Diagnose data for cleaning

CLEANING DATA IN PYTHON

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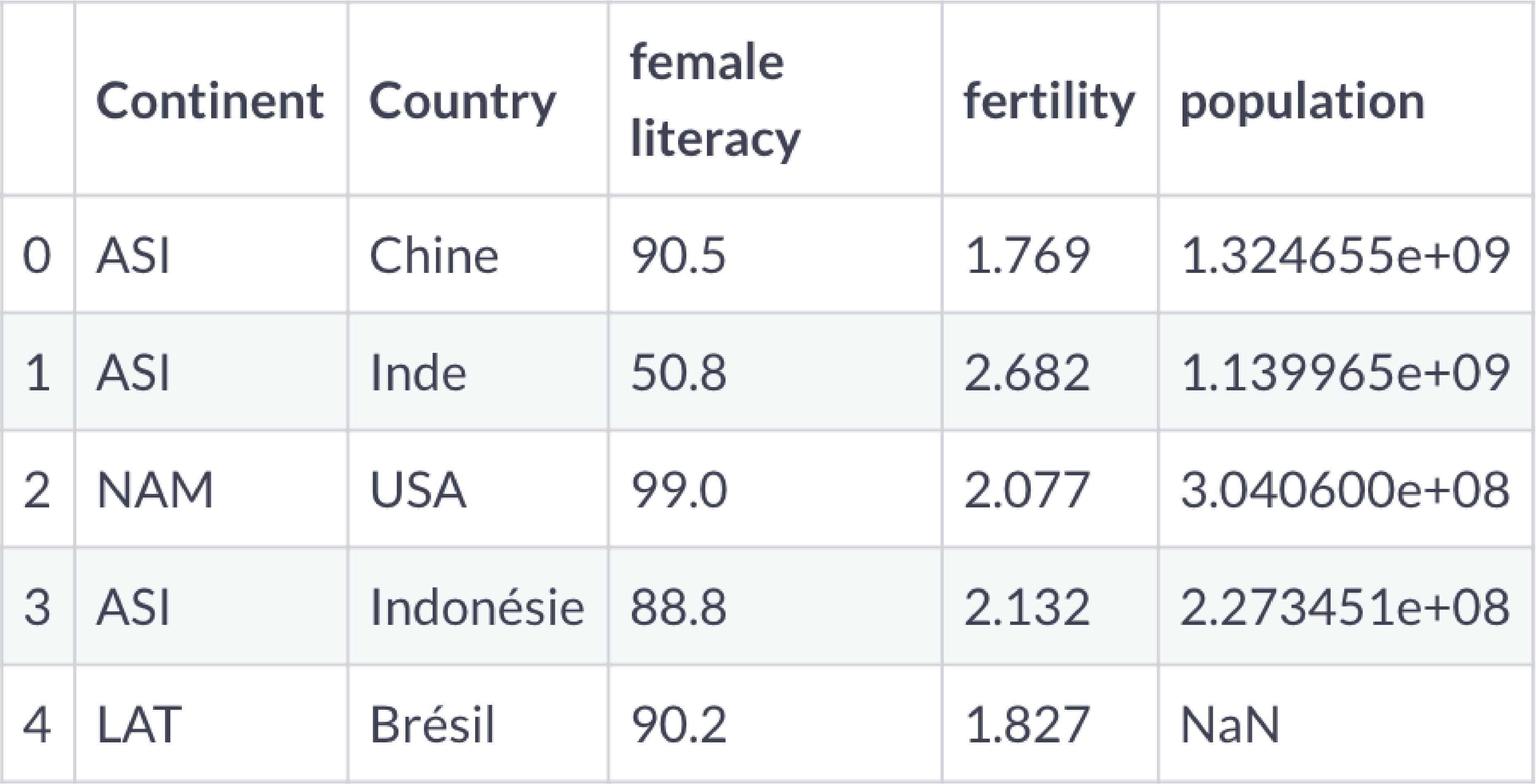
Instructor

Cleaning data

- Prepare data for analysis
- Data almost never comes in clean
- Diagnose your data for problems

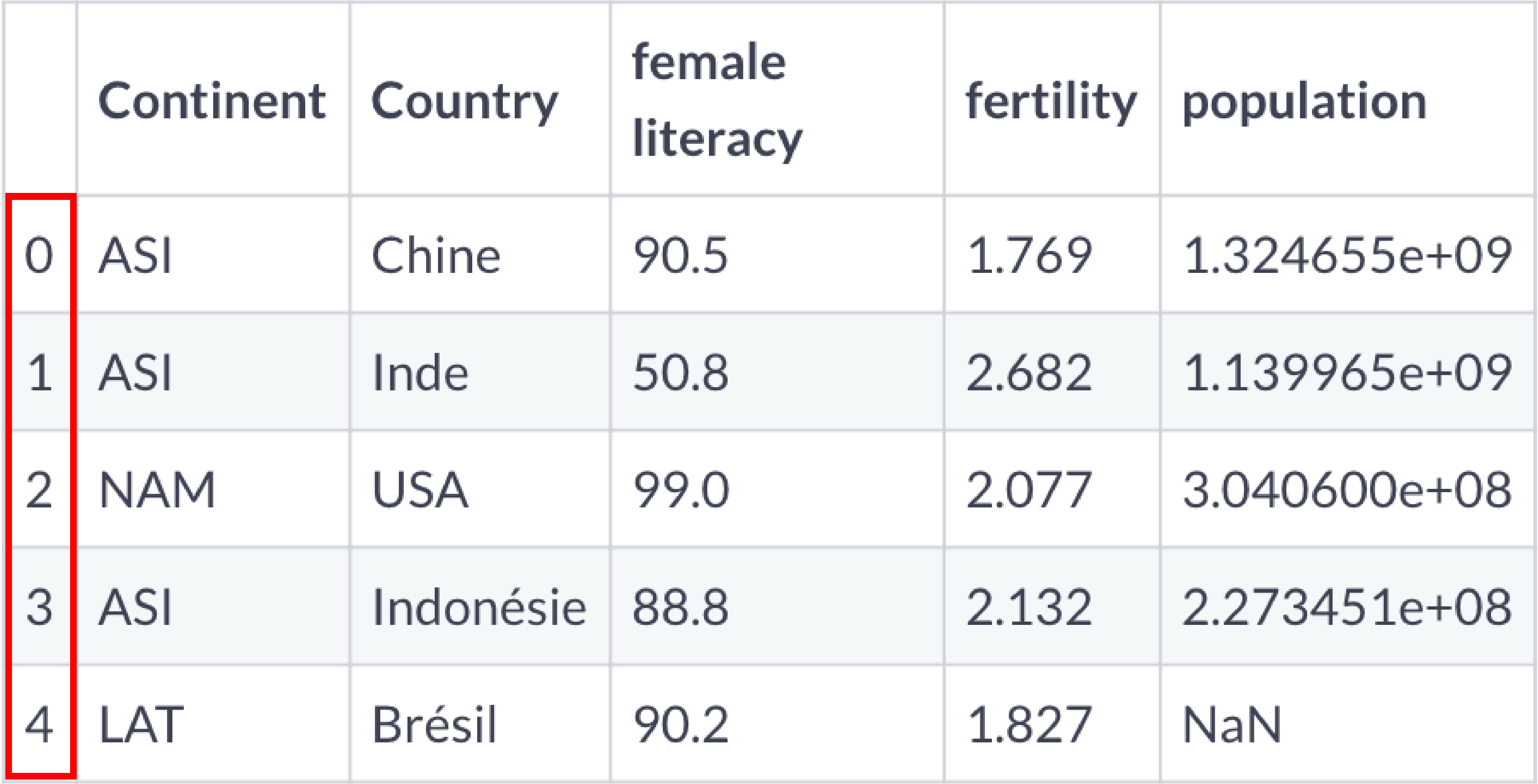
Common data problems

- Inconsistent column names
- Missing data
- Outliers
- Duplicate rows
- Untidy
- Need to process columns
- Column types can signal unexpected data values



	Continent	Country	female literacy	fertility	population
0	ASI	Chine	90.5	1.769	1.324655e+09
1	ASI	Inde	50.8	2.682	1.139965e+09
2	NAM	USA	99.0	2.077	3.040600e+08
3	ASI	Indonésie	88.8	2.132	2.273451e+08
4	LAT	Brésil	90.2	1.827	NaN

[1] Source: www.eea.europa.eu/data [2] and [3] maps/figures/correlation [4] between [5] fertility [6] and [7] female [8] education



	Continent	Country	female literacy	fertility	population
0	ASI	Chine	90.5	1.769	1.324655e+09
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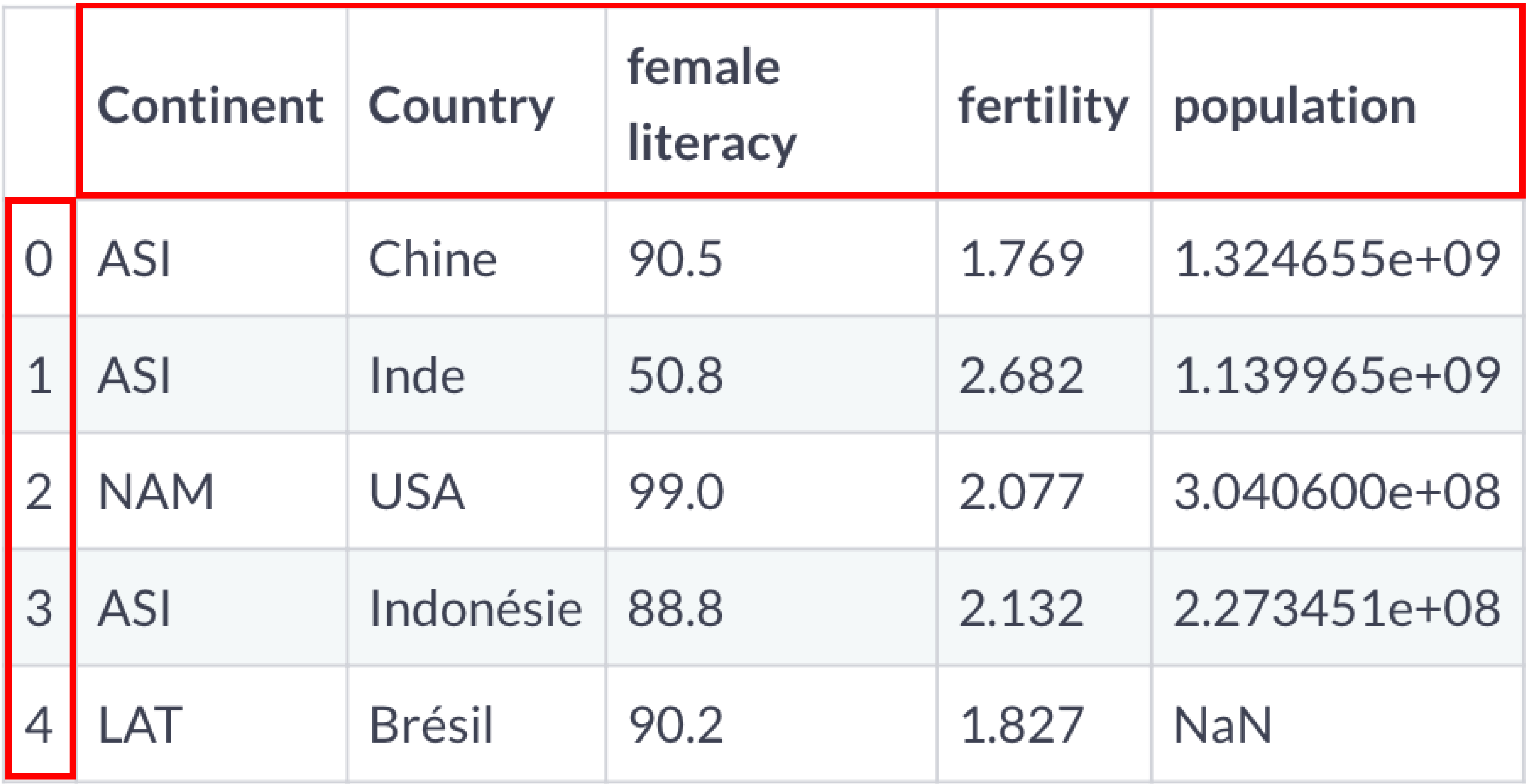

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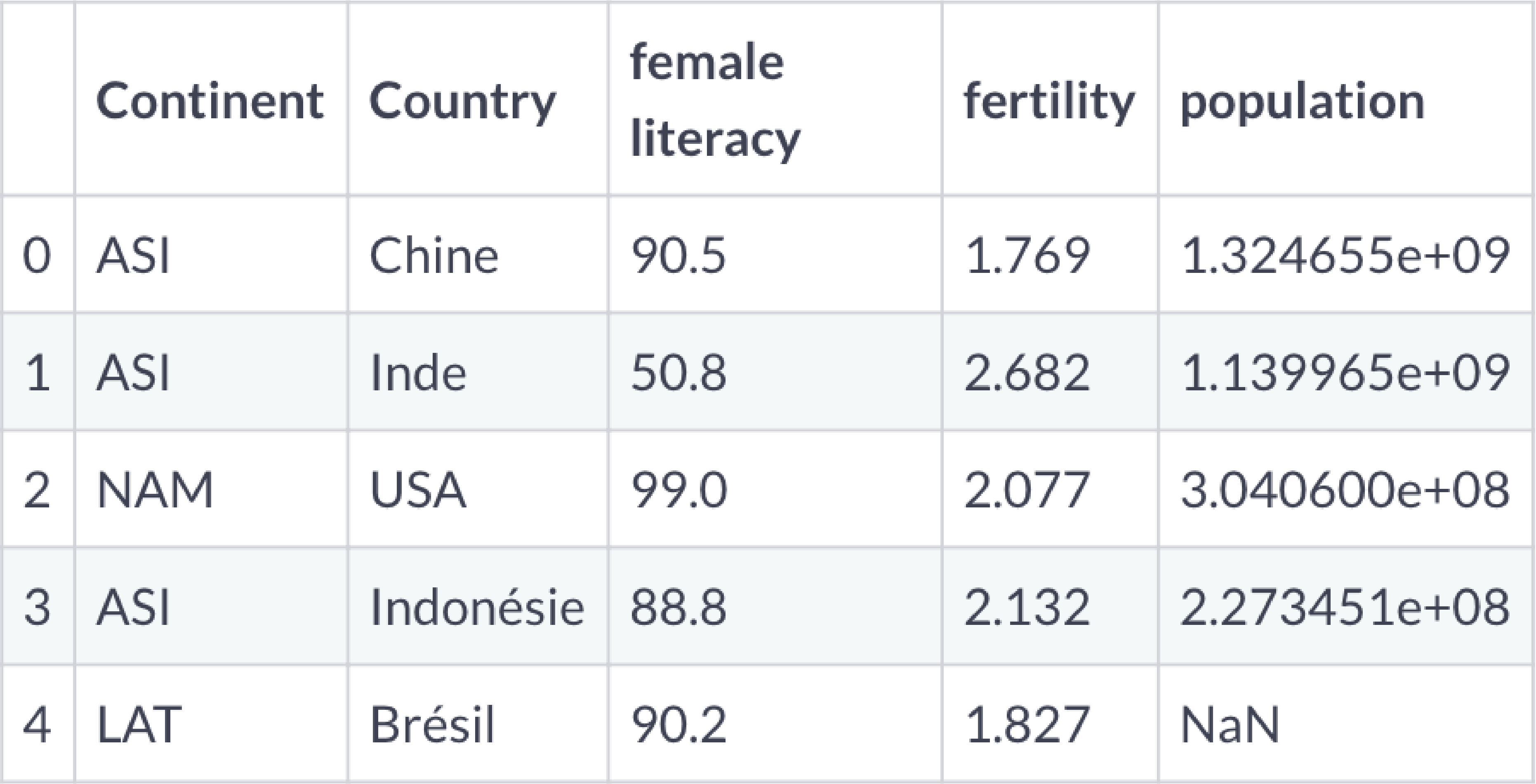

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- Column name inconsistencies

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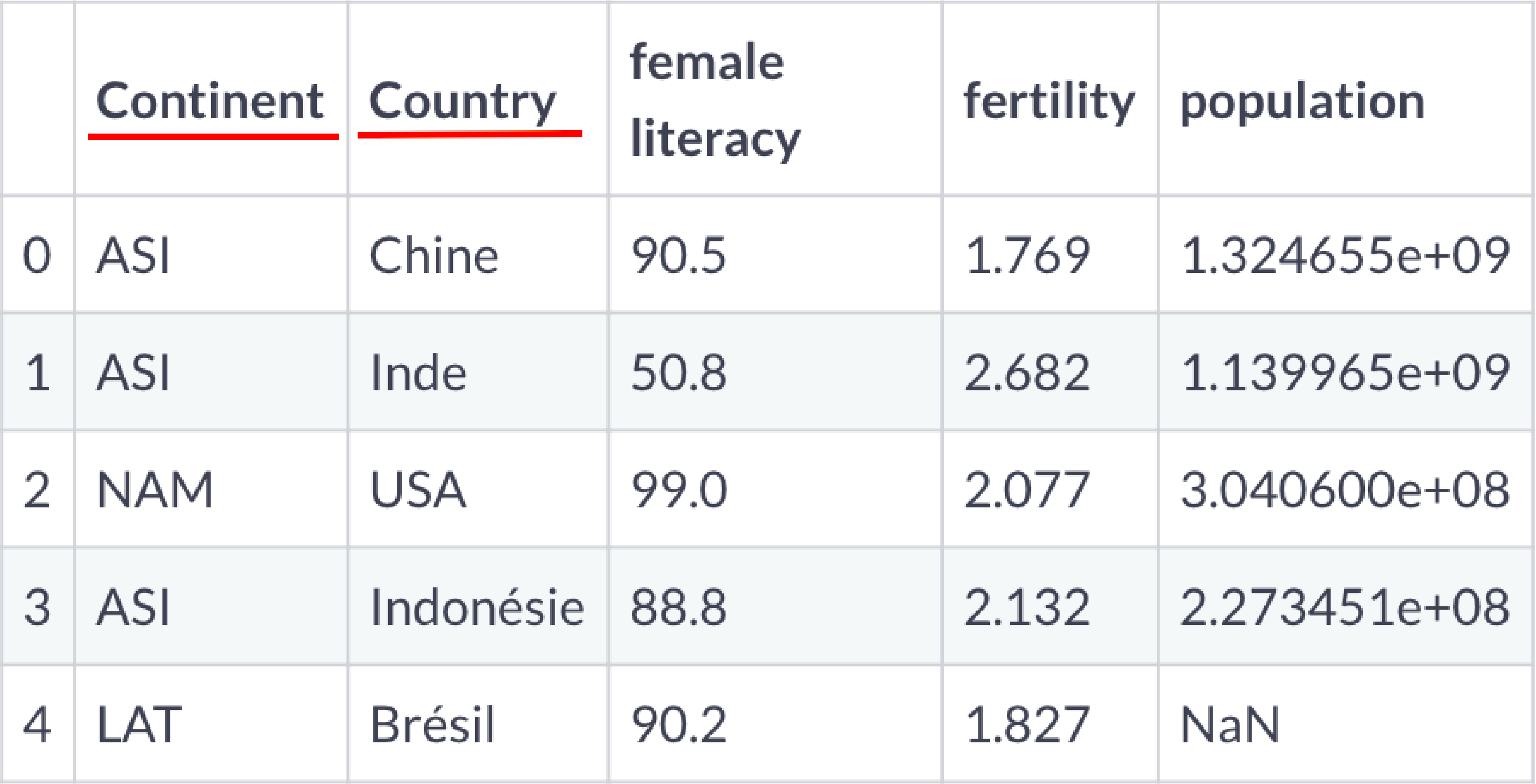

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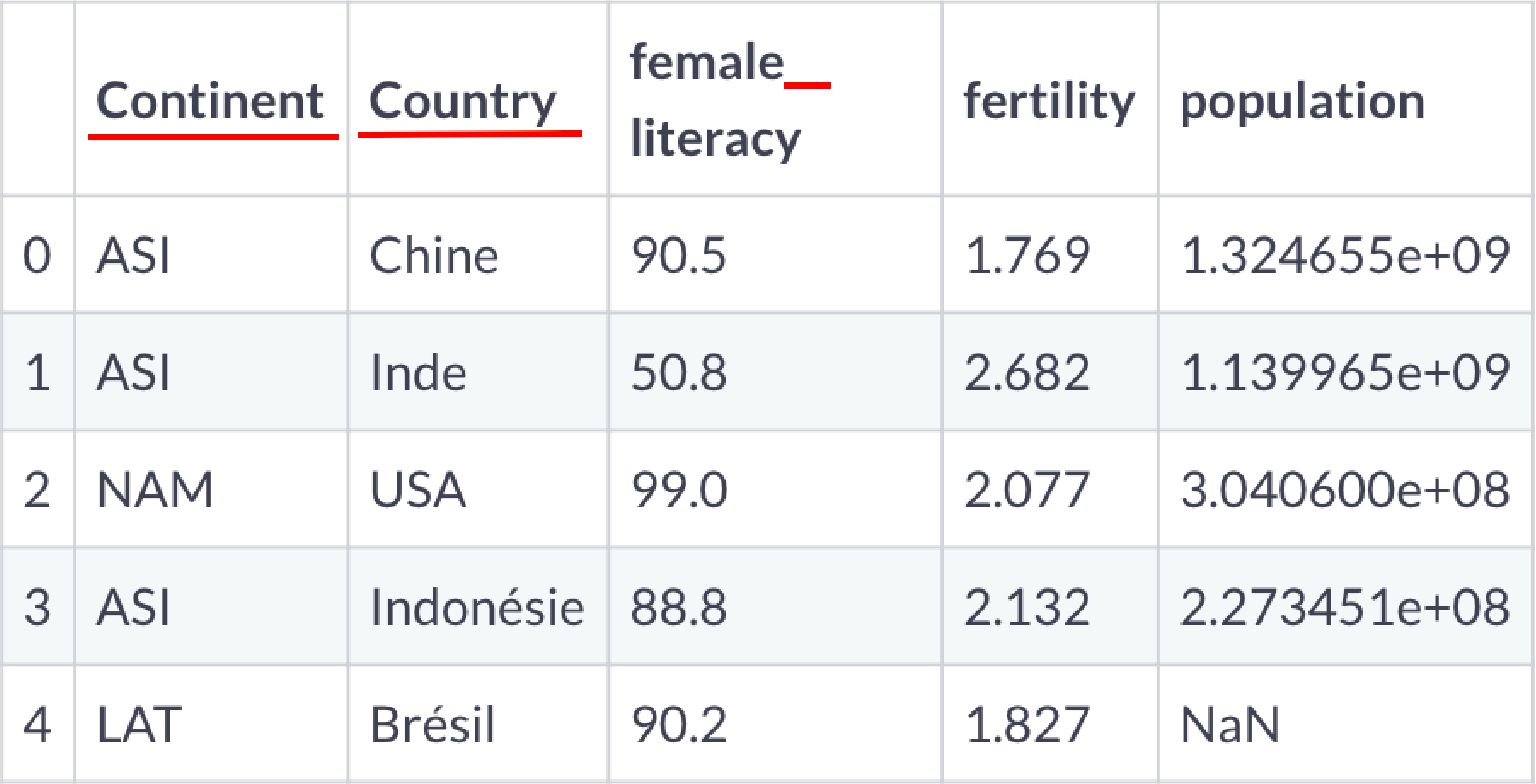

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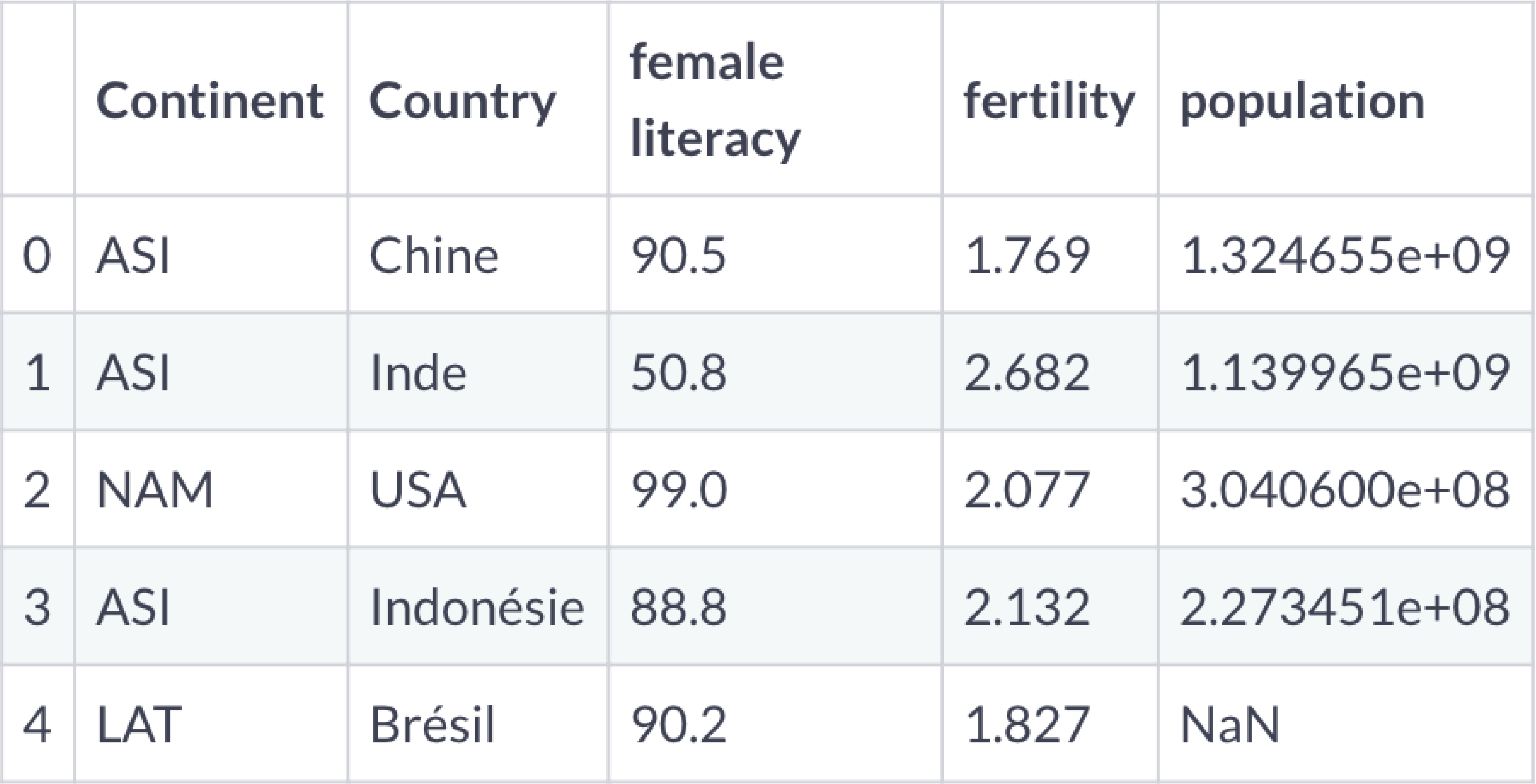

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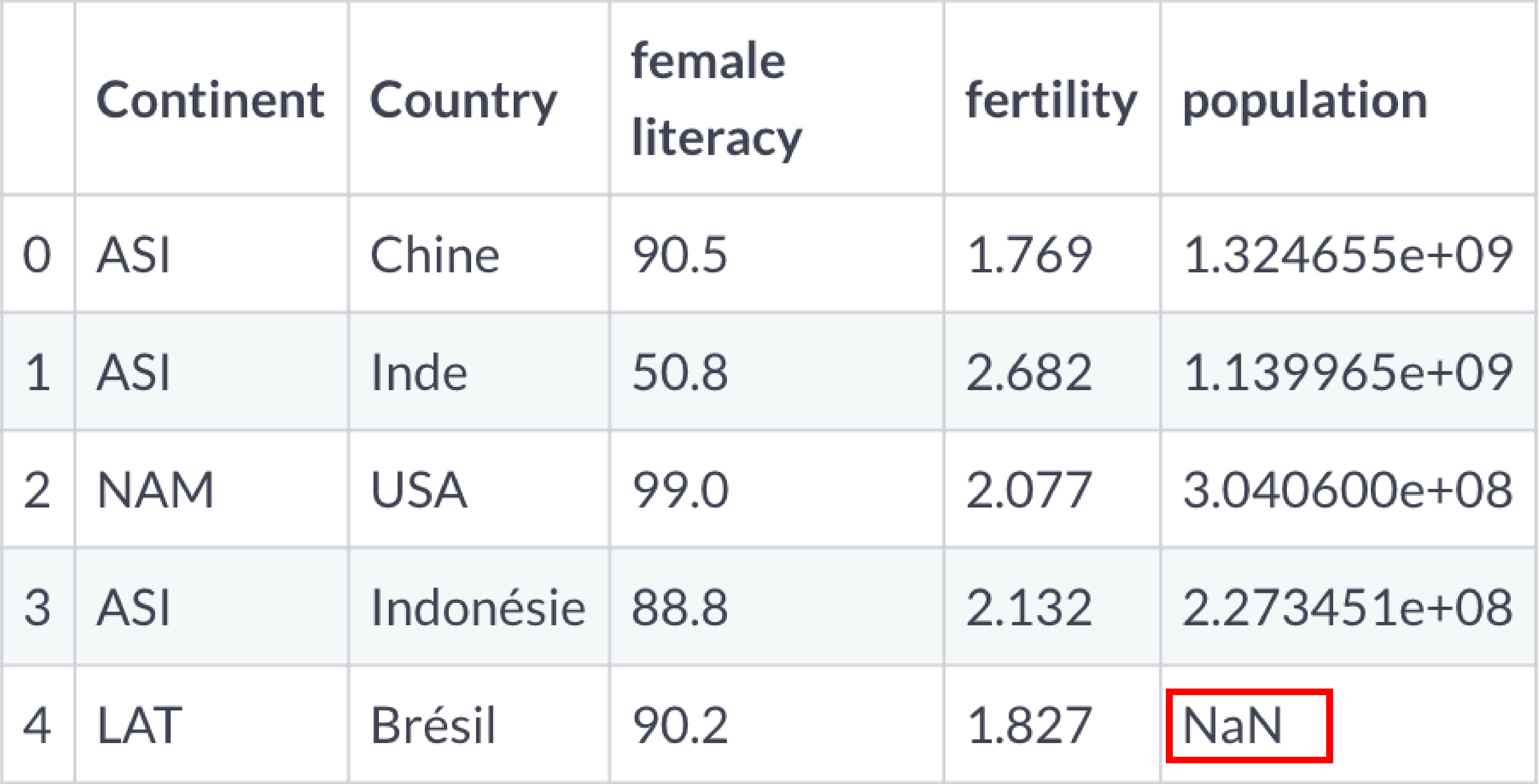

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- Column name inconsistencies
- Missing data

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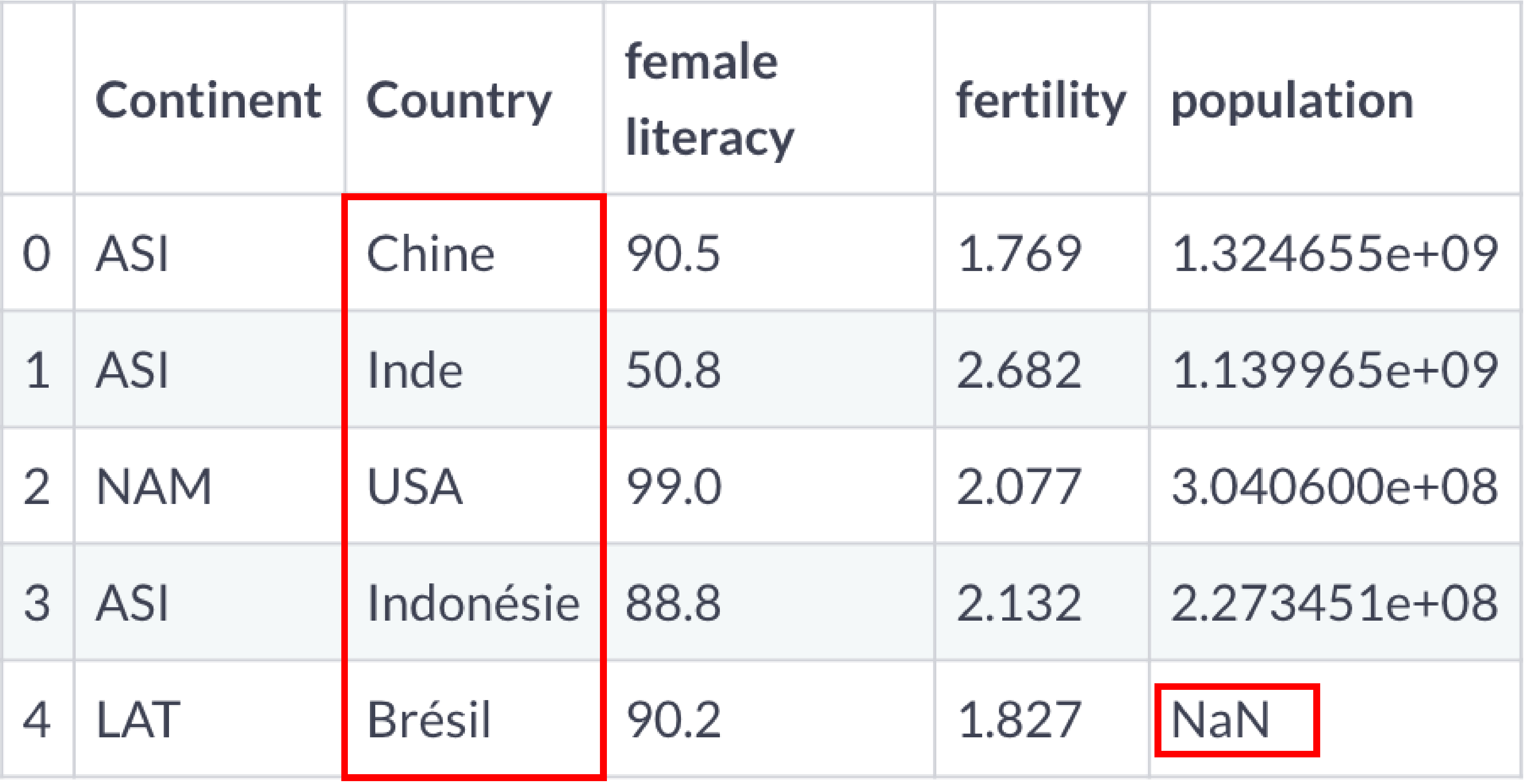

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4	LAT	Brésil	90.2	1.827	NaN

- Column name inconsistencies
- Missing data
- Country names are in French

[1] Source: www.eea.europa.eu/data [2] and [3] maps/figures/correlation [4] between [5] fertility [6] and [7] female [8] education

Load your data

```
import pandas as pd

df = pd.read_csv('literary_birth_rate.csv')
```

Visually inspect

```
df.head()
```

```
  Continent    Country  female literacy  fertility    population
0       ASI      Chine             90.5      1.769  1.324655e+09
1       ASI       Inde             50.8      2.682  1.139965e+09
2       NAM        USA             99.0      2.077  3.040600e+08
3       ASI  Indonésie             88.8      2.132  2.273451e+08
4       LAT     Brésil             90.2      1.827           NaN
```

```
df.tail()
```

```
  Continent               Country  female literacy  fertility    population
0        AF  Sao Tomé-et-Principe             90.5      1.769  1.324655e+09
1       LAT                 Aruba             50.8      2.682  1.139965e+09
2       ASI                 Tonga             99.0      2.077  3.040600e+08
3       OCE             Australia             88.8      2.132  2.273451e+08
4       OCE                Sweden             90.2      1.827           NaN
```

Visually inspect

```
df.columns
```

```
Index(['Continent', 'Country ', 'female literacy', 'fertility', 'population'], dtype='object')
```

```
df.shape
```

```
(164, 5)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 164 entries, 0 to 163
Data columns (total 5 columns):
Continent          164 non-null object
Country            164 non-null object
female literacy    164 non-null float64
fertility          164 non-null object
population         122 non-null float64
dtypes float64(2), object(3)
memory usage: 6.5+ KB
```

Let's practice!

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Exploratory data analysis

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Frequency counts

- Count the number of unique values in our data

Data type of each column

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 164 entries, 0 to 163
Data columns (total 5 columns):
continent          164 non-null object
country            164 non-null object
female literacy    164 non-null float64
fertility          164 non-null object
population         122 non-null float64
dtypes float64(2), object(3)
memory usage: 6.5+ KB
```

Frequency counts: continent

```
df.continent.value_counts(dropna=False)
```

```
AF     49
ASI    47
EUR    36
LAT    24
OCE     6
NAM     2
Name:  continent, dtype: int64
```

Frequency counts: continent

```
df['continent'].value_counts(dropna=False)
```

```
AF     49
ASI    47
EUR    36
LAT    24
OCE     6
NAM     2
Name:  continent, dtype: int64
```

Frequency counts: country

```
df.country.value_counts(dropna=False).head()
```

```
Sweden      2
Algerie     1
Germany     1
Angola      1
Indonésie   1
Name: country, dtype: int64
```

Frequency counts: fertility

```
df.fertility.value_counts(dropna=False).head()
```

```
missing  5
1.854    2
1.93     2
1.841    2
1.393    2
Name: fertility, dtype: int64
```

Frequency counts: population

```
df.population.value_counts(dropna=False).head()
```

```
NaN             42
5.667325e+06     1
3.773100e+06     1
1.333388e+06     1
1.661115e+08     1
Name: population, dtype: int64
```

Summary statistics

- Numeric columns
- Outliers
  - Considerably higher or lower
  - Require further investigation

Summary statistics: numeric data

```
df.describe()
```

```
       female_literacy    population
count       164.000000  1.220000e+02
mean         80.301220  6.345768e+07
std          22.977265  2.605977e+08
min          12.600000  1.035660e+05
25%          66.675000  3.778175e+06
50%          90.200000  9.995450e+06
75%          98.500000  2.642217e+07
max         100.000000  2.313000e+09
```

Let's practice!

CLEANING DATA IN PYTHON

Visual exploratory data analysis

CLEANING DATA IN PYTHON

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Data visualization

- Great way to spot outliers and obvious errors
- More than just looking for patterns
- Plan data cleaning steps

Summary statistics

```
df.describe()
```

```
      female_literacy   fertility    population
count      164.000000  163.000000  1.220000e+02
mean        80.301220    2.872853  6.345768e+07
std         22.977265    1.425122  2.605977e+08
min         12.600000    0.966000  1.035660e+05
25%         66.675000    1.824500  3.778175e+06
50%         90.200000    2.362000  9.995450e+06
75%         98.500000    3.877500  2.642217e+07
max        100.000000    7.069000  2.313000e+09
```

Bar plots and histograms

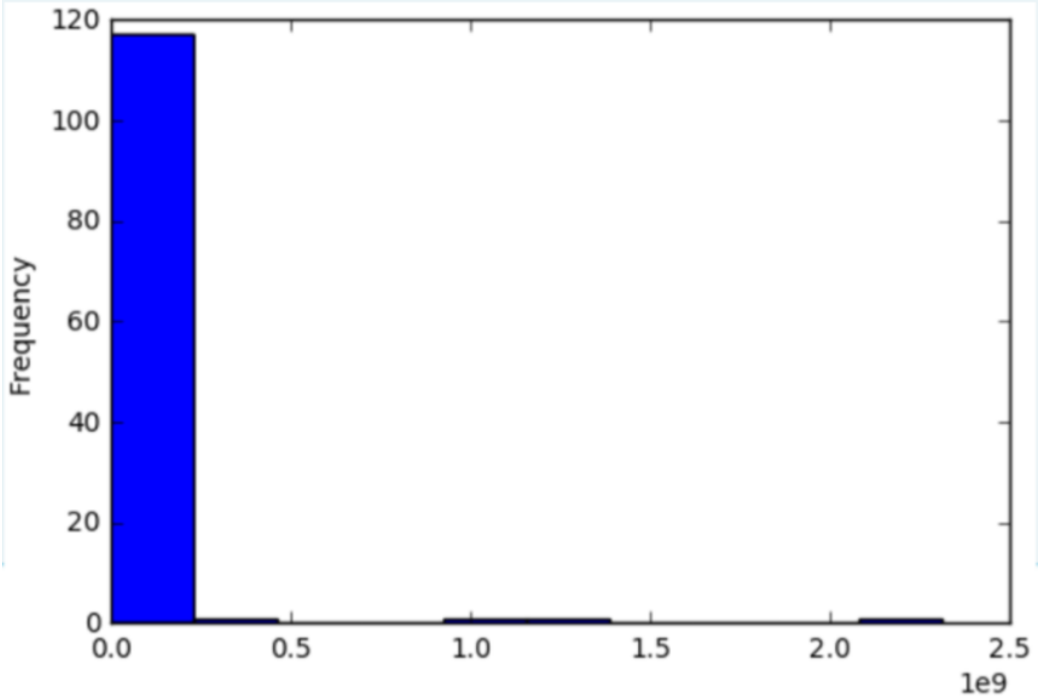
- Bar plots for discrete data counts
- Histograms for continuous data counts
- Look at frequencies

Histogram

```python
df.population.plot('hist')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f78e4abafd0>
```

```python
import matplotlib.pyplot as plt
plt.show()
```



Identifying the error

```
df[df.population > 1000000000]
```

```
   continent    country  female literacy  fertility    population
0        ASI      Chine             90.5      1.769  1.324655e+09
1        ASI       Inde             50.8      2.682  1.139965e+09
162      OCE  Australia             96.0      1.930  2.313000e+09
```

- Not all outliers are bad data points
- Some can be an error, but others are valid values

Box plots

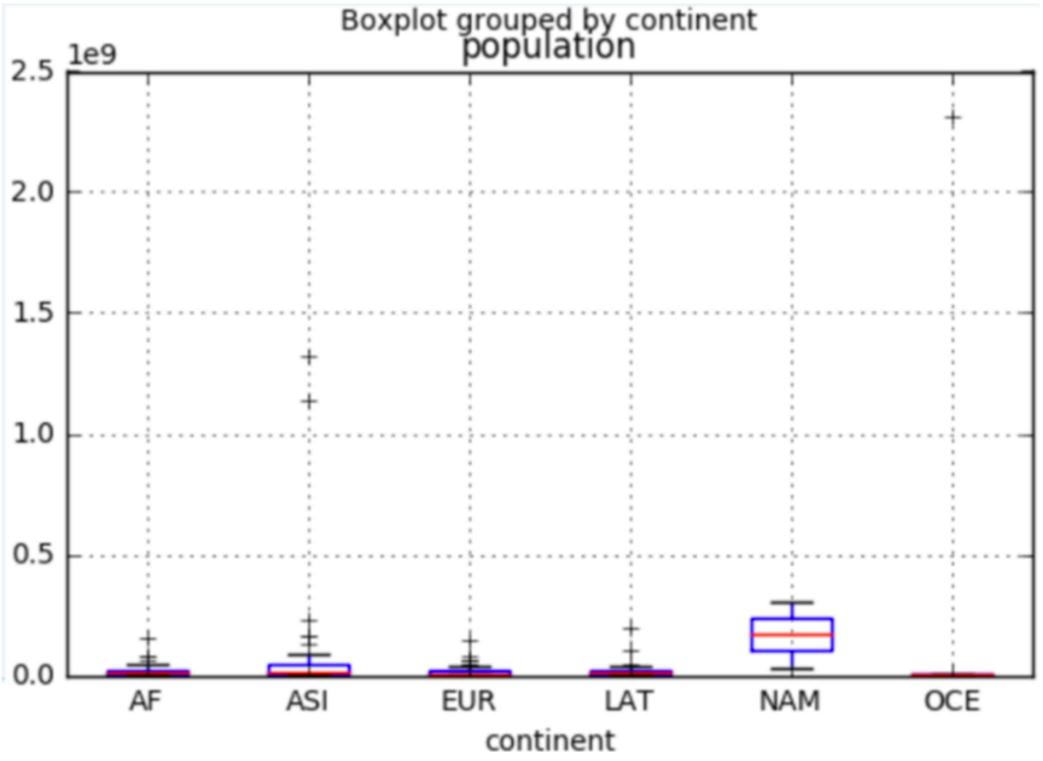
- Visualize basic summary statistics
  - Outliers
  - Min/max
  - 25th, 50th, 75th percentiles

Box plot

```
df.boxplot(column='population', by='continent')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5581bb630>
```

```
plt.show()
```

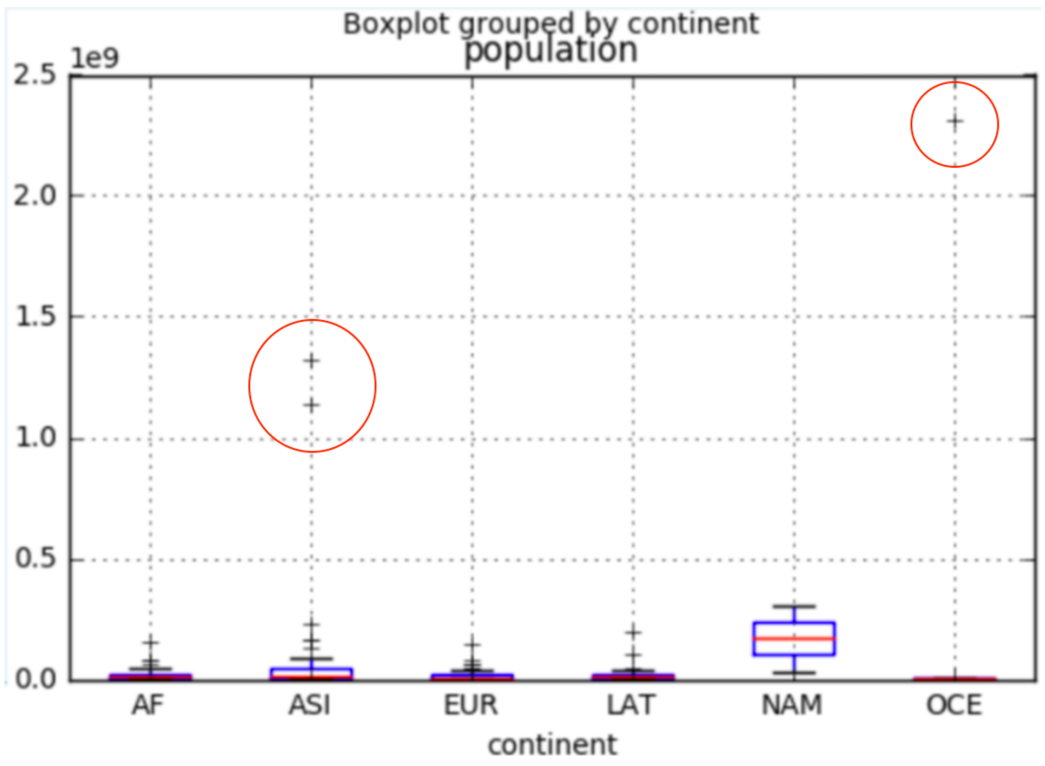


Box plot

```
df.boxplot(column='population', by='continent')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5581bb630>
```

```
plt.show()
```



Scatter plots

- Relationship between 2 numeric variables
- Flag potentially bad data
  - Errors not found by looking at 1 variable

Let's practice!

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