Why deal with missing data?

DEALING WITH MISSING DATA IN PYTHON

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Why does missing data exist?

- Real world data is messy data

> Did you know that 72% of organizations believe that data quality issues hinder customer trust and perception?

[1] [Top 9 Benefits of Data Cleansing for Businesses](https://bit.ly/2QwMrab)

Why does missing data exist?

- Values are missed during data acquisition process
  - Faulty weather sensors during weather analysis
  - Incomplete patient information for medical diagnosis etc.
- Values deleted accidentally
  - Data loss
  - Mistakenly deleted due to human error

In this course, you'll learn

- the significance of treating missing values
- to detect missing values in your messy data
- analyze the types for missingness
- treat the missing values appropriately for
  - numerical
  - time-series
  - categorical values

In this course, you'll learn

- to impute(replace) missing values using simple techniques
- to impute using advanced techniques
- to finally evaluate the best method of treating missing values

Workflow for treating missing values

1. Convert all missing values to null values.
2. Analyze the amount and type of missingness in the data.
3. Appropriately delete or impute missing values.
4. Evaluate & compare the performance of the treated/imputed dataset.

NULL value Operations

None

```
None or True # Same for False
```

```
True
```

```
None + True # For all operators
```

```
TypeError: unsupported operand
```

```
None / 3 # For all operators
```

```
TypeError: unsupported operand
```

```
type(None)
```

```
NoneType
```

np.nan

```
import numpy as np
np.nan or True  # Same for False
```

```
nan
```

```
np.nan * True # For all operators
```

```
nan
```

```
np.nan - 3 # For all operators
```

```
nan
```

```
type(np.nan)
```

```
float
```

NULL value operations

`None`

```python
None == None
```

```
True
```

```python
np.isnan(None)
```

```
False
```

`np.nan`

```python
np.nan == np.nan
```

```
False
```

```python
np.isnan(np.nan)
```

```
True
```

Let's practice!

Handling missing values

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Missing values

- Usually filled with values like `'NA'`, `'-'` or `'.'` etc.

Detect missing values in College dataset

College Dataset

```
college = pd.read_csv('college.csv')
college.head()
```

```
  gradrat            lenroll rmbrd  private stufac    csat   act
0    59.0       5.1761497326  3.75      1.0   10.8       .  21.0
1    52.0       4.7791234931  3.74      1.0   17.7       .  21.0
2    75.0  6.122492809500001     .      1.0   11.4  1052.0  24.0
3    56.0       5.3181199938   4.1      1.0   11.6   940.0  23.0
4    71.0  5.631211781799999     .      1.0   18.3       .  17.0
```

Detect missing values in College dataset

```
college.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 7 columns):
 #   Column   Non-Null Count  Dtype
 --  ------   --------------  -----
 0   gradrat  200 non-null    object
 1   lenroll  200 non-null    object
 2   rmbrd    200 non-null    object
 3   private  200 non-null    float64
 4   stufac   200 non-null    object
 5   csat     200 non-null    object
 6   act      200 non-null    object
dtypes: float64(1), object(6)
memory usage: 11.1+ KB
```

Detect missing values in College dataset

```
csat_unique = college.csat.unique()
np.sort(csat_unique)
```

```
array(['.', '1000.0', '1006.0', '1010.0', '1013.0', '1020.0', '1024.0',
       '1026.0', '1028.0', '1036.0', '1039.0', '1040.0', '1044.0',
       '1045.0', '1050.0', '1052.0', '1060.0', '1070.0', '1080.0',
       '1092.0', '1096.0', '1109.0', '1111.0', '1120.0', '1139.0',
          ...      ...       ...       ...       ...       ...
          ...      ...       ...       ...       ...       ...
       '940.0', '943.0', '947.0', '950.0', '951.0', '964.0', '970.0',
       '979.0', '980.0', '989.0', '992.0', '994.0', '996.0', '997.0',
       '998.0'], dtype=object)
```

Replace missing values in College dataset

```
college = pd.read_csv('college.csv', na_values='.')
college.head()
```

```
   gradrat   lenroll  rmbrd  private  stufac    csat   act
0     59.0  5.176150   3.75      1.0    10.8     NaN  21.0
1     52.0  4.779123   3.74      1.0    17.7     NaN  21.0
2     75.0  6.122493    NaN      1.0    11.4  1052.0  24.0
3     56.0  5.318120   4.10      1.0    11.6   940.0  23.0
4     71.0  5.631212    NaN      1.0    18.3     NaN  17.0
```

Replace missing values in College dataset

```
college.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 7 columns):
 #   Column   Non-Null Count  Dtype
--   ------   --------------  -----
 0   gradrat  187 non-null    float64
 1   lenroll  199 non-null    float64
 2   rmbrd    114 non-null    float64
 3   private  200 non-null    float64
 4   stufac   199 non-null    float64
 5   csat     105 non-null    float64
 6   act      104 non-null    float64
dtypes: float64(7)
memory usage: 11.0 KB
```

Detect missing values in Diabetes dataset

Pima Indian Diabetes dataset

- contains various clinical diagnostic information of the patients from the Pima community

```
diabetes = pd.read_csv('pima-indians-diabetes.csv')
```

```
   Pregnant  Glucose  Diastolic_BP  Skin_Fold  Serum_Insulin   BMI   Diabetes_Pedigree  Age  Class
0       6.0    148.0          72.0       35.0            NaN  33.6               0.627   50    1.0
1       1.0     85.0          66.0       29.0            NaN  26.6               0.351   31    0.0
2       8.0    183.0          64.0        NaN            NaN  23.3               0.672   32    1.0
3       1.0     89.0          66.0       23.0           94.0  28.1               0.167   21    0.0
4       0.0    137.0          40.0       35.0          168.0  43.1               2.288   33    1.0
```

Detect missing values in Diabetes dataset

```
diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
 --  ------             --------------  -----
 0   Pregnant           768 non-null    float64
 1   Glucose            763 non-null    float64
 2   Diastolic_BP       733 non-null    float64
 3   Skin_Fold          541 non-null    float64
 4   Serum_Insulin      394 non-null    float64
 5   BMI                757 non-null    float64
 6   Diabetes_Pedigree  768 non-null    float64
 7   Age                768 non-null    int64
 8   Class              768 non-null    float64
dtypes: float64(8), int64(1)
memory usage: 54.1 KB
```

Detect missing values in Diabetes dataset

```python
diabetes.describe()
```

```
         Pregnant     Glucose  Diastolic_BP  Skin_Fold  Serum_Insulin           BMI  Diabetes_Pedigree         Age       Class

count  768.000000  763.000000    733.000000  541.000000     394.000000    768.000000         768.000000  768.000000  768.000000
mean     3.845052  121.686763     72.405184   29.153420     155.548223     31.992578           0.471876   33.240885    0.348958
std      3.369578   30.535641     12.382158   10.476982     118.775855      7.884160           0.331329   11.760232    0.476951
min      0.000000   44.000000     24.000000    7.000000      14.000000      0.000000           0.078000   21.000000    0.000000
25%      1.000000   99.000000     64.000000   22.000000      76.250000     27.300000           0.243750   24.000000    0.000000
50%      3.000000  117.000000     72.000000   29.000000     125.000000     32.000000           0.372500   29.000000    0.000000
75%      6.000000  141.000000     80.000000   36.000000     190.000000     36.600000           0.626250   41.000000    1.000000
max     17.000000  199.000000    122.000000   99.000000     846.000000     67.100000           2.420000   81.000000    1.000000
```

Detect missing values in Diabetes dataset

```
diabetes.BMI[diabetes.BMI == 0]
```

```
9  |    0.0
49 |    0.0
60 |    0.0
81 |    0.0
145|    0.0
371|    0.0
426|    0.0
494|    0.0
522|    0.0
684|    0.0
706|    0.0
Name: BMI, dtype: float64
```

Replace missing values with NaN

```
diabetes.BMI[diabetes.BMI == 0] = np.nan
diabetes.BMI[np.isnan(diabetes.BMI)]
```

```
9  |   NaN
49 |   NaN
60 |   NaN
81 |   NaN
145|   NaN
371|   NaN
426|   NaN
494|   NaN
522|   NaN
684|   NaN
706|   NaN
Name: BMI, dtype: float64
```

Summary

- detect missing value characters like '.' etc.
- detect the inherent missing values within the data like '0'.
- replace them values with `NaN`

Let's practice!

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Analyze the amount of missingness

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Load Air Quality dataset

Air Quality dataset

- contains the sensor recordings of Ozone, Solar, Temperature and Wind

```
df_air = pd.read_csv('air-quality.csv',
                            parse_dates=['Date'],
                            index_col='Date')
df_air.head()
```

```
              Ozone  Solar  Wind  Temp
Date
1976-05-01   41.0  190.0   7.4    67
1976-05-02   36.0  118.0   8.0    72
1976-05-03   12.0  149.0  12.6    74
1976-05-04   18.0  313.0  11.5    62
1976-05-05    NaN    NaN  14.3    56
```

Nullity DataFrame

- Use either `.isnull()` or `.isna()` methods on the DataFrame

```
airquality_nullity = airquality.isnull()
airquality_nullity.head()
```

```
            Ozone  Solar   Wind   Temp
Date
1976-05-01  False  False  False  False
1976-05-02  False  False  False  False
1976-05-03  False  False  False  False
1976-05-04  False  False  False  False
1976-05-05   True   True  False  False
```

Total missing values

```
airquality_nullity.sum()
```

```
Ozone    37
Solar     7
Wind      0
Temp      0
dtype: int64
```

Percentage of missingness

```
airquality_nullity.mean() * 100
```

```
Ozone     24.183007
Solar      4.575163
Wind       0.000000
Temp       0.000000
dtype: float64
```

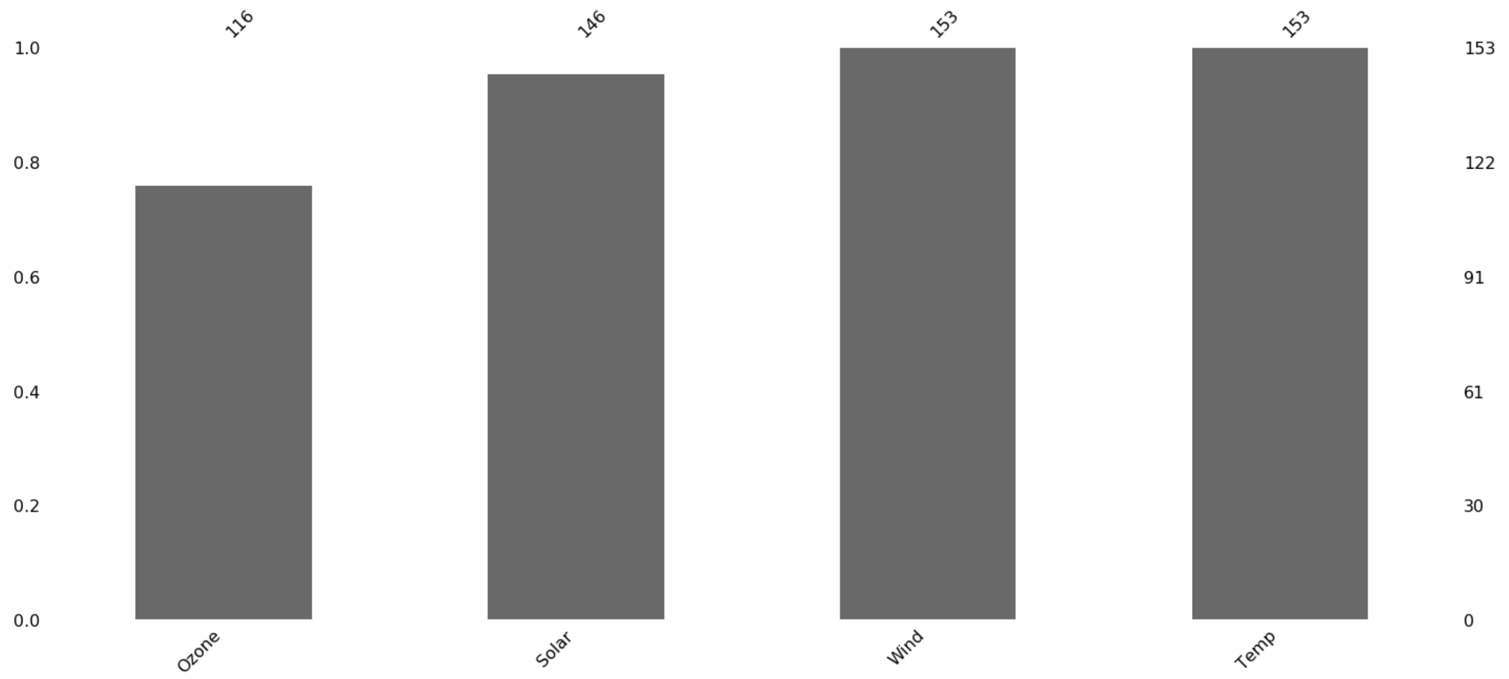
Nullity Bar

Missingno package

- Package for graphical analysis of missing values

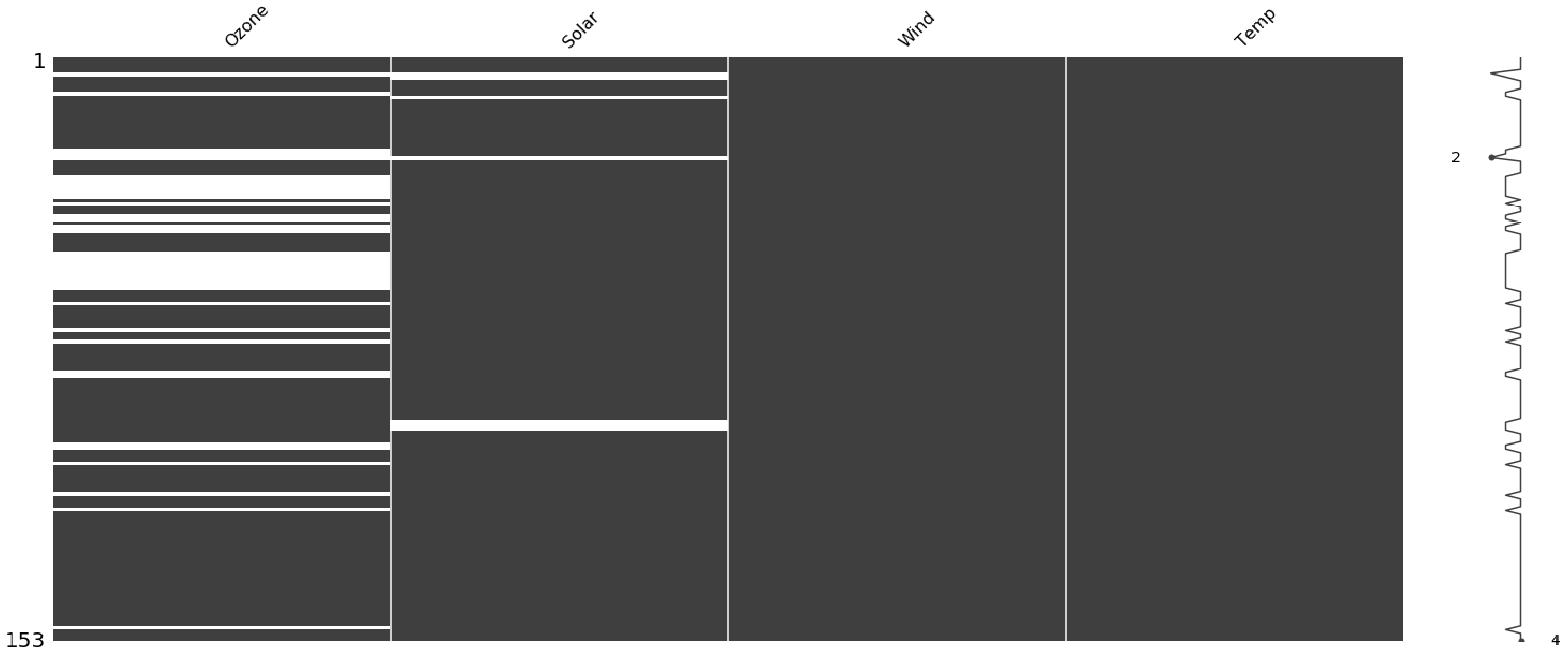
```
import missingno as msno
```

```
msno.bar(airquality)
```



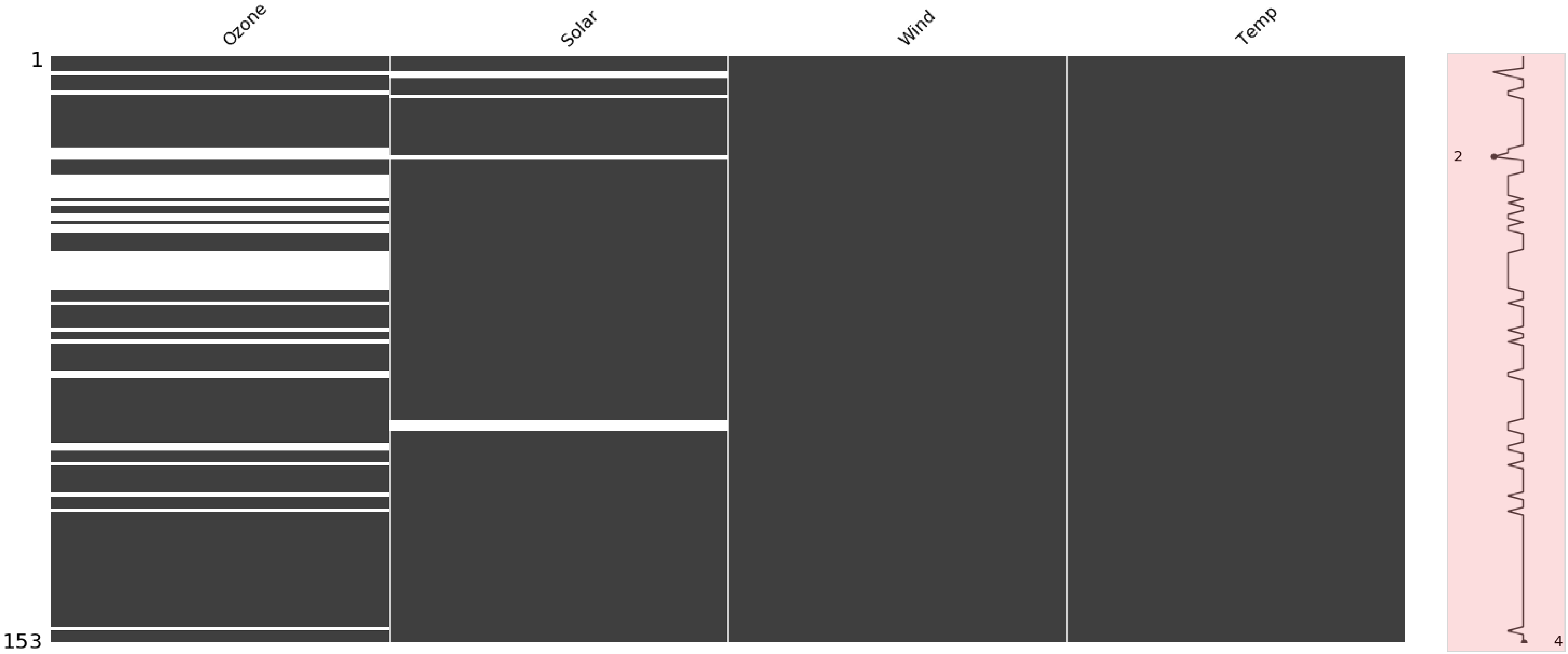
Nullity Matrix

```
msno.matrix(airquality)
```



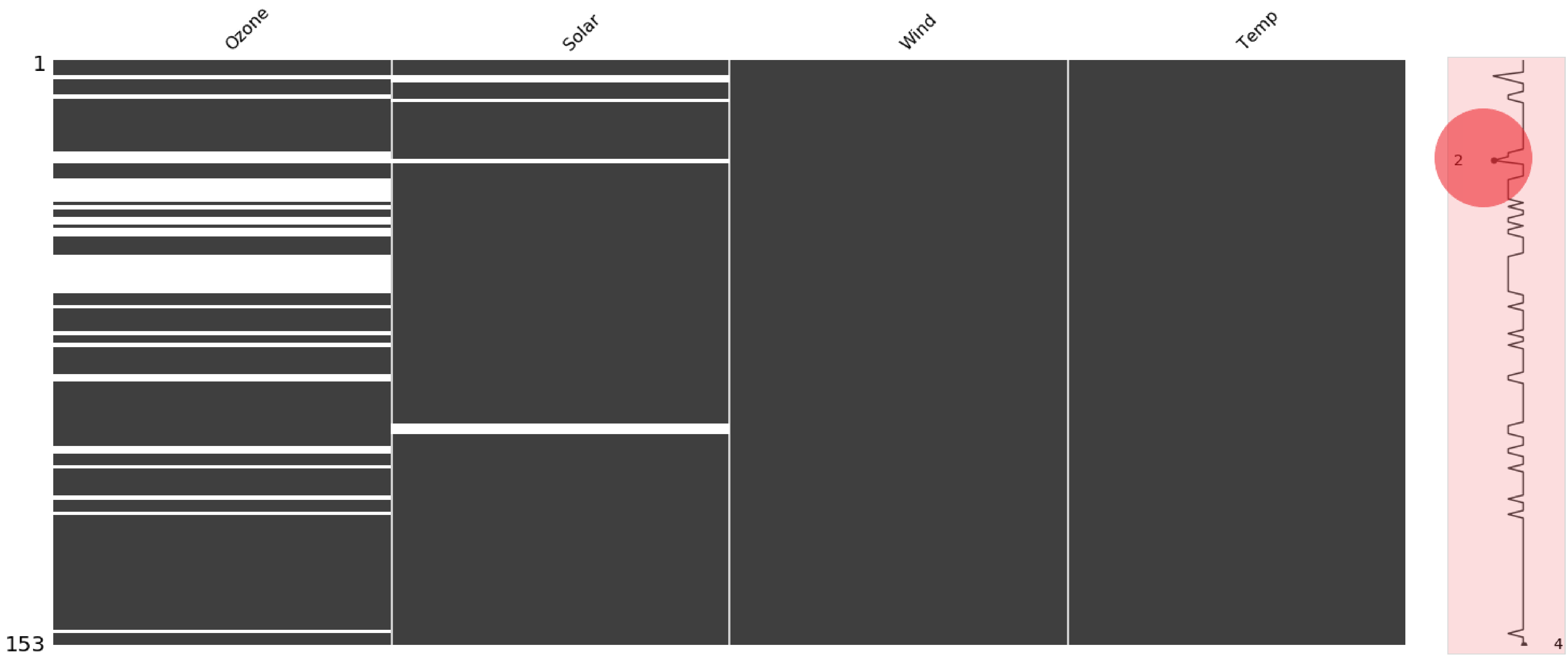
Nullity Matrix

```
msno.matrix(airquality)
```



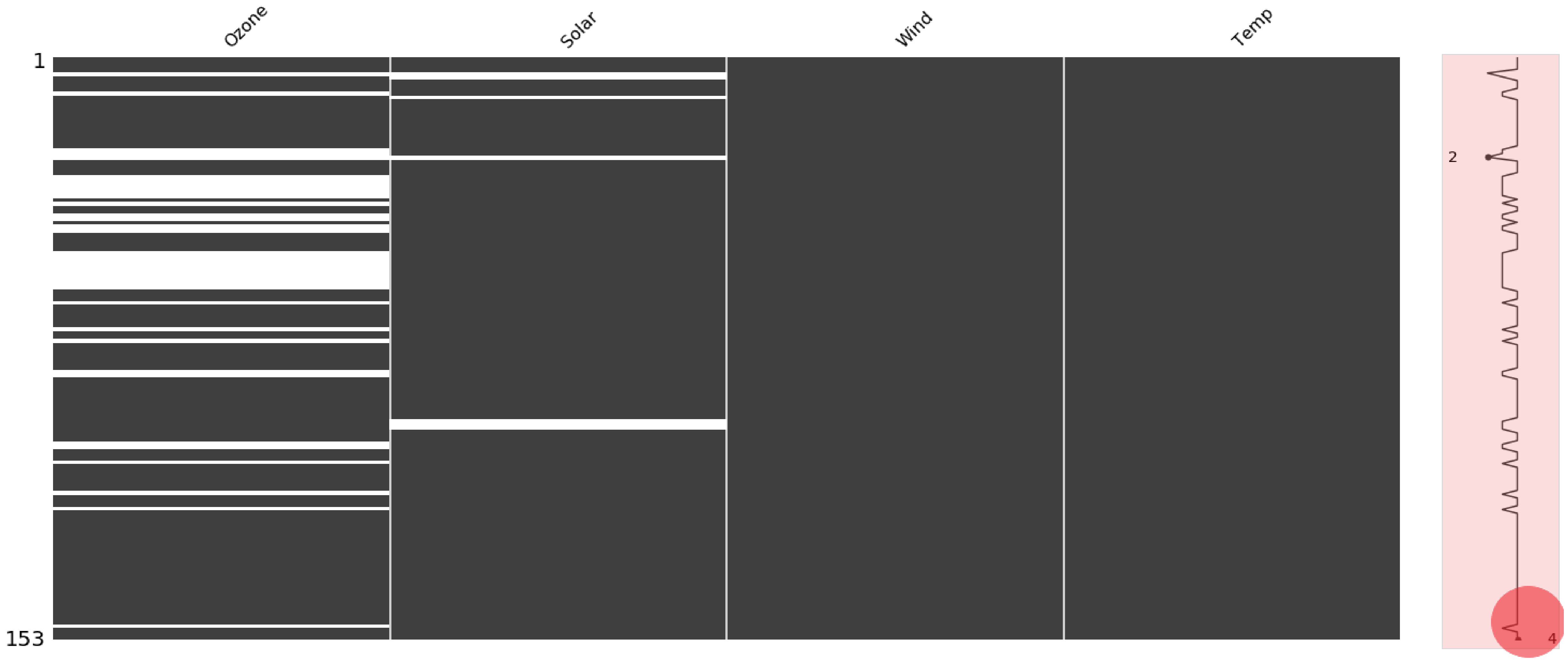
Nullity Matrix

```
msno.matrix(airquality)
```



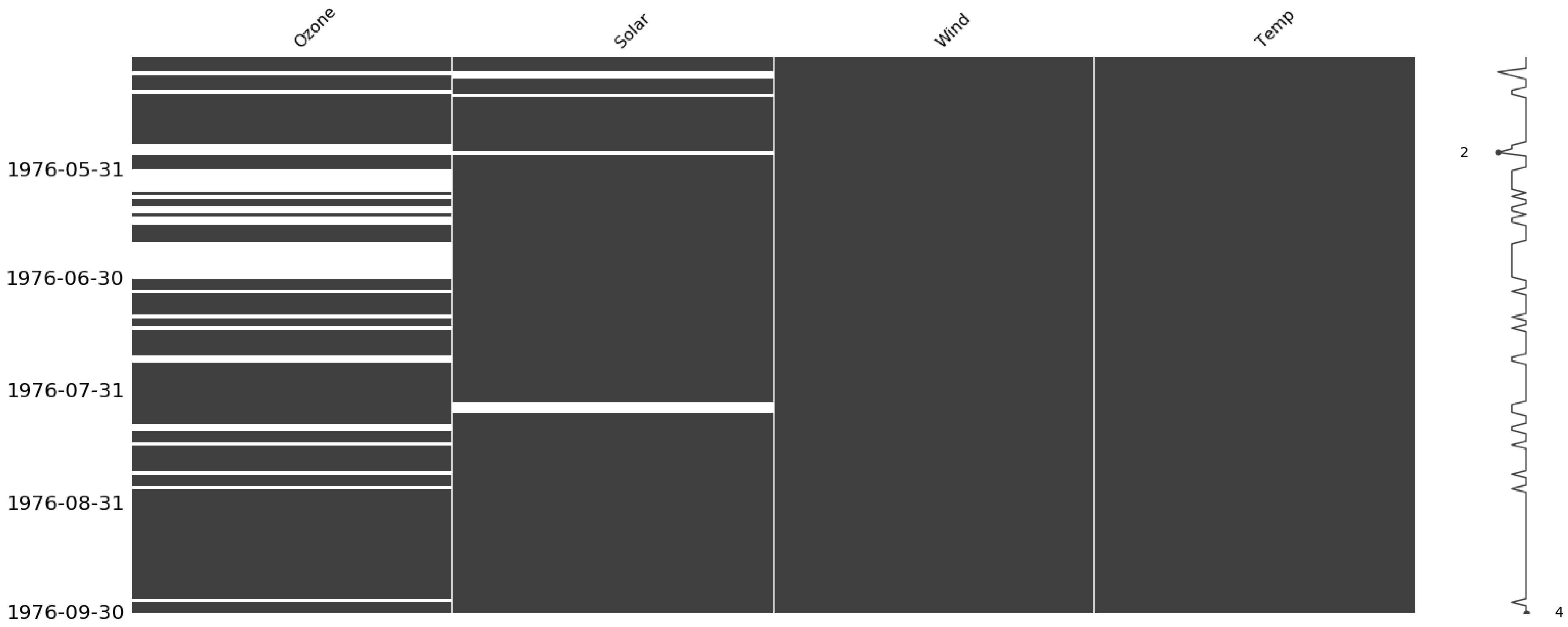
Nullity Matrix

```
msno.matrix(airquality)
```



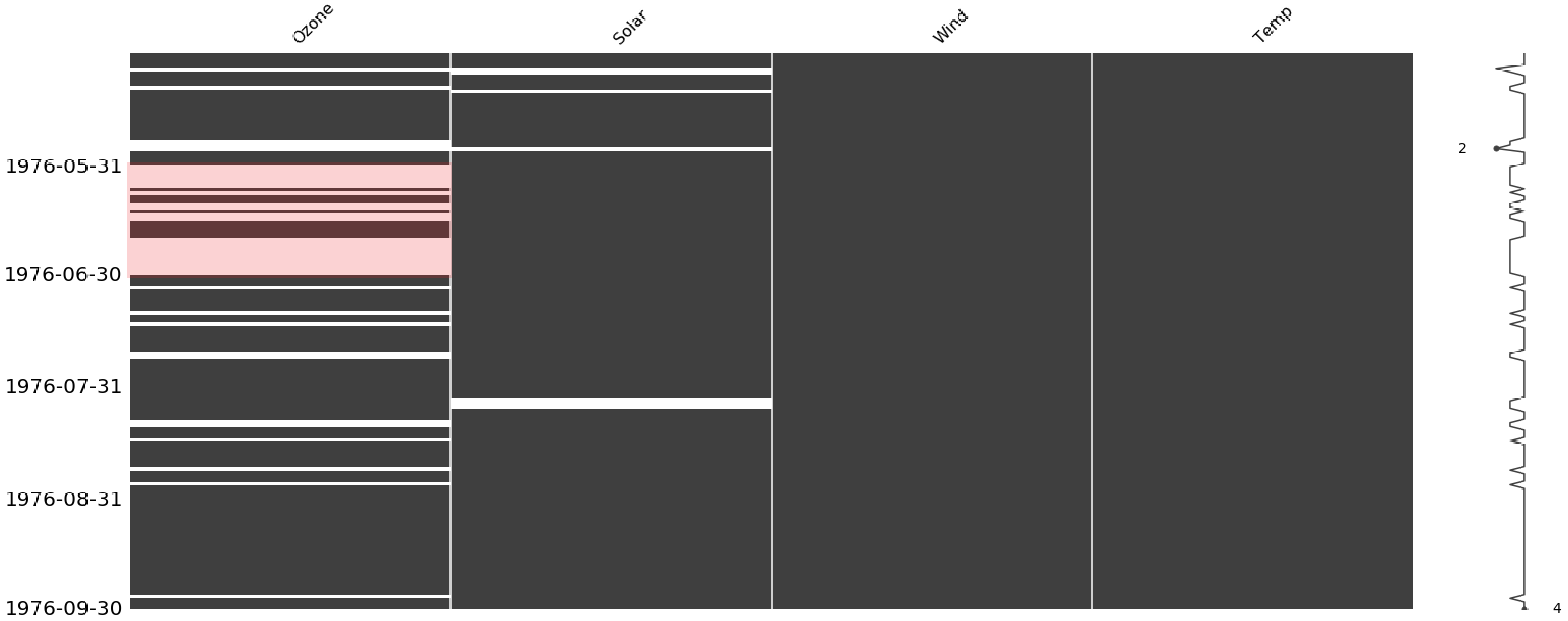
Nullity Matrix for time-series data

```
msno.matrix(airquality, freq='M')
```



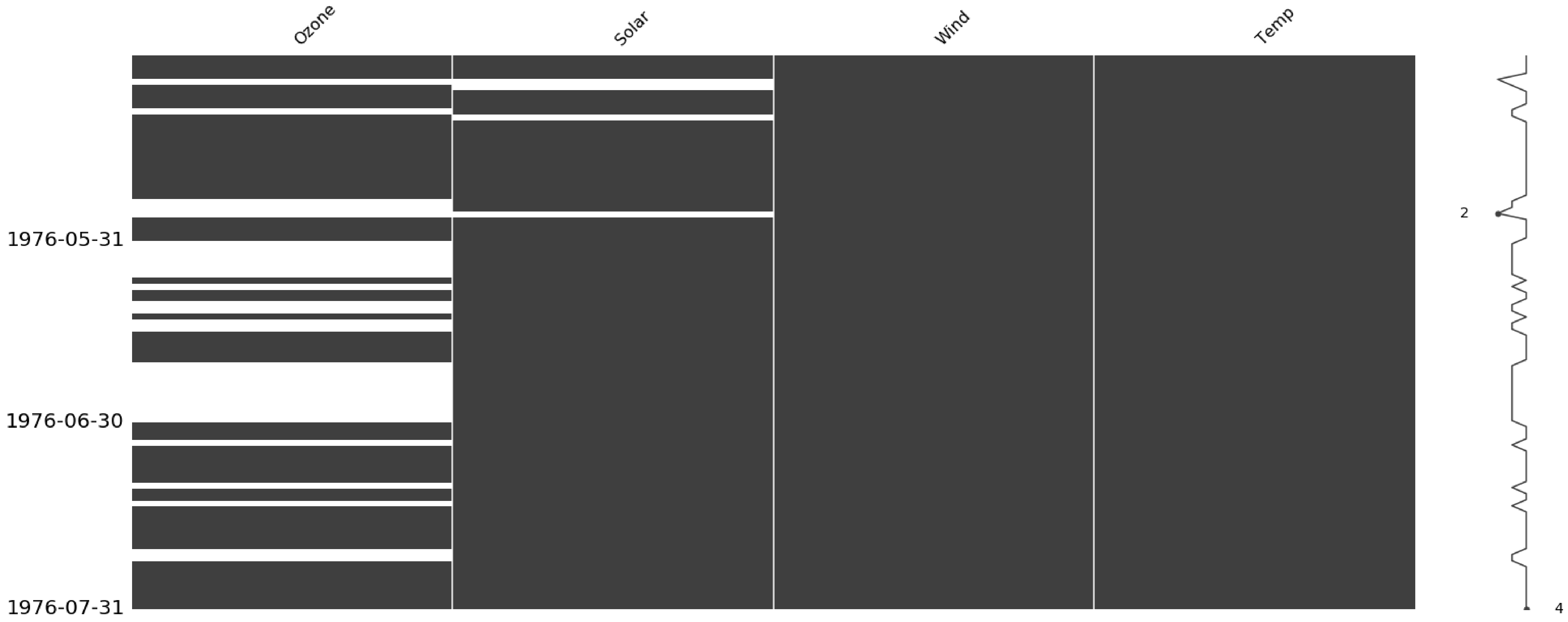
Nullity Matrix for time-series data

```
msno.matrix(airquality, freq='M')
```



Fine tuning the matrix

```
msno.matrix(airquality.loc['May-1976': 'Jul-1976'], freq='M')
```



Summary

In this lesson we learned to analyze

- the amount of missingness numerically
- the amount of missingness graphically
- the percentage of missingness
- the nullity matrix for regular datasets
- the nullity matrix for time-series datasets

Let's practice!

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