Correlation

INTRODUCTION TO STATISTICS IN PYTHON

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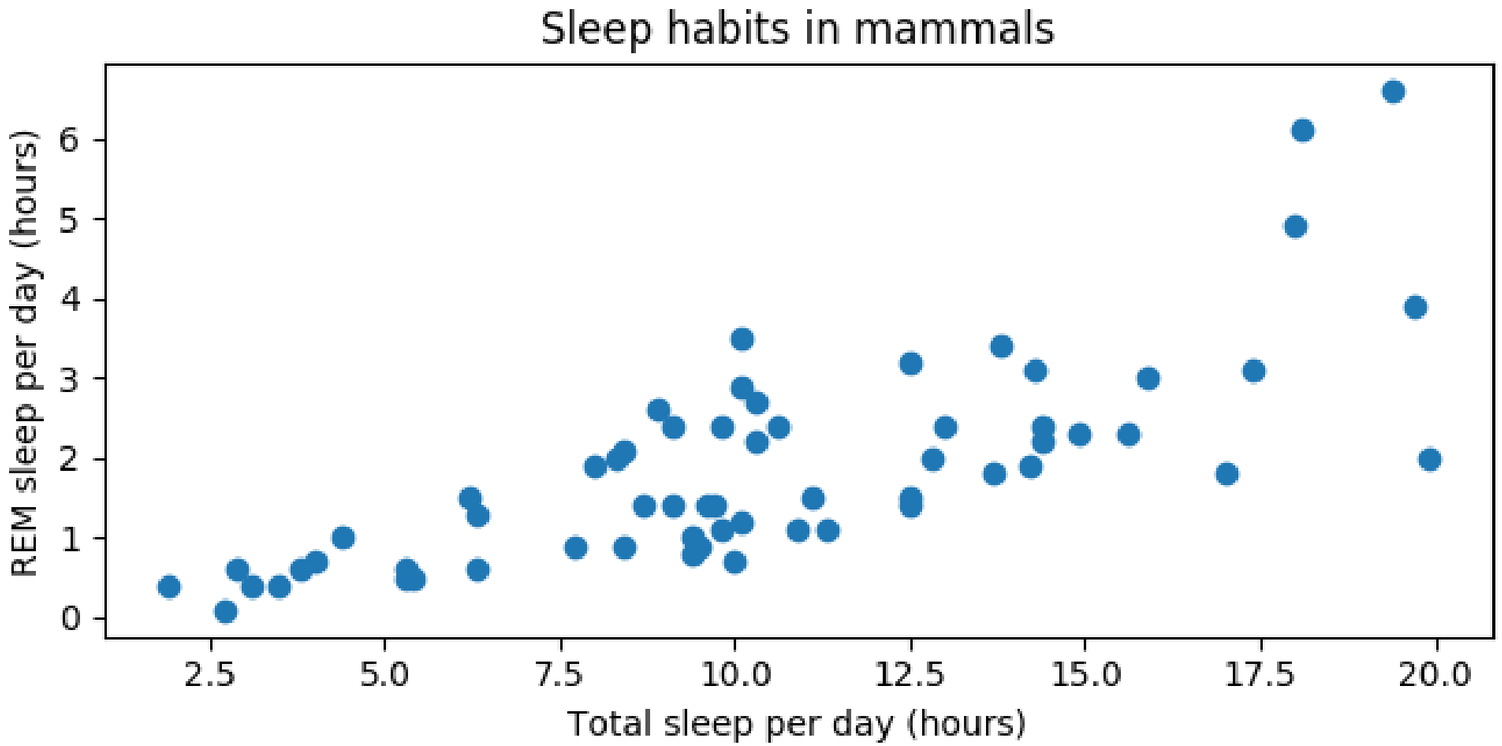
Relationships between two variables



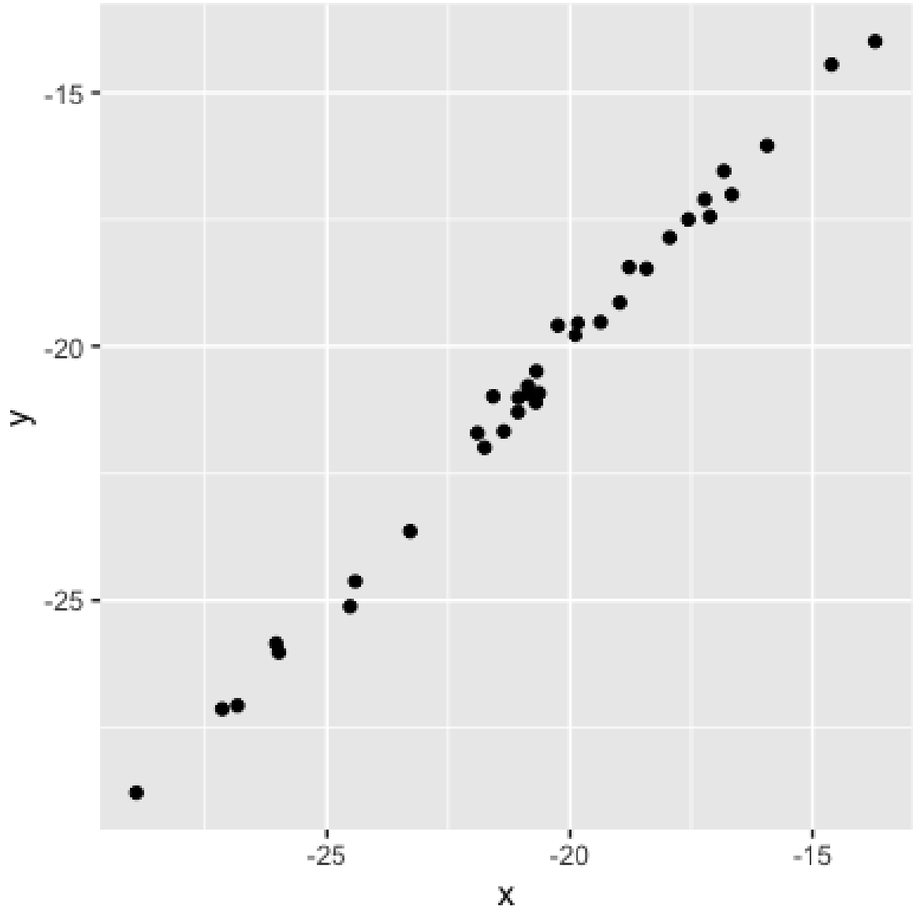
- x = explanatory/independent variable
- y = response/dependent variable

Correlation coefficient

- Quantifies the linear relationship between two variables
- Number between -1 and 1
- Magnitude corresponds to strength of relationship
- Sign (+ or -) corresponds to direction of relationship

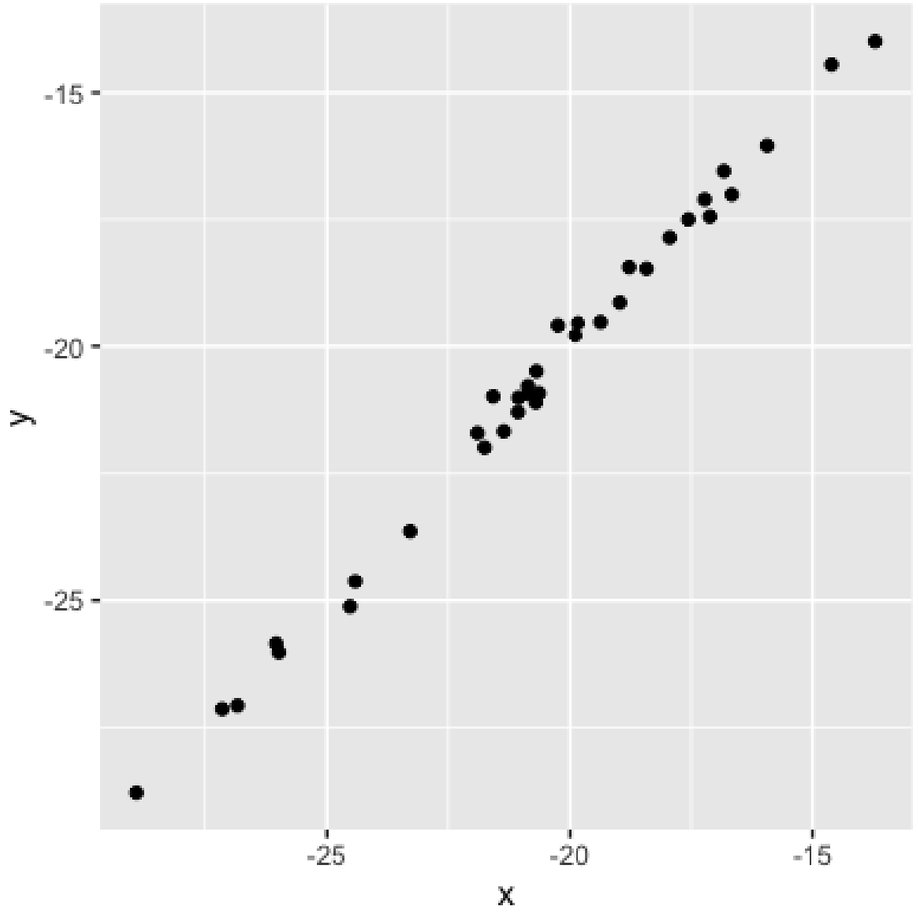
Magnitude = strength of relationship

0.99 (very strong relationship)

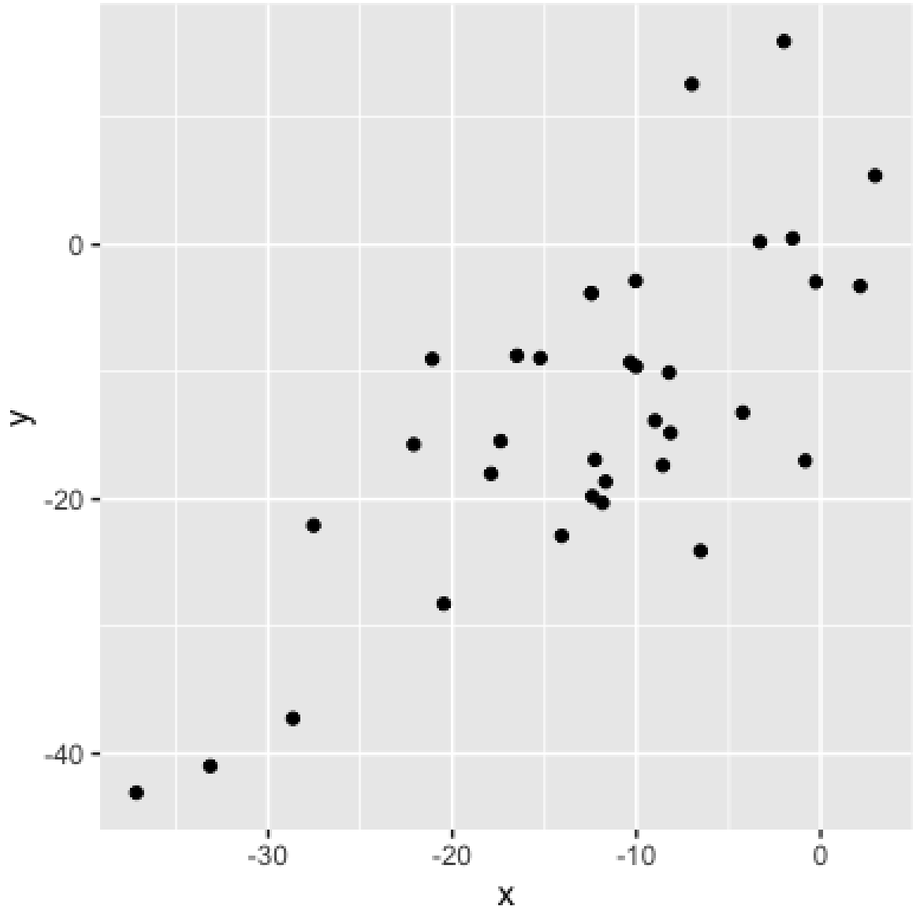


Magnitude = strength of relationship

0.99 (very strong relationship)

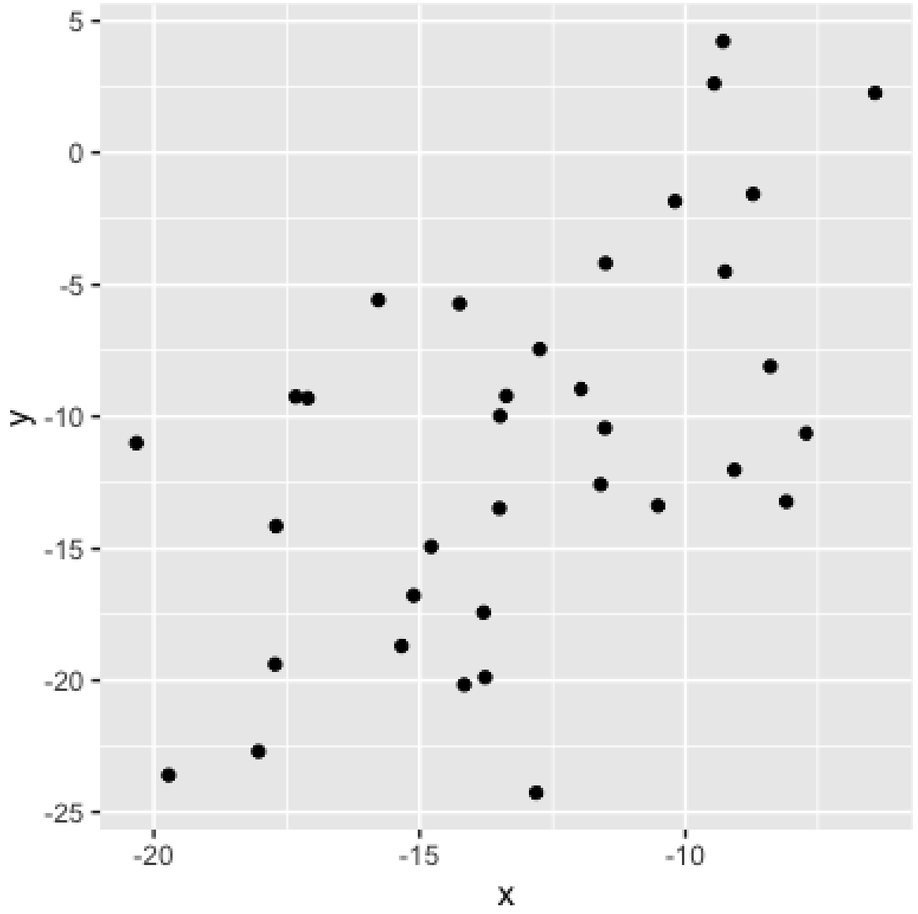


0.75 (strong relationship)



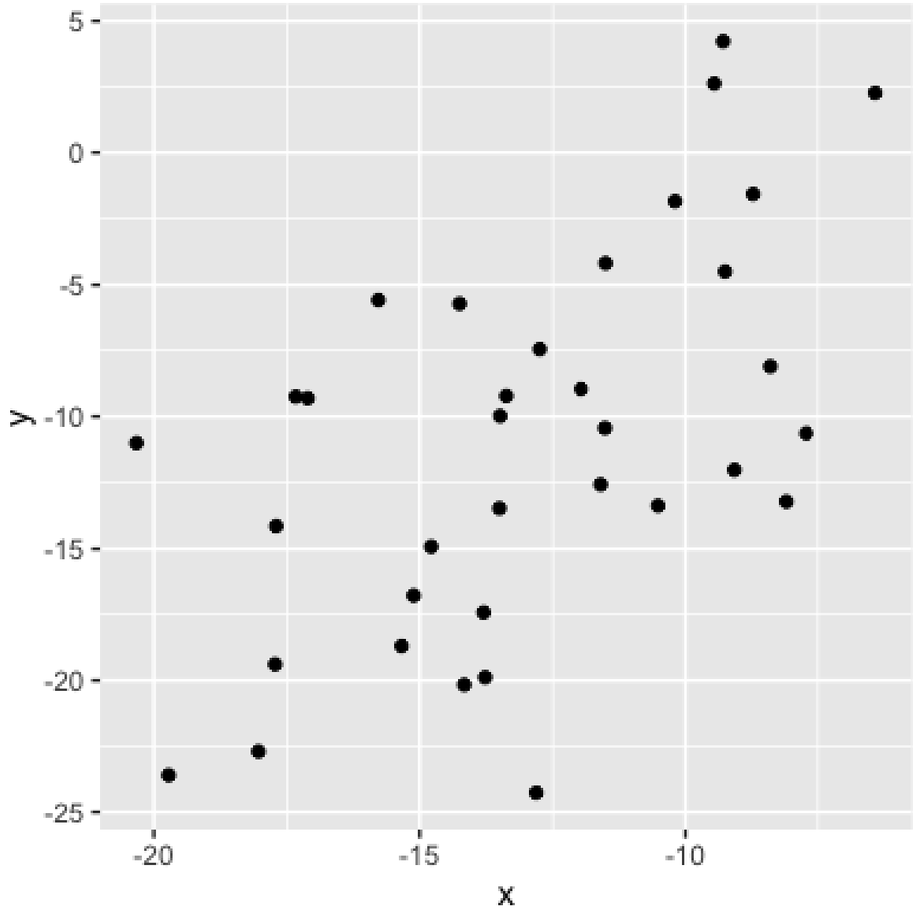
Magnitude = strength of relationship

0.56 (moderate relationship)

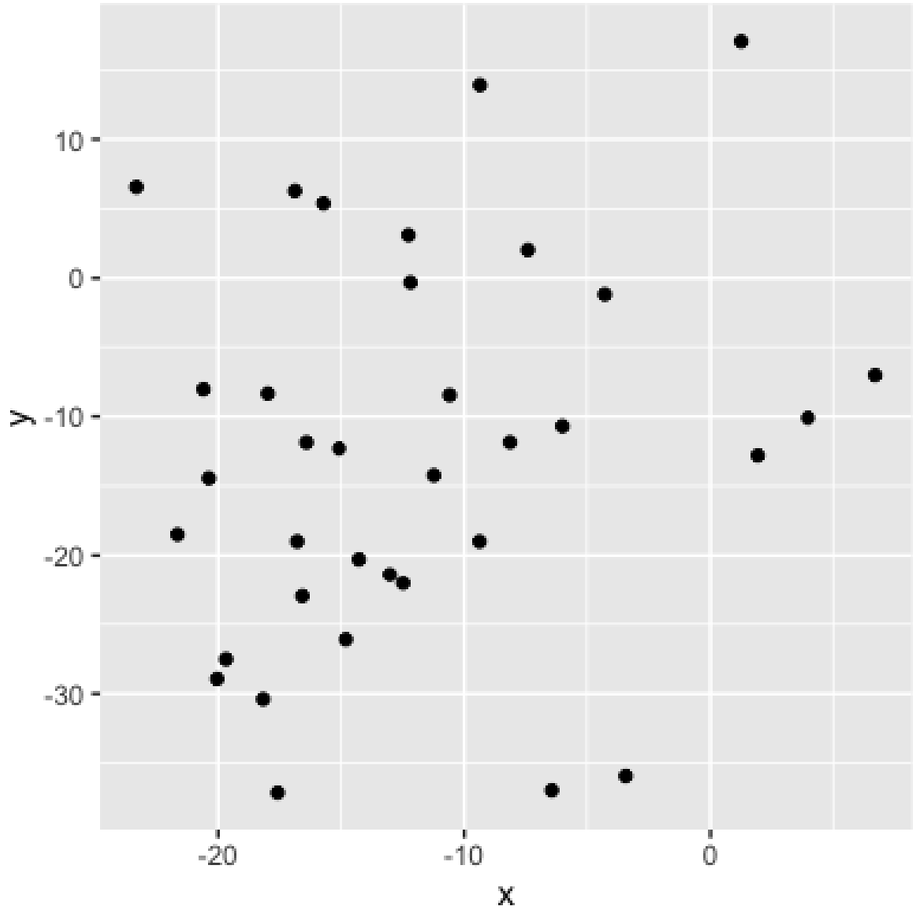


Magnitude = strength of relationship

0.56 (moderate relationship)

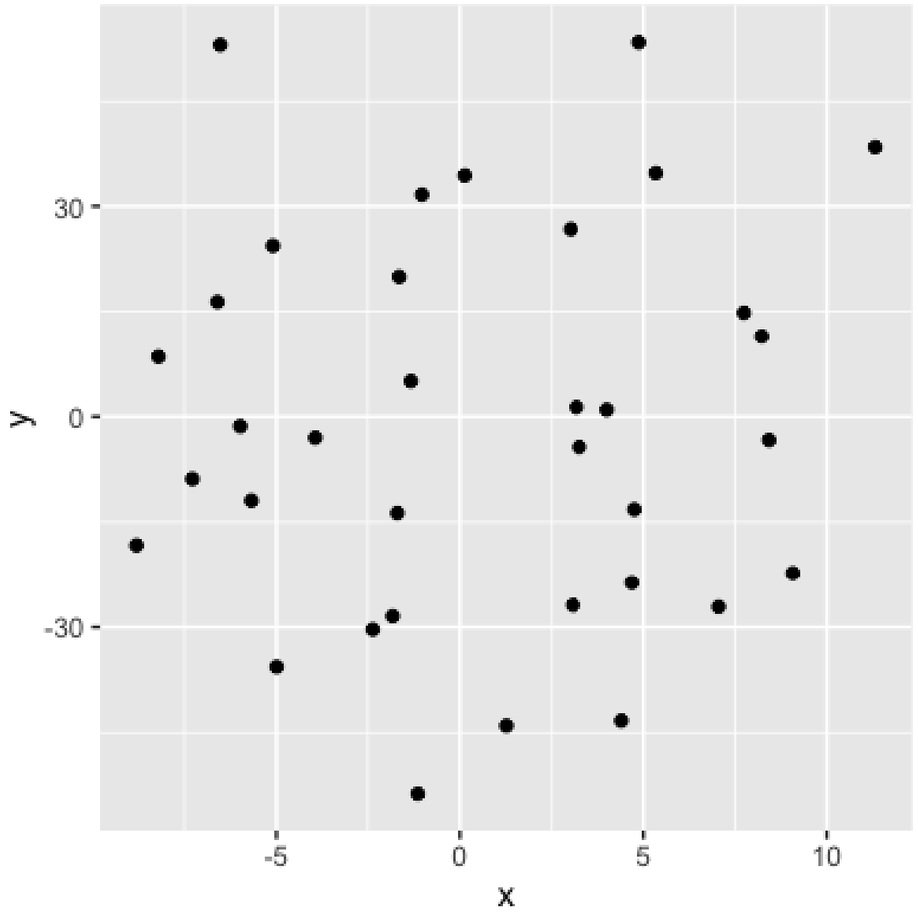


0.21 (weak relationship)



Magnitude = strength of relationship

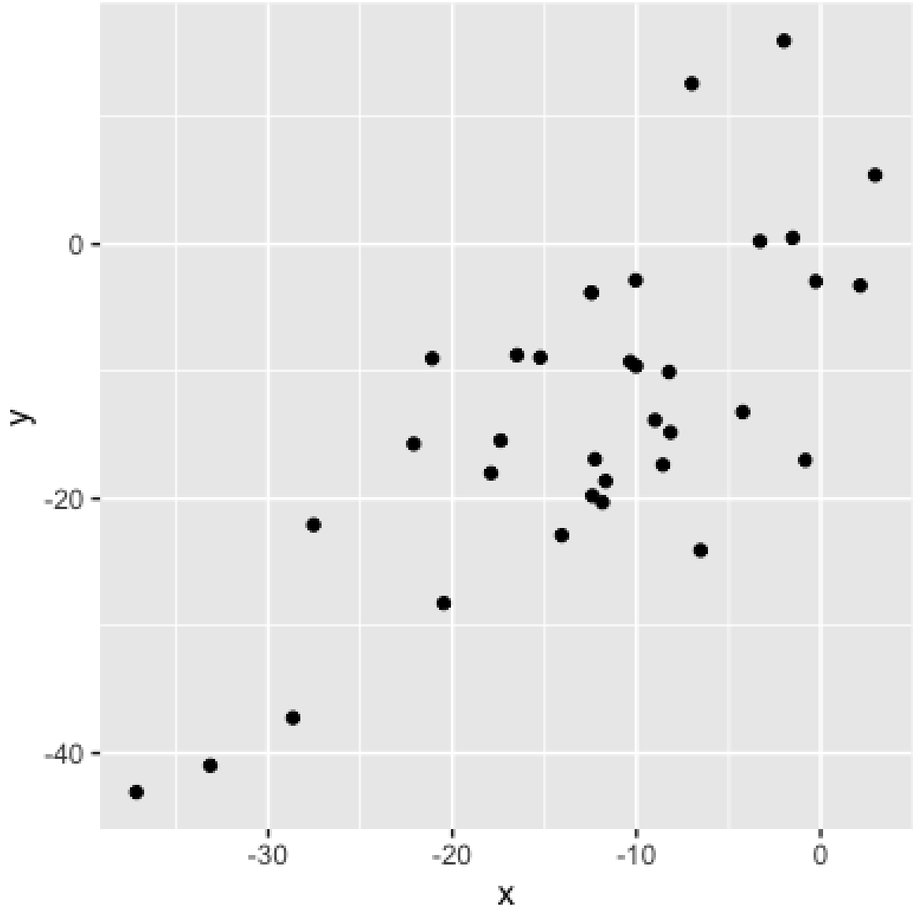
0.04 (no relationship)



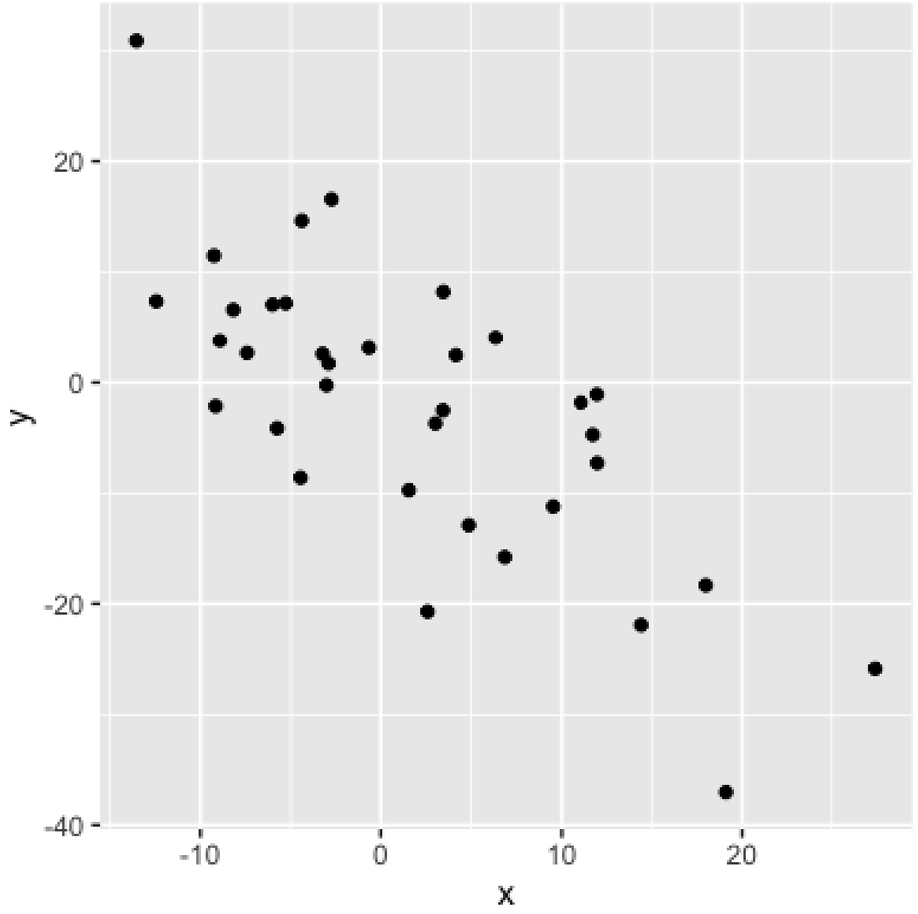
- Knowing the value of `x` doesn't tell us anything about `y`

Sign = direction

0.75: as `x` increases, `y` increases

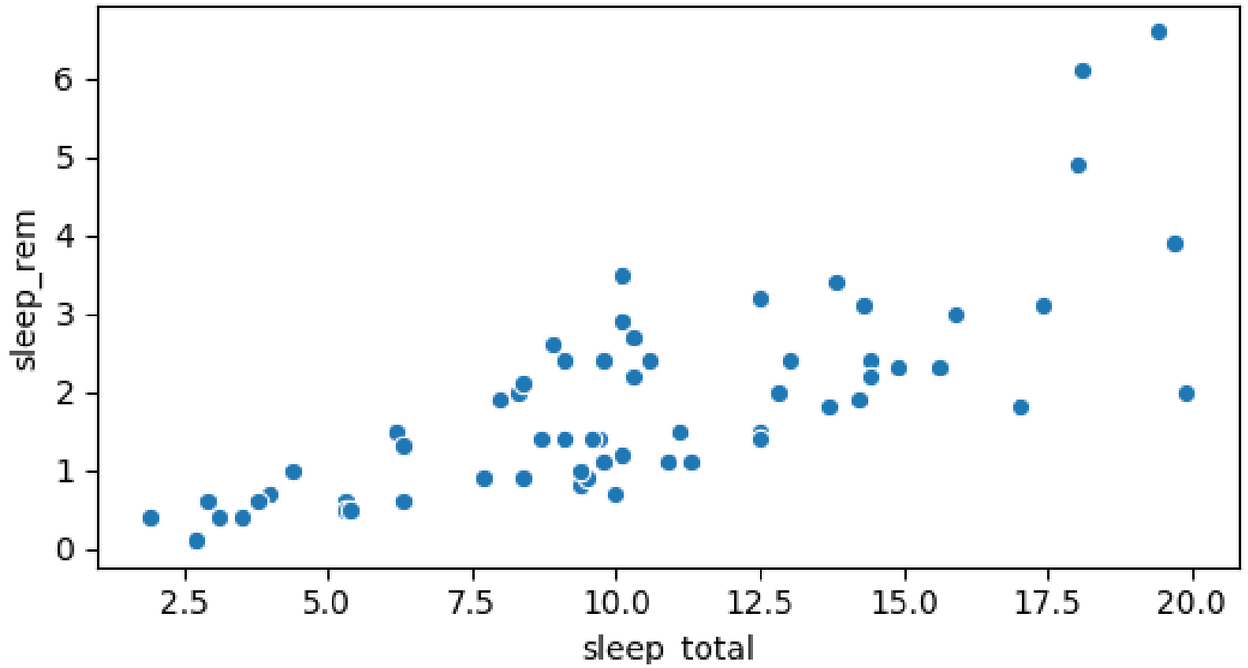


-0.75: as `x` increases, `y` decreases



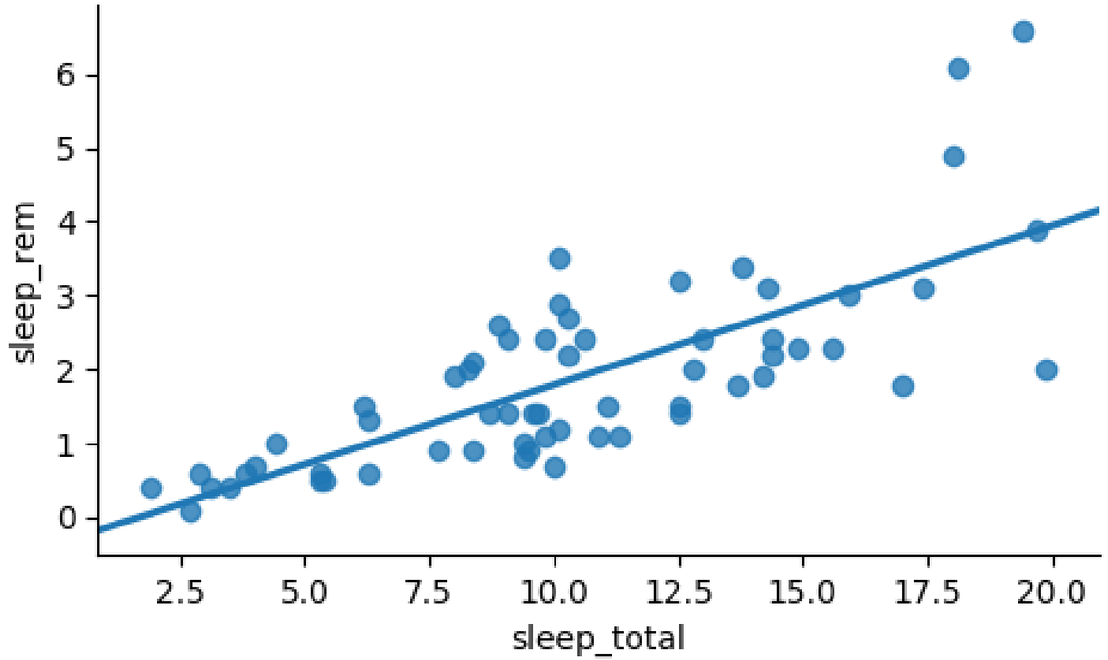
Visualizing relationships

```
import seaborn as sns
sns.scatterplot(x="sleep_total", y="sleep_rem", data=msleep)
plt.show()
```



Adding a trendline

```
import seaborn as sns
sns.lmplot(x="sleep_total", y="sleep_rem", data=msleep, ci=None)
plt.show()
```



Computing correlation

```
msleep['sleep_total'].corr(msleep['sleep_rem'])
```

```
0.751755
```

```
msleep['sleep_rem'].corr(msleep['sleep_total'])
```

```
0.751755
```

Many ways to calculate correlation

- Used in this course: Pearson product-moment correlation (r)
  - Most common
  - $\bar{x} =$ mean of x
  - $\sigma_x =$ standard deviation of x

$$r = \sum_{i=1}^{n} \frac{(x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \times \sigma_y}$$

- Variations on this formula:
  - Kendall's tau
  - Spearman's rho

Let's practice!

INTRODUCTION TO STATISTICS IN PYTHON

Correlation caveats

INTRODUCTION TO STATISTICS IN PYTHON

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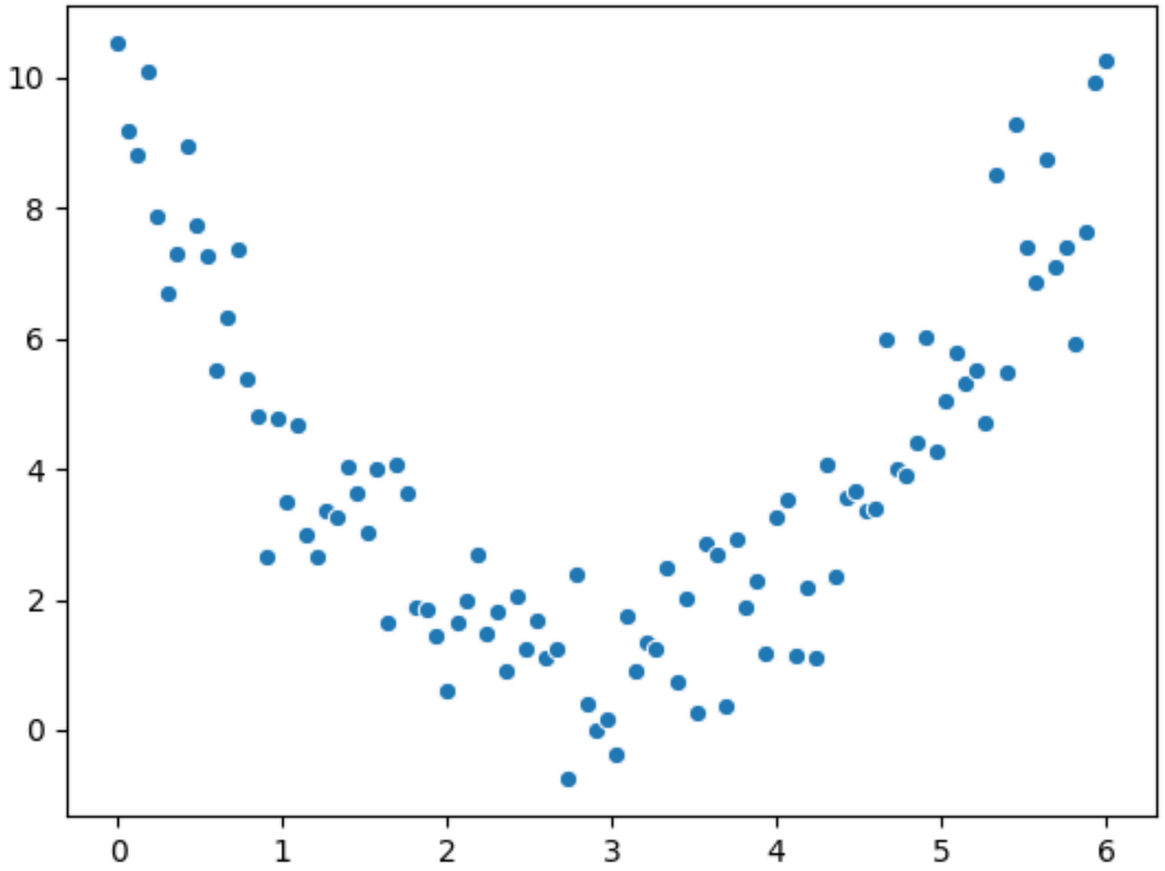
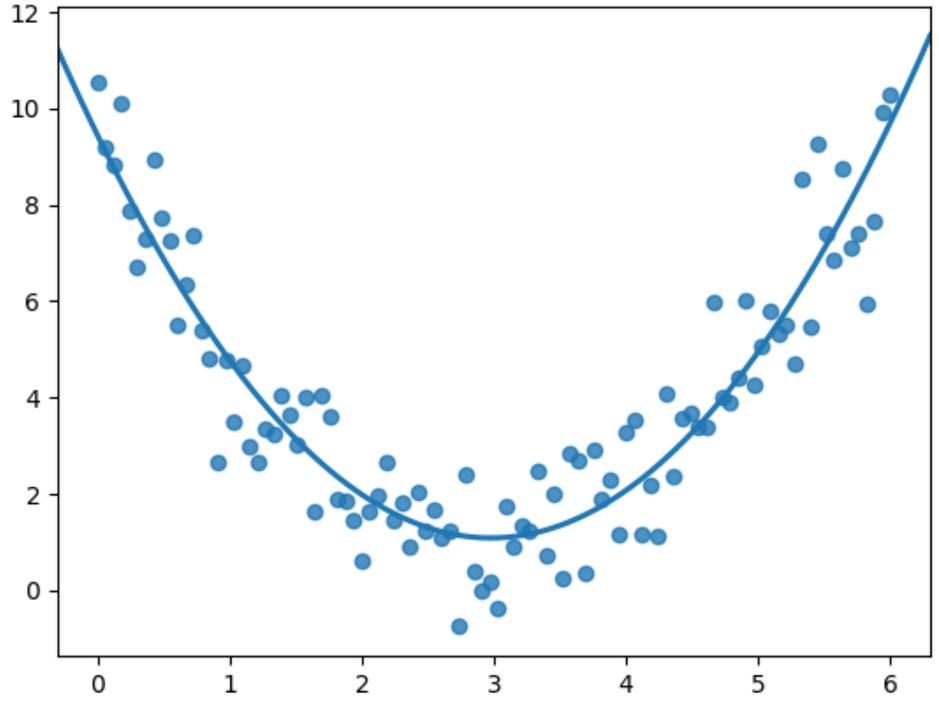
Non-linear relationships



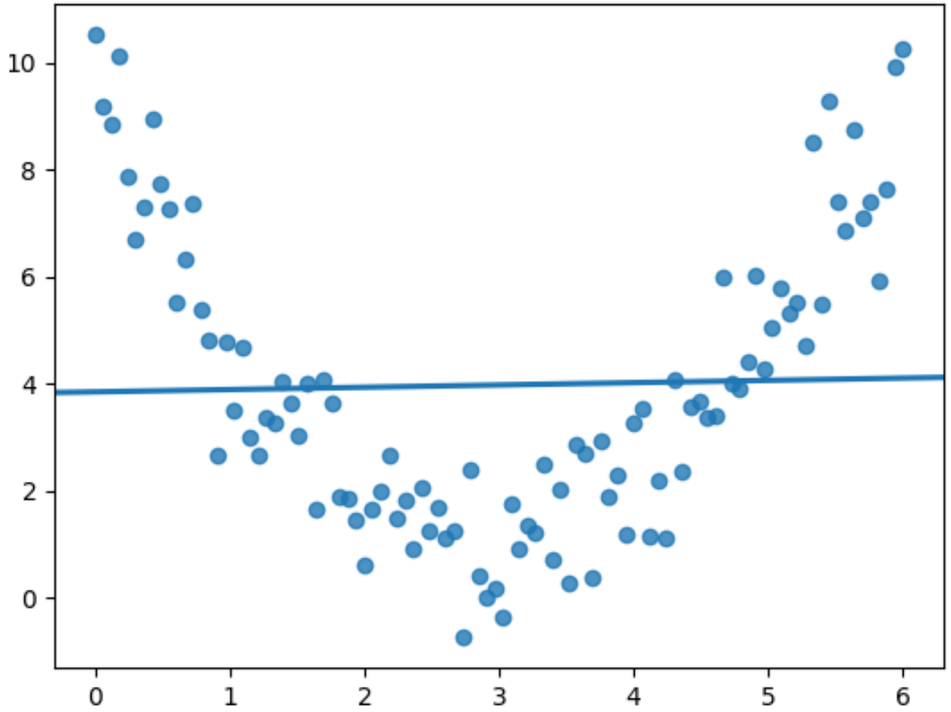
$$r = 0.18$$

Non-linear relationships

What we see:



What the correlation coefficient sees:



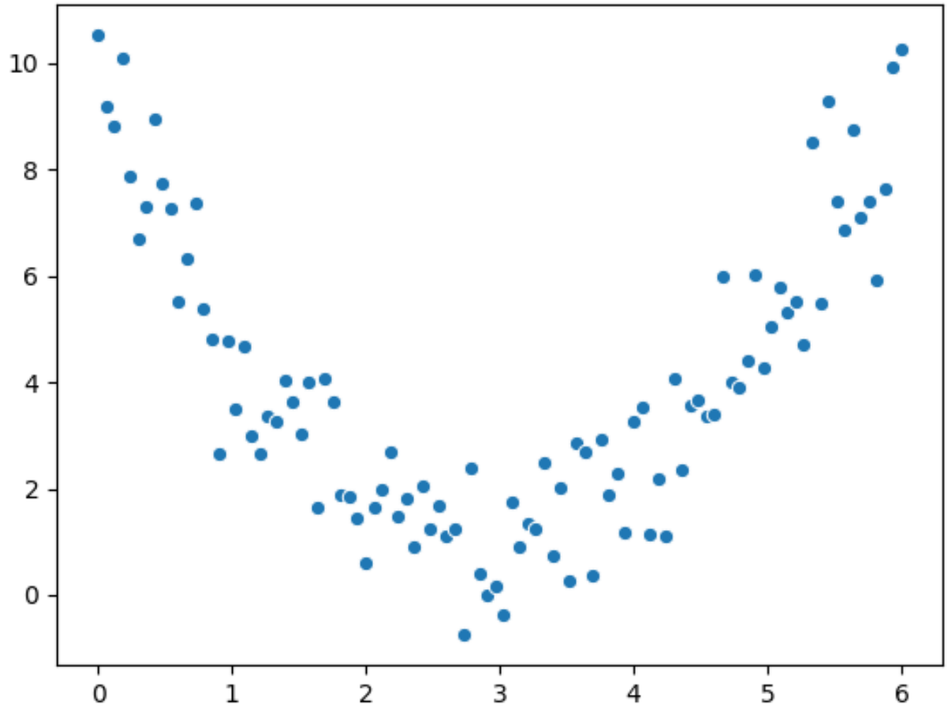
Correlation only accounts for linear relationships

Correlation shouldn't be used blindly

```
df['x'].corr(df['y'])
```

```
0.081094
```

Always visualize your data

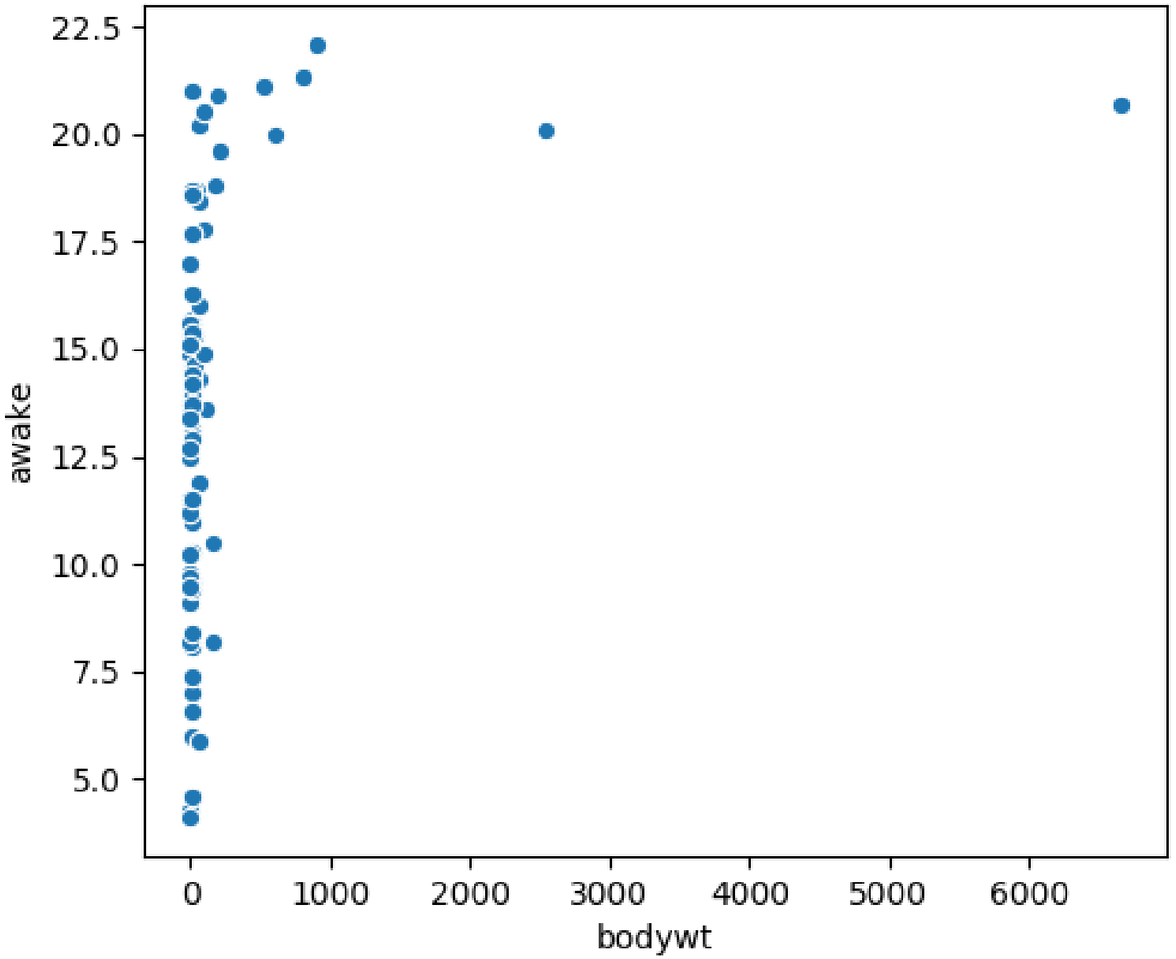


Mammal sleep data

```
print(msleep)
```

```
                 name       genus   vore         order  ... sleep_cycle  awake  brainwt   bodywt
1             Cheetah    Acinonyx  carni     Carnivora  ...         NaN   11.9      NaN   50.000
2          Owl monkey       Aotus   omni      Primates  ...         NaN    7.0  0.01550    0.480
3     Mountain beaver  Aplodontia  herbi      Rodentia  ...         NaN    9.6      NaN    1.350
4 Greater short-ta...     Blarina   omni  Soricomorpha  ...    0.133333    9.1  0.00029    0.019
5                 Cow         Bos  herbi  Artiodactyla  ...    0.666667   20.0  0.42300  600.000
..                ...         ...    ...           ...  ...         ...    ...      ...      ...
79         Tree shrew       Tupaia   omni    Scandentia  ...    0.233333   15.1  0.00250    0.104
80 Bottle-nosed do...    Tursiops  carni       Cetacea  ...         NaN   18.8      NaN  173.330
81              Genet     Genetta  carni     Carnivora  ...         NaN   17.7  0.01750    2.000
82         Arctic fox       Vulpes  carni     Carnivora  ...         NaN   11.5  0.04450    3.380
83            Red fox       Vulpes  carni     Carnivora  ...    0.350000   14.2  0.05040    4.230
```

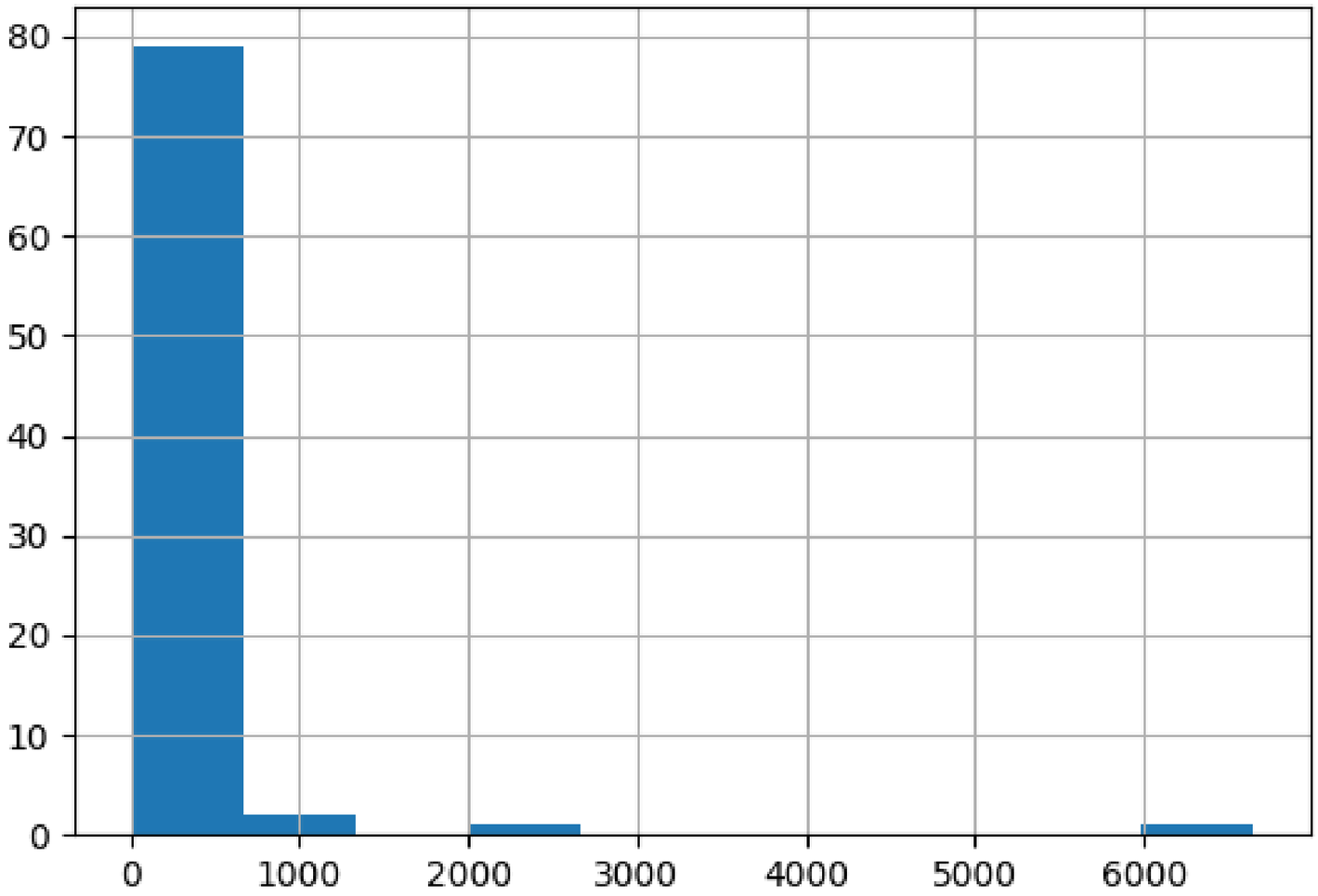
Body weight vs. awake time




```
msleep['bodywt'].corr(msleep['awake'])
```

```
0.3119801
```

Distribution of body weight



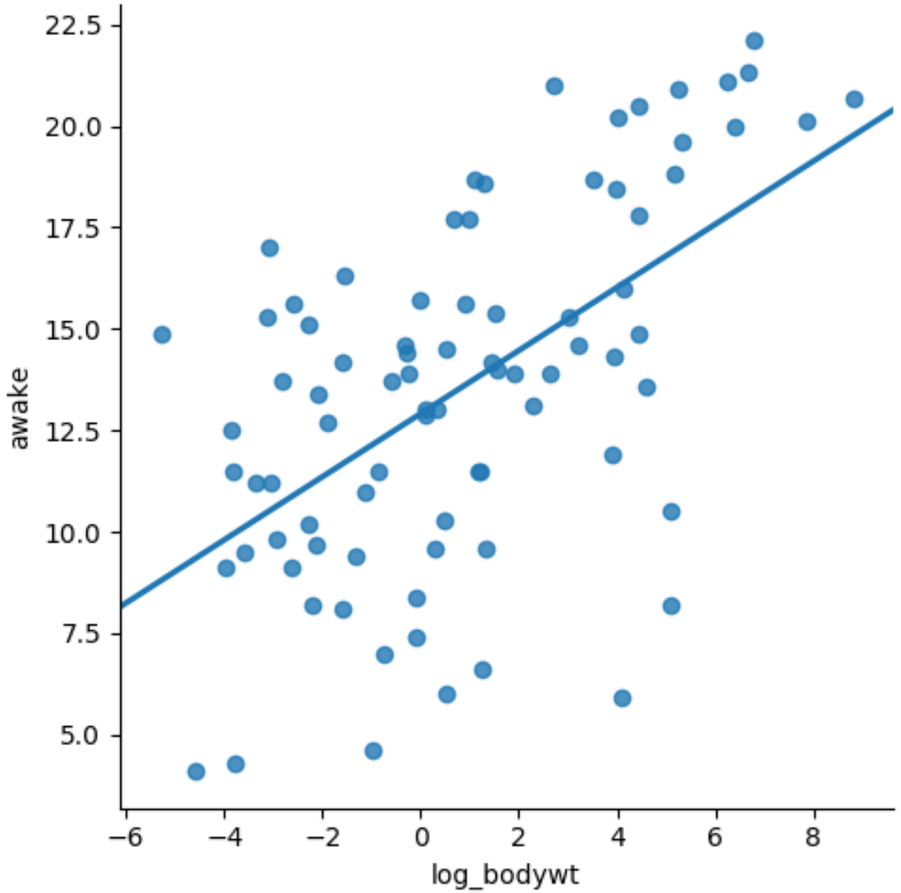
Log transformation

```
msleep['log_bodywt'] = np.log(msleep['bodywt'])

sns.lmplot(x='log_bodywt',
           y='awake',
           data=msleep,
           ci=None)
plt.show()
```

```
msleep['log_bodywt'].corr(msleep['awake'])
```

```
0.5687943
```



Other transformations

- Log transformation (`log(x)`)
- Square root transformation (`sqrt(x)`)
- Reciprocal transformation (`1 / x`)
- Combinations of these, e.g.:
  - `log(x)` and `log(y)`
  - `sqrt(x)` and `1 / y`

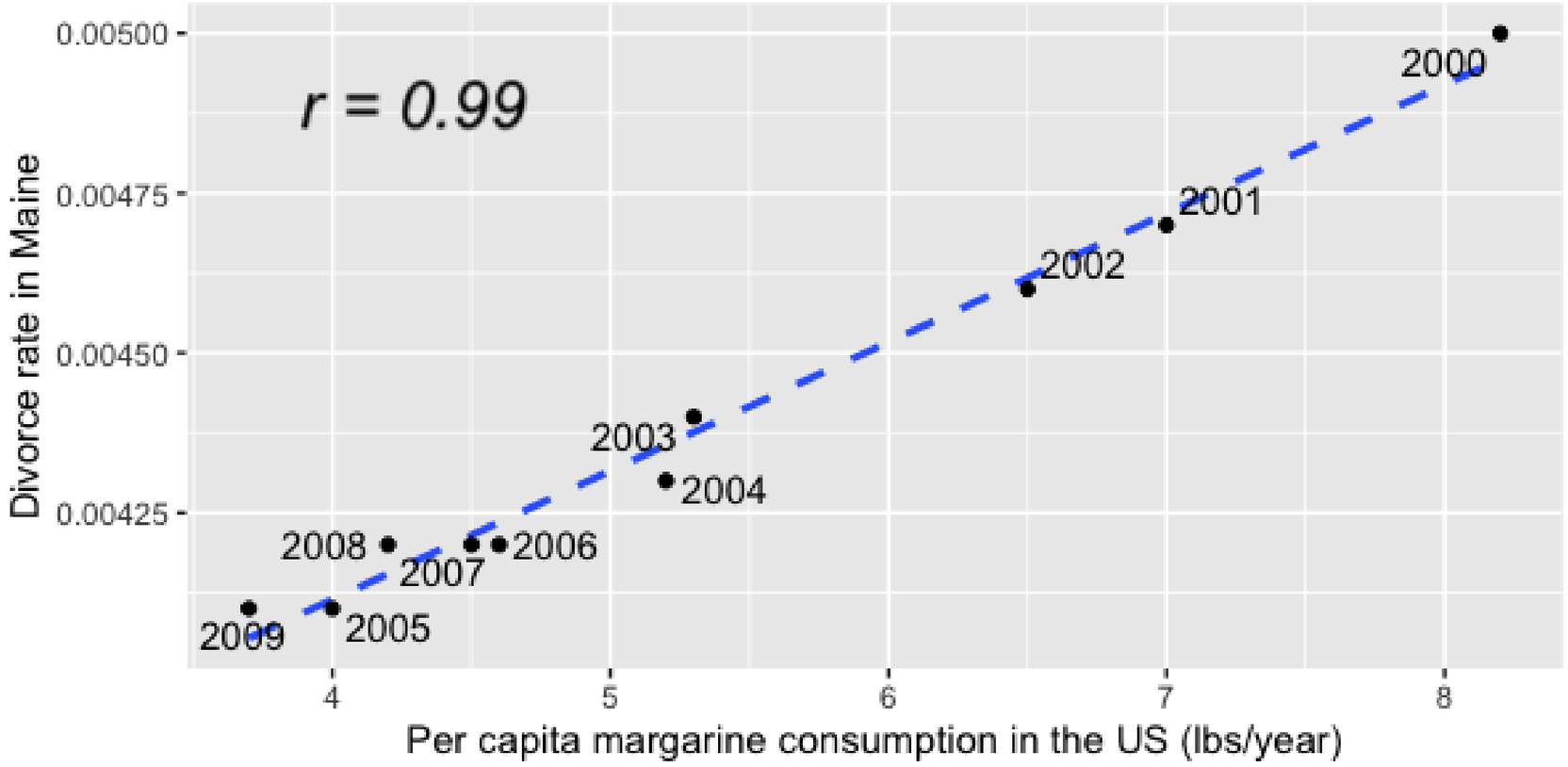
Why use a transformation?

- Certain statistical methods rely on variables having a linear relationship
  - Correlation coefficient
  - Linear regression

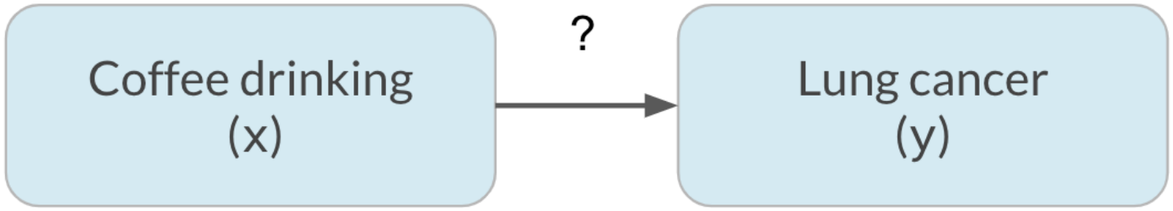
Introduction to Linear Modeling in Python

Correlation does not imply causation

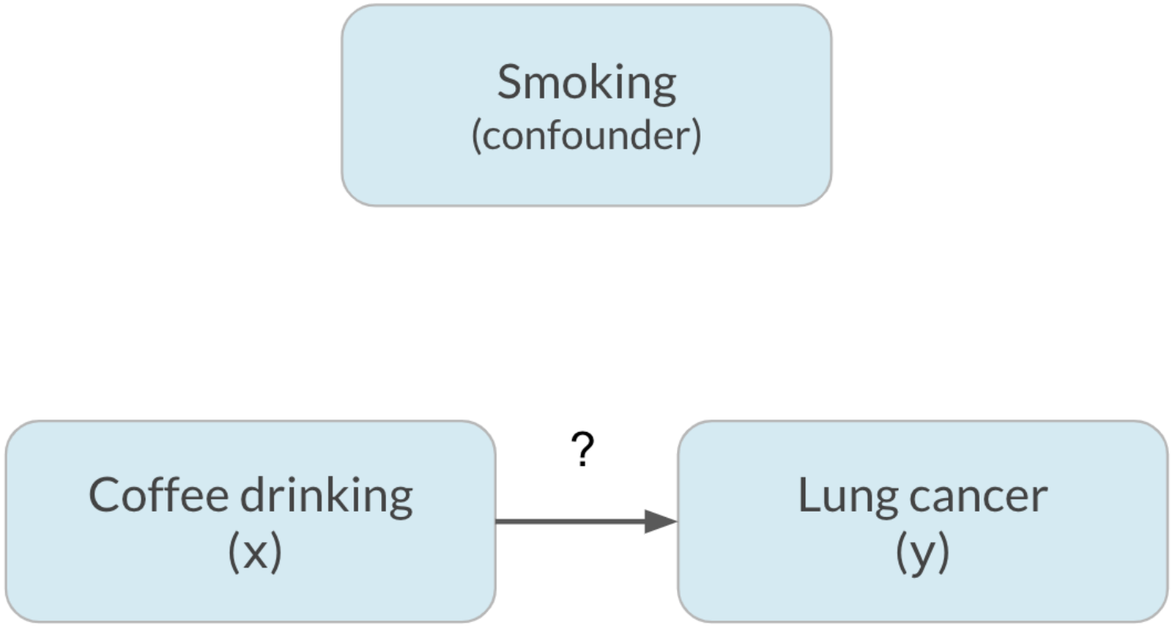
`x` *is correlated with* `y` **does not mean** `x` *causes* `y`



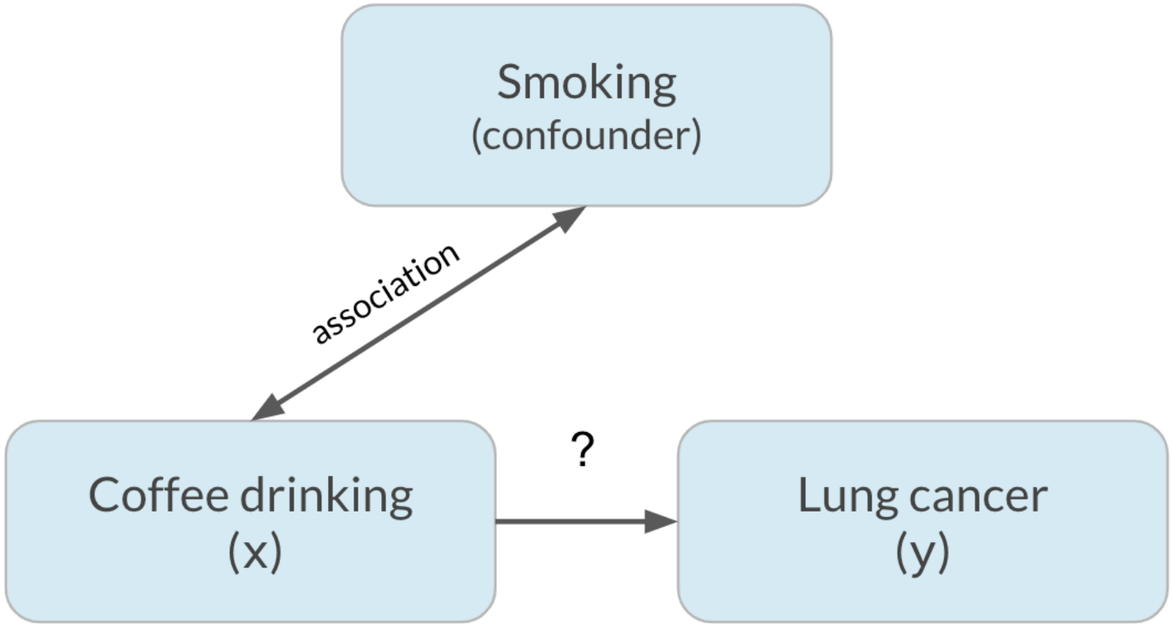
Confounding



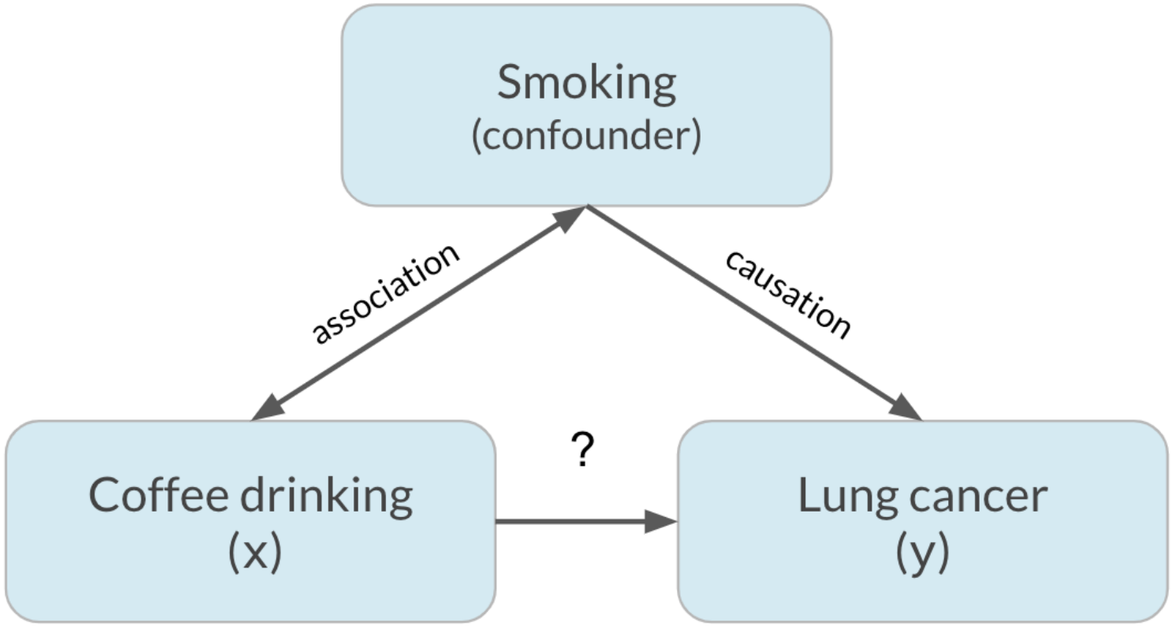
Confounding



Confounding



Confounding



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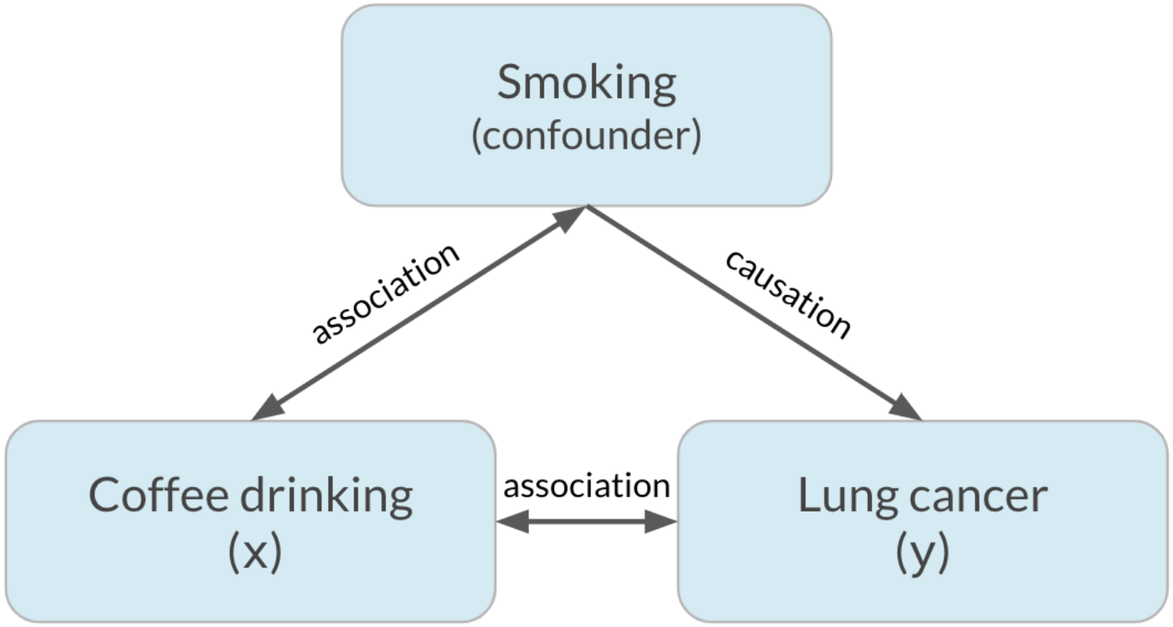

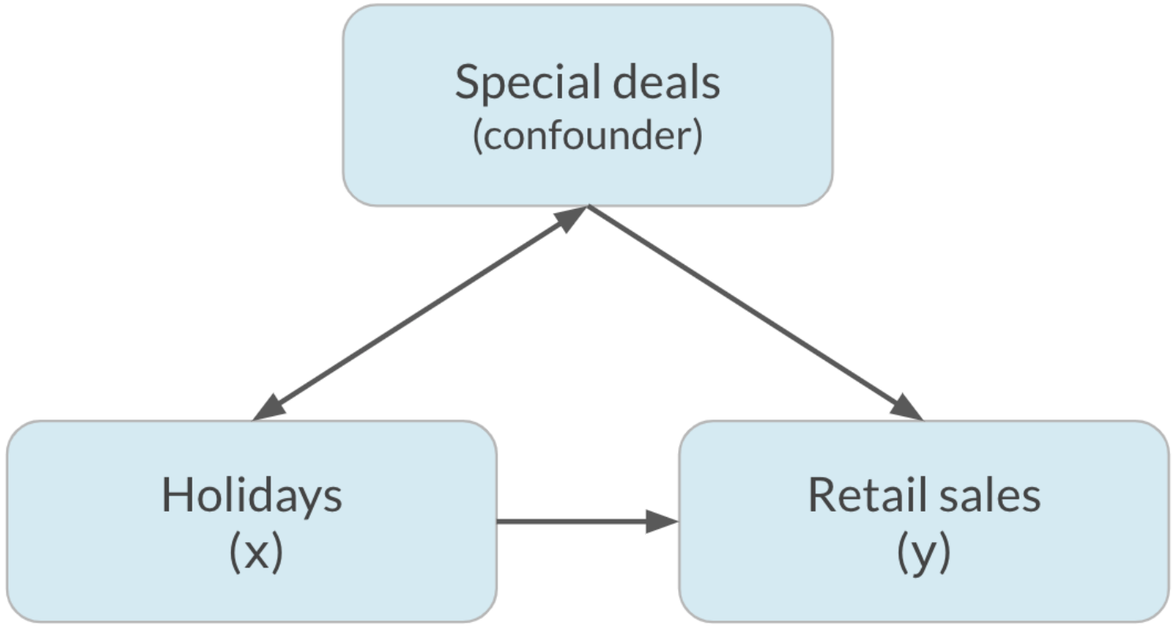

Let's practice!

INTRODUCTION TO STATISTICS IN PYTHON

Design of experiments

INTRODUCTION TO STATISTICS IN PYTHON

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Vocabulary

Experiment aims to answer: *What is the effect of the treatment on the response?*

- Treatment: explanatory/independent variable
- Response: response/dependent variable

E.g.: *What is the effect of an advertisement on the number of products purchased?*

- Treatment: advertisement
- Response: number of products purchased

Controlled experiments

- Participants are assigned by researchers to either treatment group or control group
  - Treatment group sees advertisement
  - Control group does not
- Groups should be comparable so that causation can be inferred
- If groups are not comparable, this could lead to confounding (bias)
  - Treatment group average age: 25
  - Control group average age: 50
  - Age is a potential confounder

The gold standard of experiments will use...

- Randomized controlled trial
  - Participants are assigned to treatment/control *randomly*, not based on any other characteristics
  - Choosing randomly helps ensure that groups are comparable
- Placebo
  - Resembles treatment, but has no effect
  - Participants will not know which group they're in
  - In clinical trials, a sugar pill ensures that the effect of the drug is actually due to the drug itself and not the idea of receiving the drug

The gold standard of experiments will use...

- Double-blind trial
  - Person administering the treatment/running the study doesn't know whether the treatment is real or a placebo
  - Prevents bias in the response and/or analysis of results

Fewer opportunities for bias = more reliable conclusion about causation

Observational studies

- Participants are not assigned randomly to groups
  - Participants assign themselves, usually based on pre-existing characteristics
- Many research questions are not conducive to a controlled experiment
  - You can't force someone to smoke or have a disease
  - You can't make someone have certain past behavior
- Establish association, not causation
  - Effects can be confounded by factors that got certain people into the control or treatment group
  - There are ways to control for confounders to get more reliable conclusions about association

Longitudinal vs. cross-sectional studies

Longitudinal study

- Participants are followed over a period of time to examine effect of treatment on response
- Effect of age on height is not confounded by generation
- More expensive, results take longer

Cross-sectional study

- Data on participants is collected from a single snapshot in time
- Effect of age on height is confounded by generation
- Cheaper, faster, more convenient

Let's practice!

INTRODUCTION TO STATISTICS IN PYTHON

Congratulations!

INTRODUCTION TO STATISTICS IN PYTHON

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Overview

Chapter 1

- What is statistics?
- Measures of center
- Measures of spread

Chapter 2

- Measuring chance
- Probability distributions
- Binomial distribution

Chapter 3

- Normal distribution
- Central limit theorem
- Poisson distribution

Chapter 4

- Correlation
- Controlled experiments
- Observational studies

Build on your skills

- Introduction to Linear Modeling in Python

Congratulations!

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