

# Lecture 18: Data transformations

Imputation and normalization and standardization, oh my!

# Contents

- Transformations
  - Log scale
  - Stationarity, percent change, first-differencing
  - Normalization
  - Standardization
- Missing values
  - Dropping
  - Imputing

# Log rule

Logging turns exponential values linear

$$\log(x^y) = y * \log(x)$$

```
In [2]: log(10**2)
Out[2]: 4.605170185988092

In [3]: 2 * log(10)
Out[3]: 4.605170185988092
```

# Log rule

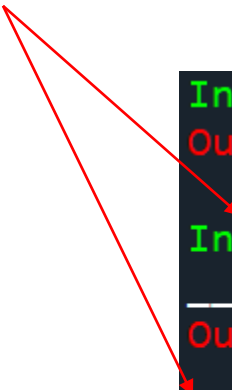
Logging turns exponential values linear

$$\log(x^y) = y * \log(x)$$

```
In [2]: log(10**2)
Out[2]: 4.605170185988092

In [3]: 2 * log(10)
Out[3]: 4.605170185988092
```

Data can't have zeros or negatives if you are logging!



```
In [4]: log(1)
Out[4]: 0.0

In [5]: log(0)
__main__:1: RuntimeWarning: divide by zero encountered in log
Out[5]: -inf

In [6]: log(-1)
__main__:1: RuntimeWarning: invalid value encountered in log
Out[6]: nan
```

# Log rule

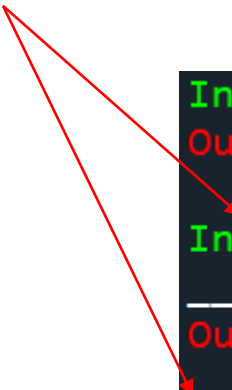
Logging turns exponential values linear

$$\log(x^y) = y * \log(x)$$

```
In [2]: log(10**2)
Out[2]: 4.605170185988092

In [3]: 2 * log(10)
Out[3]: 4.605170185988092
```

Data can't have zeros or  
negatives if you are  
logging!



```
In [4]: log(1)
Out[4]: 0.0

In [5]: log(0)
__main__:1: RuntimeWarning: divide by zero encountered in log
Out[5]: -inf

In [6]: log(-1)
__main__:1: RuntimeWarning: invalid value encountered in log
Out[6]: nan
```

# Inverse Hyperbolic Sine (HIS) Transformation

$$\ln( x + \sqrt{x^2 + 1} )$$

- Closely approximates the log transformation
- Handles zeroes and negatives
- See *Burbridge, Magee, and Robb, Journal of the American Statistical Association, 1988*

```
def ihs(x):  
    return log(x + sqrt(x**2 + 1))
```

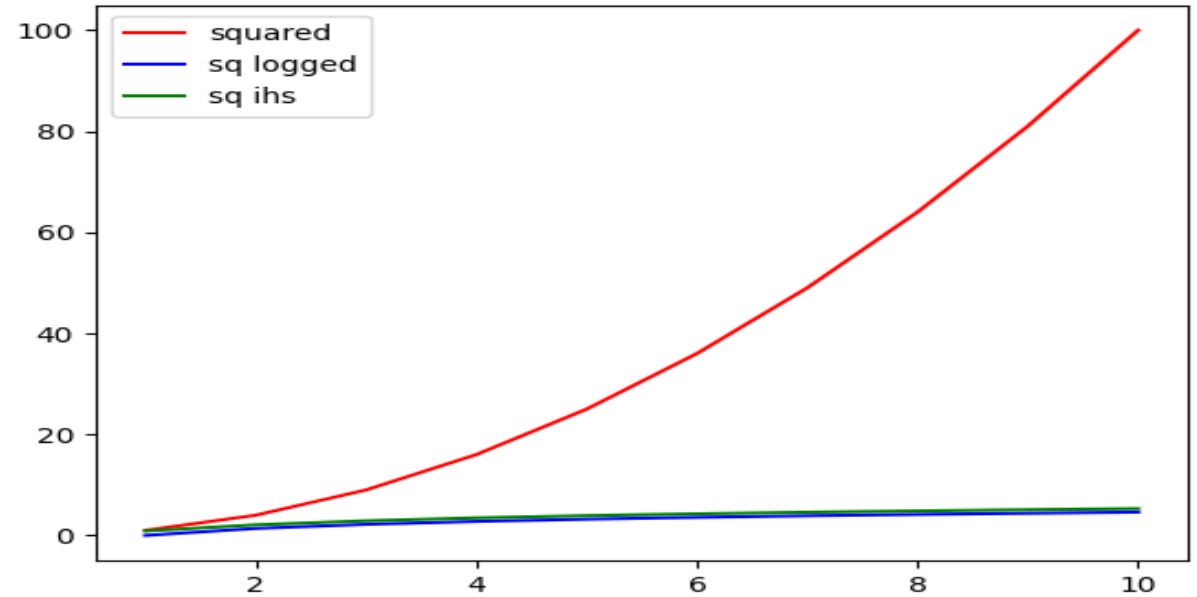
# Logged vs un-logged

```
17 linear = range(1, 11)
18 squared = [v**2 for v in linear]
19 logged = [log(s) for s in squared]
20 ihsted = [ihs(s) for s in squared]
```

# Logged vs un-logged

```
17 linear = range(1, 11)
18 squared = [v**2 for v in linear]
19 logged = [log(s) for s in squared]
20 ihsted = [ih(s) for s in squared]

22 fig, ax = plt.subplots()
23 ax.plot(linear, squared, 'r-', label='squared')
24 ax.plot(linear, logged, 'b-', label='logged')
25 ax.plot(linear, ihsted, 'g-', label='ih')
26 ax.legend()
```

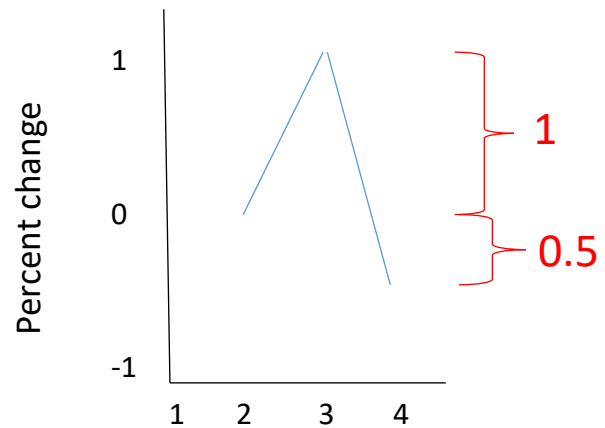




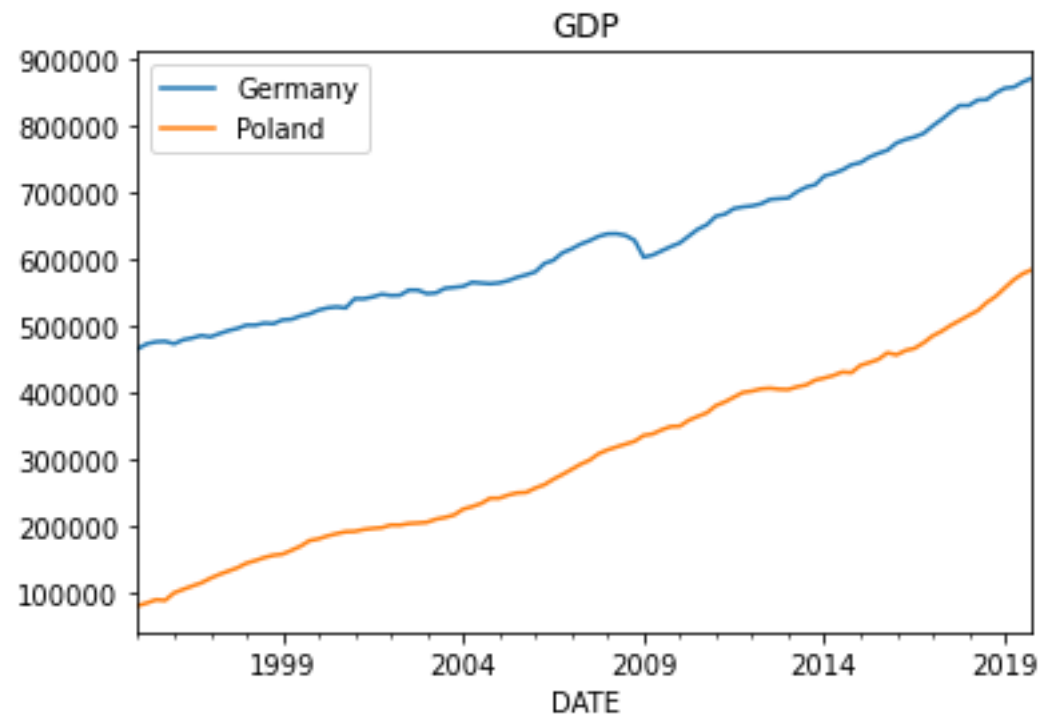
# Percent change?

Series: 2, 2, 4, 2, 4

Percent change:    NA  $\rightarrow$  2 = NA  
                          2  $\rightarrow$  2 = 0%  
                          2  $\rightarrow$  4 = 100%  
                          4  $\rightarrow$  2 = -50%



# Stationarity



# Stationarity

```
42 model = smf.ols('GDPGermany ~ GDPPoland ', data=df)
43 result = model.fit()
```

```

OLS Regression Results
=====
Dep. Variable:          GDPGermany      R-squared:          0.973
Model:                  OLS             Adj. R-squared:      0.973
Method:                 Least Squares    F-statistic:         3594.
Date:                   Wed, 26 May 2021  Prob (F-statistic):  4.85e-79
Time:                   10:48:41          Log-Likelihood:       -1125.6
No. Observations:       100              AIC:                 2255.
Df Residuals:           98                BIC:                 2260.
Df Model:               1
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	3.762e+05	4625.478	81.339	0.000	3.67e+05	3.85e+05
GDPPoland	0.8259	0.014	59.949	0.000	0.799	0.853

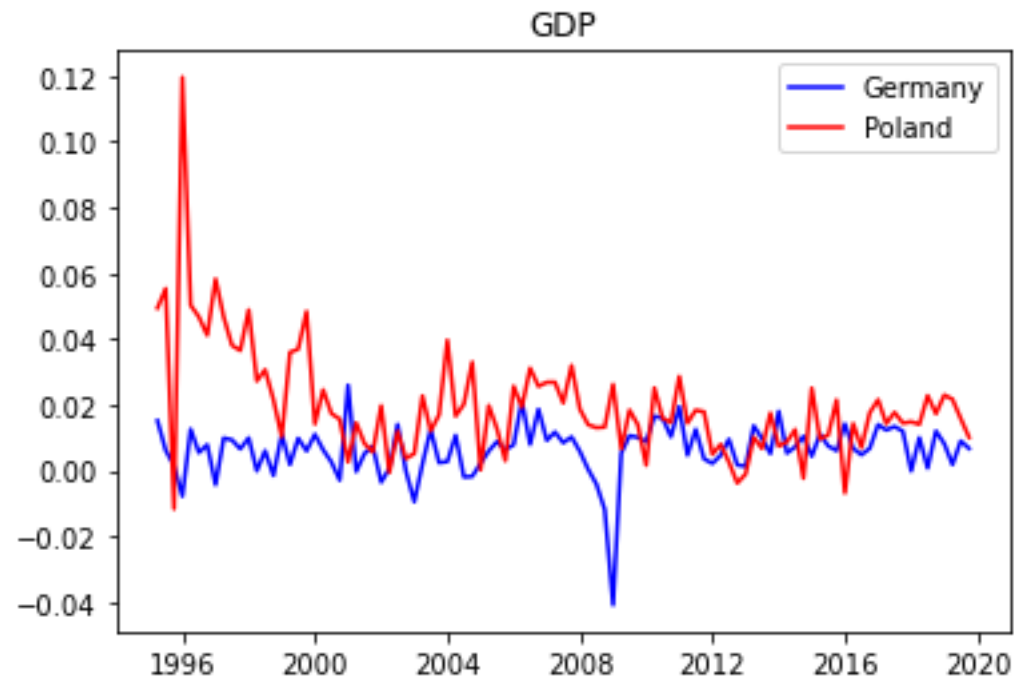
```
=====
Omnibus:                8.858      Durbin-Watson:          0.088
Prob(Omnibus):           0.012      Jarque-Bera (JB):        8.733
Skew:                   -0.705      Prob(JB):               0.0127
Kurtosis:               3.326      Cond. No.               8.22e+05
=====
```

# Log first-difference

```
48 df['Germany_GDP_Lfd'] = log(df['GDPGermany']) - log(df['GDPGermany'].shift())  
49 df['PoLand_GDP_Lfd'] = log(df['GDPPoLand']) - log(df['GDPPoLand'].shift())
```

# Log first-difference

```
48 df['Germany_GDP_Lfd'] = log(df['GDPGermany']) - log(df['GDPGermany'].shift())
49 df['PoLand_GDP_Lfd'] = log(df['GDPPoland']) - log(df['GDPPoland'].shift())
```



# Log first-difference

```

=====
Dep. Variable:      Germany_GDP_lfd      R-squared:      0.011
Model:              OLS                  Adj. R-squared:  0.001
Method:             Least Squares        F-statistic:     1.127
Date:               Wed, 26 May 2021     Prob (F-statistic): 0.291
Time:               10:59:00             Log-Likelihood:  338.64
No. Observations:   99                  AIC:             -673.3
Df Residuals:       97                  BIC:             -668.1
Df Model:           1
Covariance Type:    nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.0073	0.001	5.926	0.000	0.005	0.010
Poland_GDP_lfd	-0.0498	0.047	-1.062	0.291	-0.143	0.043

```

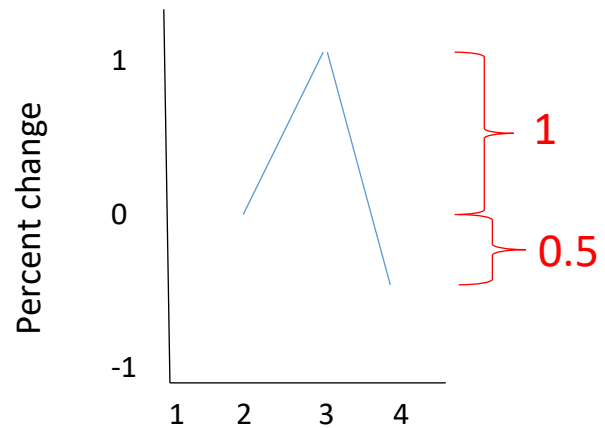
=====
Omnibus:           68.088      Durbin-Watson:      1.564
Prob(Omnibus):     0.000      Jarque-Bera (JB):   558.385
Skew:              -2.028     Prob(JB):           5.60e-122
Kurtosis:          13.905     Cond. No.           58.4
=====

```

# Percent change?

Series: 2, 2, 4, 2, 4

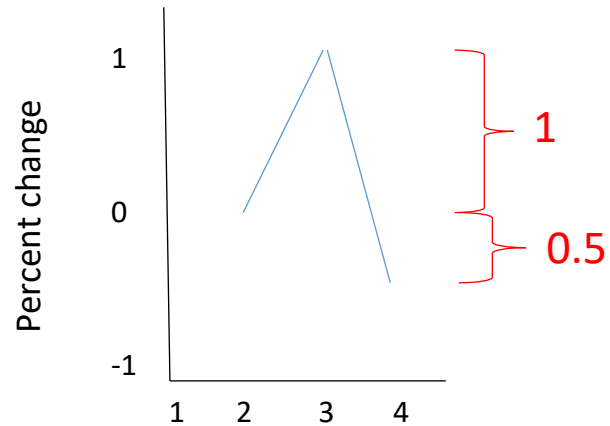
Percent change:    NA  $\rightarrow$  2 = NA  
                          2  $\rightarrow$  2 = 0%  
                          2  $\rightarrow$  4 = 100%  
                          4  $\rightarrow$  2 = -50%



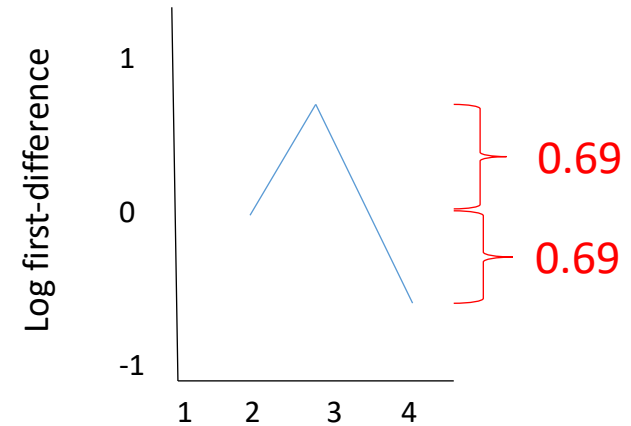
# Percent change?

Series: 2, 2, 4, 2, 4

Percent change:    NA  $\rightarrow$  2 = NA  
                          2  $\rightarrow$  2 = 0%  
                          2  $\rightarrow$  4 = 100%  
                          4  $\rightarrow$  2 = -50%



Log first-diff:     $\log(\text{NA}) - \log(2) = \text{NA}$   
                           $\log(2) - \log(2) = 0$   
                           $\log(2) - \log(4) = 0.693$   
                           $\log(4) - \log(2) = -0.693$





# Percent change vs log first-difference

	Germany_GDP_pctchange	Germany_GDP_lfd
0	NaN	NaN
1	0.015303	0.015187
2	0.006200	0.006181
3	0.001477	0.001475
4	-0.007745	-0.007775
5	0.012676	0.012597
6	0.005471	0.005456
7	0.007891	0.007860
8	-0.004282	-0.004291
9	0.009955	0.009906

# Scaling

**Normalization:** rescale data to [0, 1]

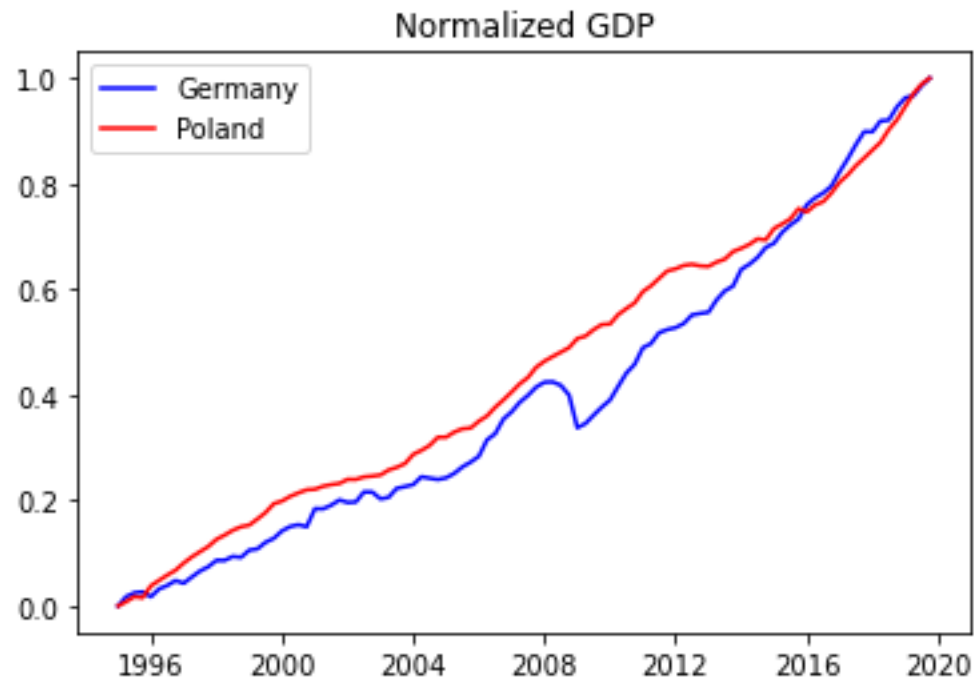
$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

**Standardization:** rescale data to mean 0 and standard deviation 1

$$X_{\text{std}} = \frac{X - \mu}{\sigma}$$

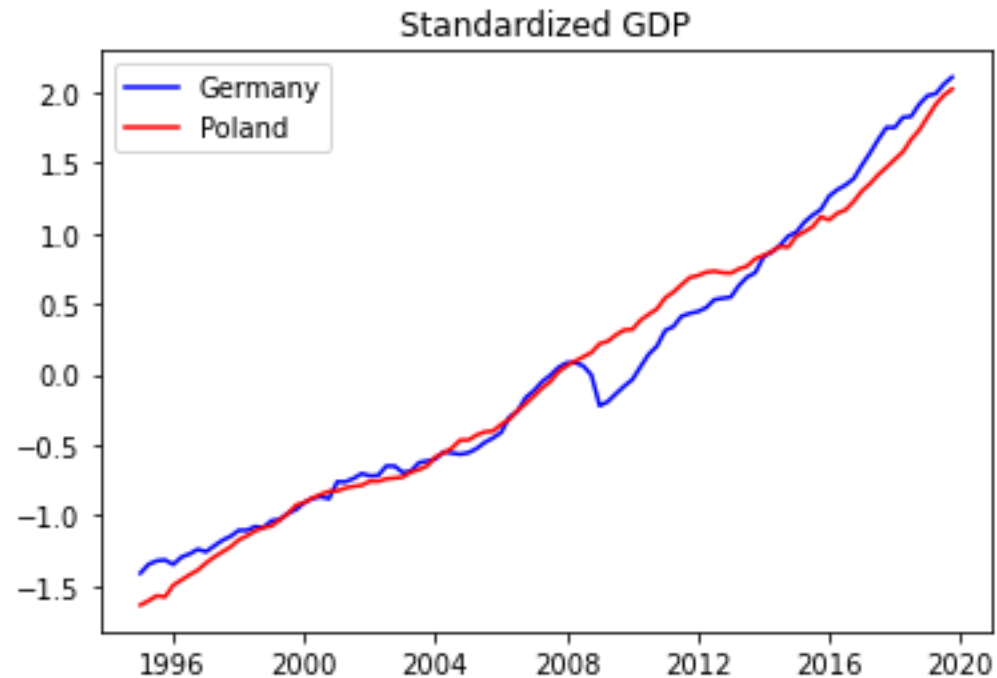
# Normalization

```
65 df['GDPGermany_norm'] = ((df['GDPGermany'] - df['GDPGermany'].min()) /  
66                          (df['GDPGermany'].max() - df['GDPGermany'].min()))  
67 df['GDPPoland_norm'] = ((df['GDPPoland'] - df['GDPPoland'].min()) /  
68                          (df['GDPPoland'].max() - df['GDPPoland'].min()))
```



# Standardization

```
77 df['GDPGermany_std'] = (df['GDPGermany'] - df['GDPGermany'].mean()) / df['GDPGermany'].std()  
78 df['GDPPoland_std'] = (df['GDPPoland'] - df['GDPPoland'].mean()) / df['GDPPoland'].std()
```



# Standardization vs Normalization

```
In [57]: df['GDPGermany_norm'].std()  
Out[57]: 0.28451997608044993
```

```
In [58]: df['GDPGermany_std'].std()  
Out[58]: 0.9999999999999998
```

```
In [59]: df['GDPGermany_norm'].max()  
Out[59]: 1.0
```

```
In [60]: df['GDPGermany_std'].max()  
Out[60]: 2.1056937374027056
```

```
In [61]: df['GDPGermany_norm'].mean()  
Out[61]: 0.40088806820142886
```

```
In [62]: df['GDPGermany_std'].mean()  
Out[62]: -2.0872192862952942e-16
```

```
In [63]: df['GDPGermany_norm'].min()  
Out[63]: 0.0
```

```
In [64]: df['GDPGermany_std'].min()  
Out[64]: -1.4089979681710474
```

# Missing values

To impute or to drop?

# Missing values

```
100 df = pd.DataFrame({'one':[1, 2, NaN, 4, 5, NaN],  
101                        'two':[2, 3, 4, 5, 6, NaN]})
```

```
In [67]: df
```

```
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

# Missing values

```
100 df = pd.DataFrame({'one':[1, 2, NaN, 4, 5, NaN],
101                      'two':[2, 3, 4, 5, 6, NaN]})
```

```
In [67]: df
```

```
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN



```
In [68]: df.isnull()
```

```
Out[68]:
```

	one	two
0	False	False
1	False	False
2	True	False
3	False	False
4	False	False
5	True	True



# Missing values

```
100 df = pd.DataFrame({'one':[1, 2, NaN, 4, 5, NaN],
101                      'two':[2, 3, 4, 5, 6, NaN]})
```

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [68]: df.isnull()
Out[68]:
```

	one	two
0	False	False
1	False	False
2	True	False
3	False	False
4	False	False
5	True	True

```
In [69]: df.isnull().sum(axis=0)
```

```
Out[69]:
one      2
two      1
dtype: int64
```

```
In [70]: df.isnull().sum(axis=1)
```

```
Out[70]:
0      0
1      0
2      1
3      0
4      0
5      2
dtype: int64
```

# Missing values: dropping

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [71]: df.dropna()
Out[71]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
3	4.0	5.0
4	5.0	6.0

```
In [72]: df.dropna(axis=1)
Out[72]:
```

Empty DataFrame  
Columns: []  
Index: [0, 1, 2, 3, 4, 5]

# Missing values: dropping

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [73]: df.dropna(how='all')
Out[73]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0

# Missing values: dropping

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [73]: df.dropna(how='all')
Out[73]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0

```
In [74]: df.dropna(subset=['one', 'two'])
Out[74]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
3	4.0	5.0
4	5.0	6.0

# Missing values: dropping

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [76]: df.dropna(thresh=1)
Out[76]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0

```
In [73]: df.dropna(how='all')
Out[73]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0

```
In [74]: df.dropna(subset=['one', 'two'])
Out[74]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
3	4.0	5.0
4	5.0	6.0

# Missing values: imputing

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [77]: df.fillna(100)
Out[77]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	100.0	4.0
3	4.0	5.0
4	5.0	6.0
5	100.0	100.0

# Missing values: imputing

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [77]: df.fillna(100)
Out[77]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	100.0	4.0
3	4.0	5.0
4	5.0	6.0
5	100.0	100.0

```
In [79]: df.fillna(df.mean())
Out[79]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	3.0	4.0
3	4.0	5.0
4	5.0	6.0
5	3.0	4.0

# Missing values: imputing

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [77]: df.fillna(100)
Out[77]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	100.0	4.0
3	4.0	5.0
4	5.0	6.0
5	100.0	100.0

```
In [79]: df.fillna(df.mean())
Out[79]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	3.0	4.0
3	4.0	5.0
4	5.0	6.0
5	3.0	4.0

```
In [80]: df['one'].fillna(df['two'])
Out[80]:
```

0	1.0
1	2.0
2	4.0
3	4.0
4	5.0
5	NaN

Name: one, dtype: float64



# Missing values: imputing

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [81]: df.ffmpeg()
Out[81]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	2.0	4.0
3	4.0	5.0
4	5.0	6.0
5	5.0	6.0

```
In [82]: df.bfill()
Out[82]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	4.0	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

# Missing values: imputing

```
In [67]: df
```

```
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [83]: df.interpolate(method='linear')
```

```
Out[83]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	3.0	4.0
3	4.0	5.0
4	5.0	6.0
5	5.0	6.0

# Missing values: imputing

```
In [67]: df
Out[67]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	NaN	4.0
3	4.0	5.0
4	5.0	6.0
5	NaN	NaN

```
In [83]: df.interpolate(method='linear')
Out[83]:
```

	one	two
0	1.0	2.0
1	2.0	3.0
2	3.0	4.0
3	4.0	5.0
4	5.0	6.0
5	5.0	6.0

?

