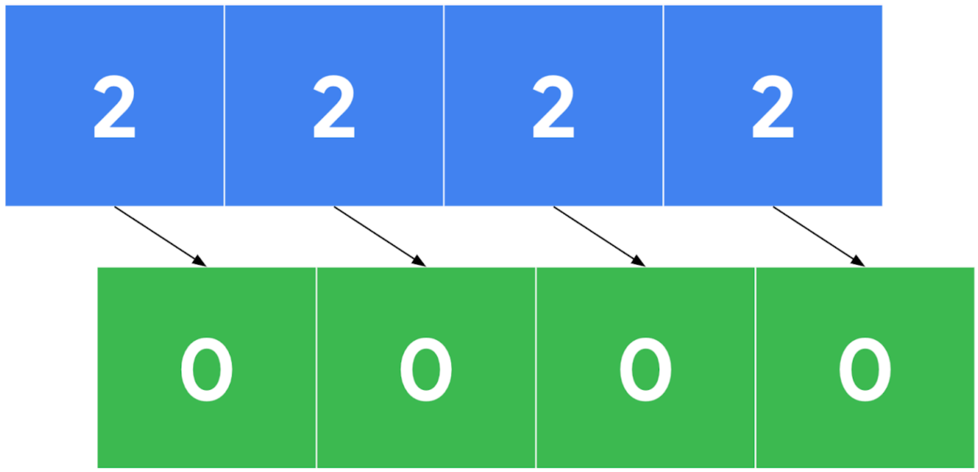
Example input:

```
print(df)
print('\n After replace(): \n')

df.replace('Aves', 'bird')
```

Example output:

```
    animal     class  color  legs
0  cardinal      Aves    red     2
1     gecko  Reptilia  green     4
2     raven      Aves  black     2

 After replace():

     animal     class  color  legs
0  cardinal      bird    red     2
1     gecko  Reptilia  green     4
2     raven      bird  black     2
```

The following image shows that four 2s in cells are replacing 0s.



df.dropna()

- **Description:** A DataFrame method that removes rows or columns that contain missing values, depending on the axis you specify.

Example input:

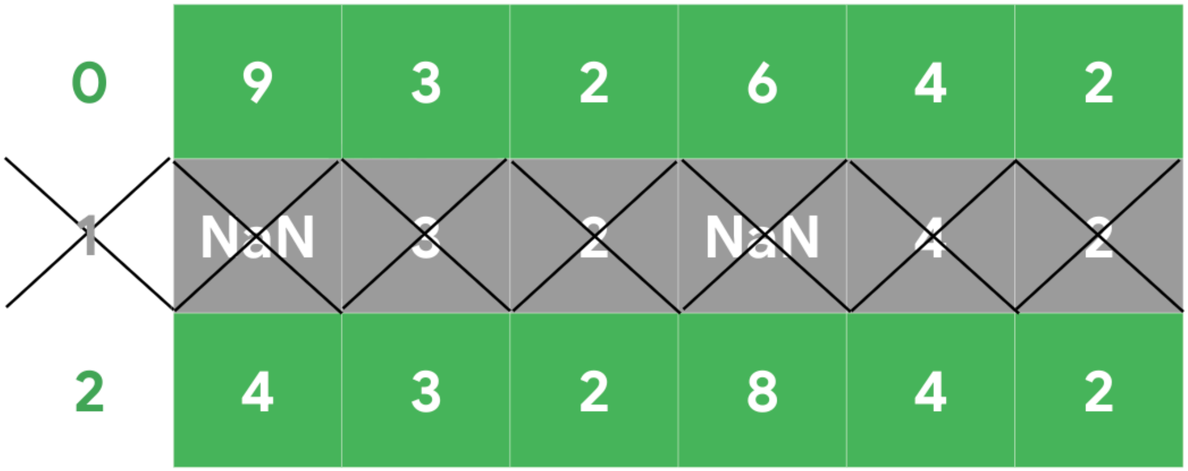
```
print('Original df: \n \n', df)
print('\n After dropna(axis=0): \n')
print(df.dropna(axis=0))

print('\n After dropna(axis=1): \n')
print(df.dropna(axis=1))
```

Example output:

```
Original df:

   animal     class  color  legs
0     NaN      Aves    red     2
1   gecko  Reptilia  green     4
2   raven      Aves    NaN     2

 After dropna(axis=0):

  animal     class  color  legs
1  gecko  Reptilia  green     4

 After dropna(axis=1):

      class  legs
0      Aves     2
```

```
1   Reptilia      4
2       Aves      2
```

The following image shows a sequence of numbers with missing value data cells being removed.



Outliers

The following tools are helpful when dealing with outliers in a dataset.

df.describe()

- **Description:** A DataFrame method that returns general statistics about the dataframe which can help determine outliers

Example input:

```
print(df)
print()
df.describe()
```

Example output:

```
    planet  radius_km  moons
0  Mercury       2440      0
1    Venus       6052      0
2    Earth       6371      1
3     Mars       3390      2
4  Jupiter      69911     80
5   Saturn      58232     83
6   Uranus      25362     27
7  Neptune      24622     14
```

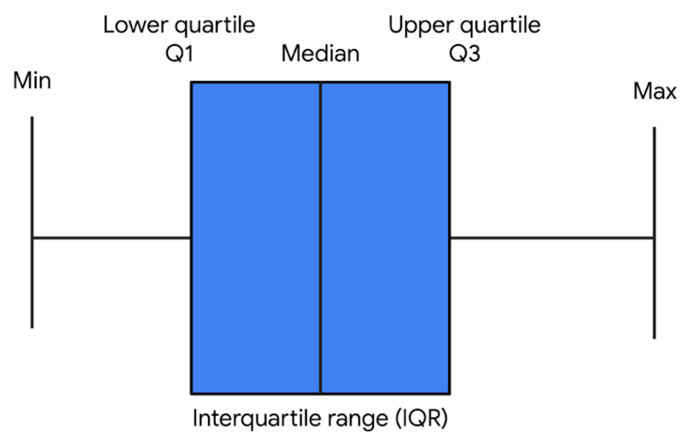
```
            radius_km      moons
count        8.000000    8.00000
mean     24547.500000   25.87500
std      26191.633528   35.58265
min       2440.000000    0.00000
25%       5386.500000    0.75000
50%      15496.500000    8.00000
75%      33579.500000   40.25000
max      69911.000000   83.00000
```

[sns.boxplot()]

- **Description:** A seaborn function that generates a box plot. Data points beyond 1.5x the interquartile range are considered outliers.

Example:

The following image shows an example graph of a box plot with min, max, lower and upper quartiles, and the median labeled.



Label encoding

The following tools are helpful when performing label encoding.

[df.astype()]

- **Description:** A DataFrame method that allows you to encode its data as a specified dtype. Note that this method can also be used on Series objects.

Example input:
```
print(df)
```

```python
print('\n Original dtypes of df: \n')

print(df.dtypes)

print('\n dtypes after casting \'class\' column as categorical: \n')

df['class'] = df['class'].astype('category')

print(df.dtypes)
```

Example output:

```
 animal     class  color  legs
0  cardinal      Aves    red     2
1     gecko  Reptilia  green     4
2     raven      Aves  black     2

 Original dtypes of df:

animal    object
class     object
color     object
legs       int64
dtype: object

 dtypes after casting 'class' column as categorical:

animal      object
class     category
color       object
legs         int64
dtype: object
```

Series.cat.codes

- **Description:** A Series attribute that returns the numeric category codes of the series

Example input:

```python
# Cast 'class' column as categorical
df['class'] = df['class'].astype('category')

print('\n \'class\' column: \n')
print(df['class'])

print('\n Category codes of \'class\' column: \n')
```

```
df['class'].cat.codes
```

Example output:

```
'class' column:

0         Aves
1     Reptilia
2         Aves
Name: class, dtype: category
Categories (2, object): [Aves, Reptilia]

 Category codes of 'class' column:

0    0
1    1
2    0
dtype: int8
```

get_dummies()

- **Description:** Converts categorical values into new binary columns—one for each different category

Example:

The following image shows a rain column with values of mild, scattered, heavy, and severe is replaced with four new binary columns—one for each category.

index	rain
0	mild
1	mild
2	heavy
3	scattered
4	heavy
5	severe
6	severe
7	mild
8	heavy
9	scattered
10	scattered

index	rain_mild	rain_scattered	rain_heavy	rain_severe
0	1	0	0	0
1	1	0	0	0
2	0	0	1	0
3	0	1	0	0
4	0	0	1	1
5	0	0	0	1
6	0	0	0	1
7	1	0	0	0
8	0	0	1	0
9	0	1	0	0
10	0	1	0	0

LabelEncoder()

- **Description:** A transformer from scikit-learn.preprocessing that encodes specified categories or labels with numeric codes. Note that when building predictive models it should only be used on target variables (i.e., *y* data).

Example:

It can be used to normalize labels:

```
from sklearn.preprocessing import LabelEncoder

# Instantiate LabelEncoder()
encoder = LabelEncoder()

data = [1, 2, 2, 6]

# Fit to the data
encoder.fit(data)

# Transform the data
transformed = encoder.transform(data)

# Reverse the transformation
inverse = encoder.inverse_transform(transformed)

print('Data =', data)
print('\n Classes: \n', encoder.classes_)
print('\n Encoded (normalized) classes: \n', transformed)
print('\n Reverse from encoded classes to original: \n', inverse)
```

Output:

```
Data = [1, 2, 2, 6]

 Classes:
 [1 2 6]

 Encoded (normalized) classes:
 [0 1 1 2]

 Reverse from encoded classes to original:
 [1 2 2 6]
```

It can be used to convert categorical labels into numeric:

```python
from sklearn.preprocessing import LabelEncoder

# Instantiate LabelEncoder()
encoder = LabelEncoder()

data = ['paris', 'paris', 'tokyo', 'amsterdam']

# Fit to the data
encoder.fit(data)

# Transform the data
transformed = encoder.transform(data)

# New data
new_data = [0, 2, 1, 1, 2]

# Get classes of new data
inverse = encoder.inverse_transform(new_data)

print('Data =', data)
print('\n Classes: \n', list(encoder.classes_))
print('\n Encoded classes: \n', transformed)
print('\n New data =', new_data)
print('\n Convert new_data to original classes: \n', list(inverse))
```

Output:

```
Data = ['paris', 'paris', 'tokyo', 'amsterdam']

 Classes:
 ['amsterdam', 'paris', 'tokyo']

 Encoded classes:
 [1 1 2 0]

 New data = [0, 2, 1, 1, 2]

 Convert new_data to original classes:
 ['amsterdam', 'tokyo', 'paris', 'paris', 'tokyo']
```

Key takeaways

There are many tools that data professionals can use to perform data cleaning on a wide range of data. The information you learn from missing data, outliers, and transforming categorical to numeric data will help you prepare datasets for further analysis throughout your career.