Setting up experiments

EXPERIMENTAL DESIGN IN PYTHON

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Experimental Design definition

- A **process**
- An **objective** and **controlled** way
- Draw **specific conclusions**
  - In reference to a **hypothesis**

[1] https://www.sciencedirect.com/topics/earth-and-planetary-sciences/experimental-design

Forming robust statements

> X **probably** had an effect on Y. There is **likely** some **small** risk of error

- **Precise and Quantified language**

> P-value analysis indicates **X had an effect on Y** with a **10% risk** of **Type I error**

- **Type I error:** incorrectly reject null hypothesis

- Goal: **Experimental design** and **statistical analysis**

Why experimental design?

Useful in many fields:

- Medical research
- Marketing
- Product analytics
- Agriculture
- Government policy

Some terminology...

- **Subjects** = *what* we are experimenting on (people, employees, users, etc.)

= Subject

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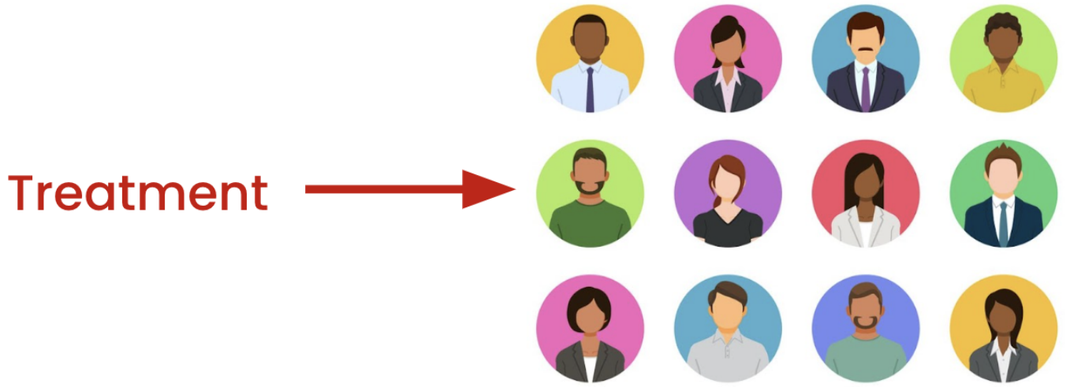
- **Treatment** = some change given to one group

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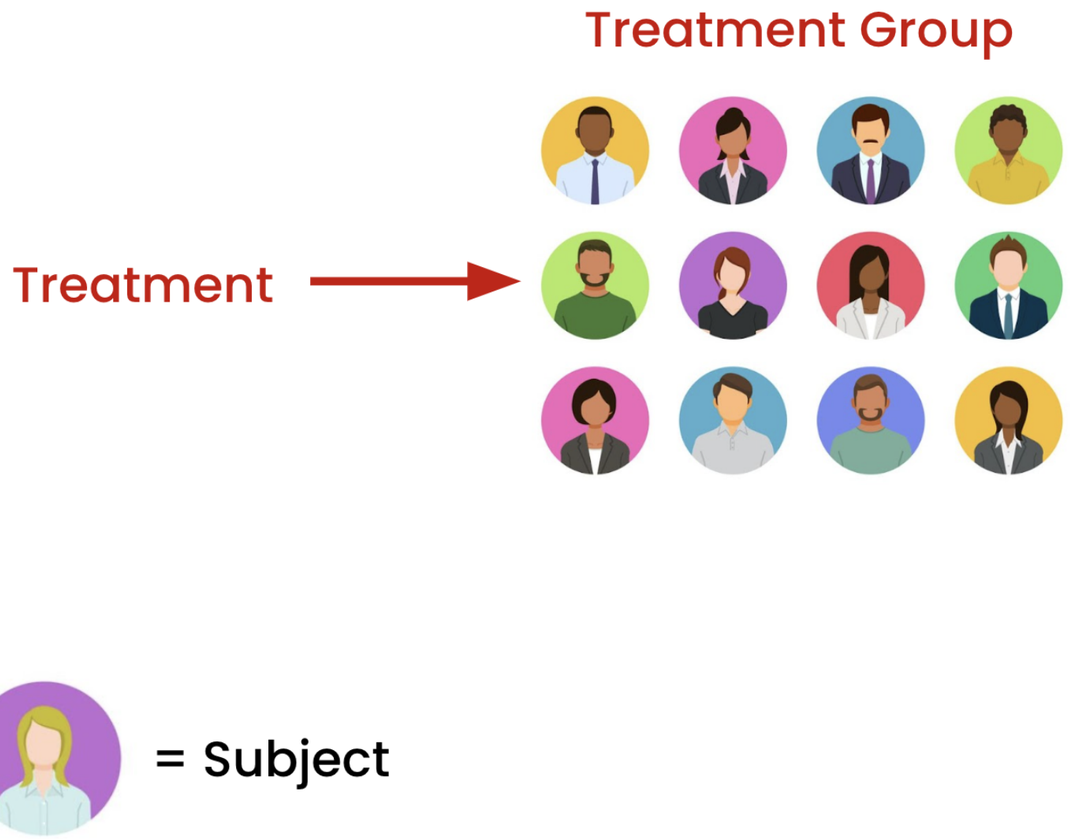
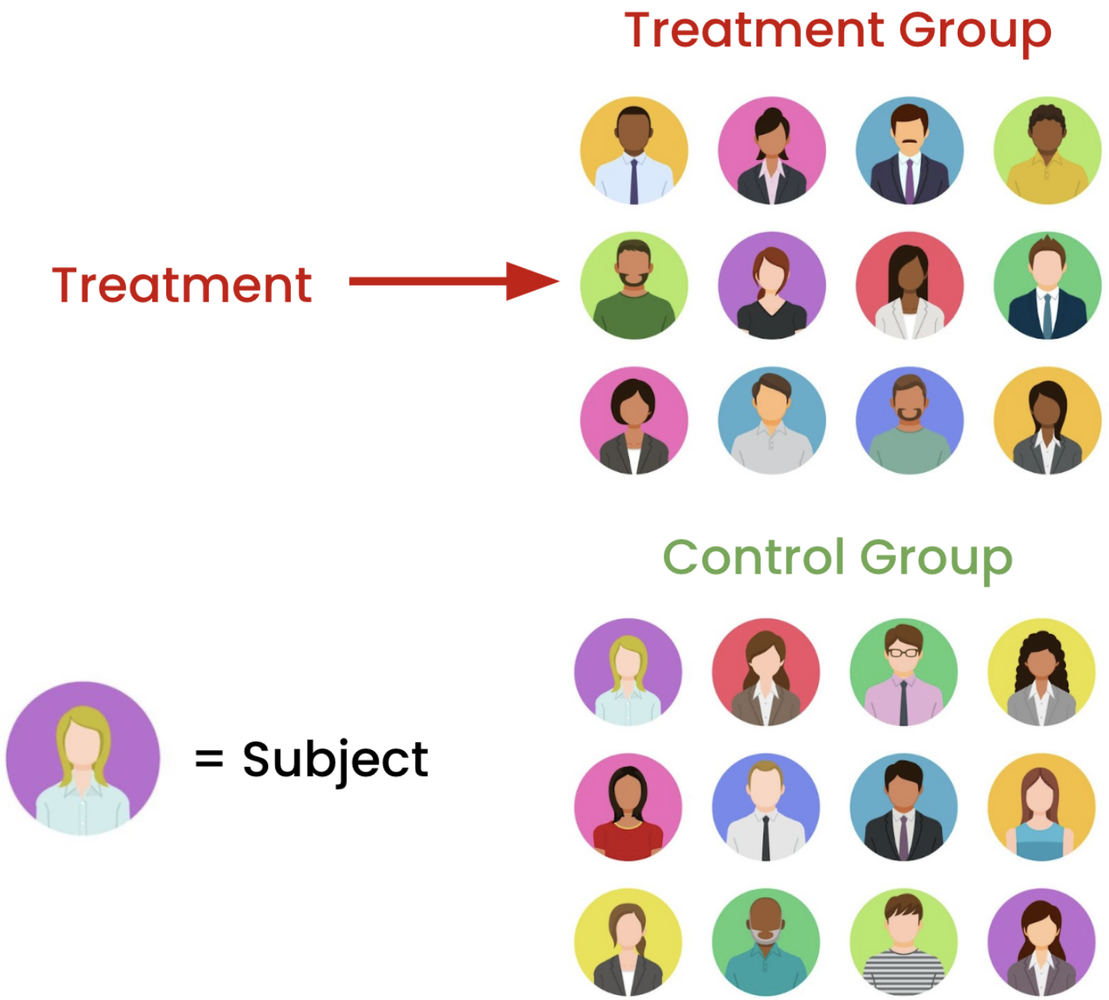


Some terminology...

- **Subjects** = *what* we are experimenting on (people, employees, users, etc.)
- **Treatment** = some change given to one group
- **Control** = the group not given any change



Assigning subjects to groups

- How to assign subjects to groups?
  - Option 1 - *non-random* ('split' the DataFrame)
  - Option 2 - *random assignment*

- **Example:** 200 subjects heights in `heights` DataFrame

```
    id  height
0    0  177.98
1    1  174.17
2    2  178.89
```

Non-random assignment

Assignment by slicing the DataFrame

```
group1_nonrandom = heights.iloc[0:100,:]
group2_nonrandom = heights.iloc[100:,:]
compare_df = pd.concat(
    [group1_nonrandom['height'].describe(),
     group2_nonrandom['height'].describe()],
    axis=1)
compare_df.columns = ['group1', 'group2']
print(compare_df)
```

```
       group1  group2
count  100.00  100.00
mean   170.32  179.19 <--
std      3.28    3.50
min    159.28  175.03
25%    168.06  176.57
50%    170.75  178.03
75%    173.09  180.79
max    174.92  191.32
```

- Very different! (Mean 9cm apart)

Random assignment

- Use `.sample()`
  - `n` or `frac` (fraction 0-1)

```
group1 = heights.sample(frac=0.5,
                        replace=False,
                        random_state=42)
group2 = heights.drop(group1.index)
```

```
print(compare_df)
```

- Much closer! (<1cm)

```
        group1  group2
count   100.00  100.00
mean    175.10  174.41 <--
std       5.39    5.78
min     163.07  159.28
25%     171.32  170.17
50%     175.22  174.86
75%     178.32  177.85
max     189.78  191.32
```

Assignment summary

- Subjects should be *randomly* assigned to groups
  - Observed changes correctly attributed

- **Random subject assignment:** `.sample()`
- **Verify differences:** `.describe()`

Let's practice!

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Experimental data setup

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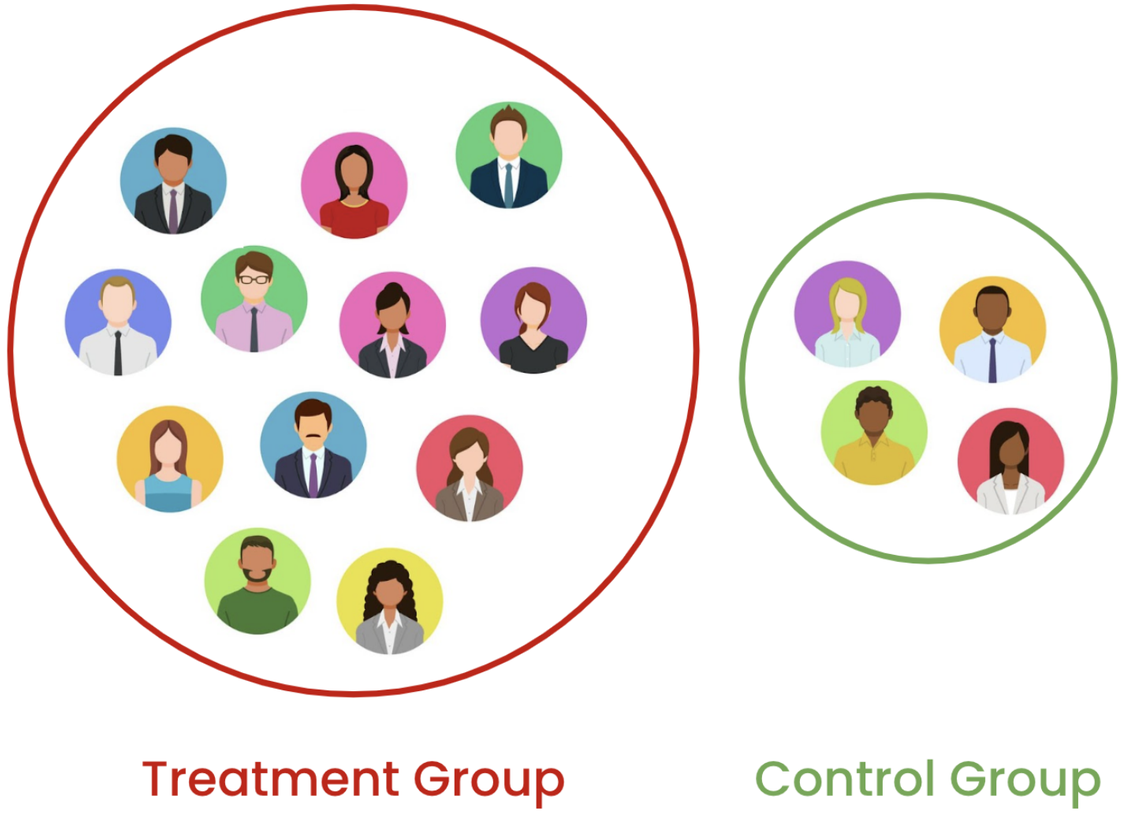
The problem with randomization

1) **Uneven issue:** different number of subjects in groups



The problem with randomization

2) **Covariate issue:** High variability in some covariates → group imbalances in randomization

Does age impact reaction times?

Control Group

Physically Active

Physical Activity = Covariate

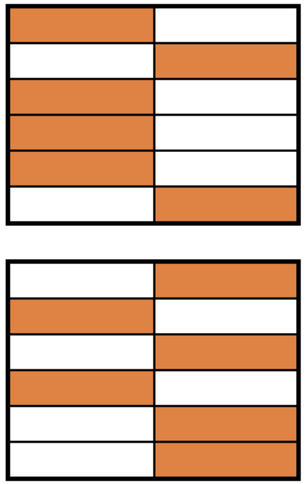
Treatment Group

Not Physically Active

Result: harder to measure treatment effect!

Block randomization

- Split into blocks of size n **first** then randomly split
  - Fixes uneven issue



- 24 subjects split into two groups then randomized

Our dataset

- E-commerce dataset (`ecom`) (1000 subjects)
  - Average basket size
  - Average time on the website
  - Power user (Average 40+ daily minutes on website)

```
   basket_size  web_time  power_user
0          227         7           0
1          123         5           0
2           98        16           0
3          211        45           1
4          133        17           0
```

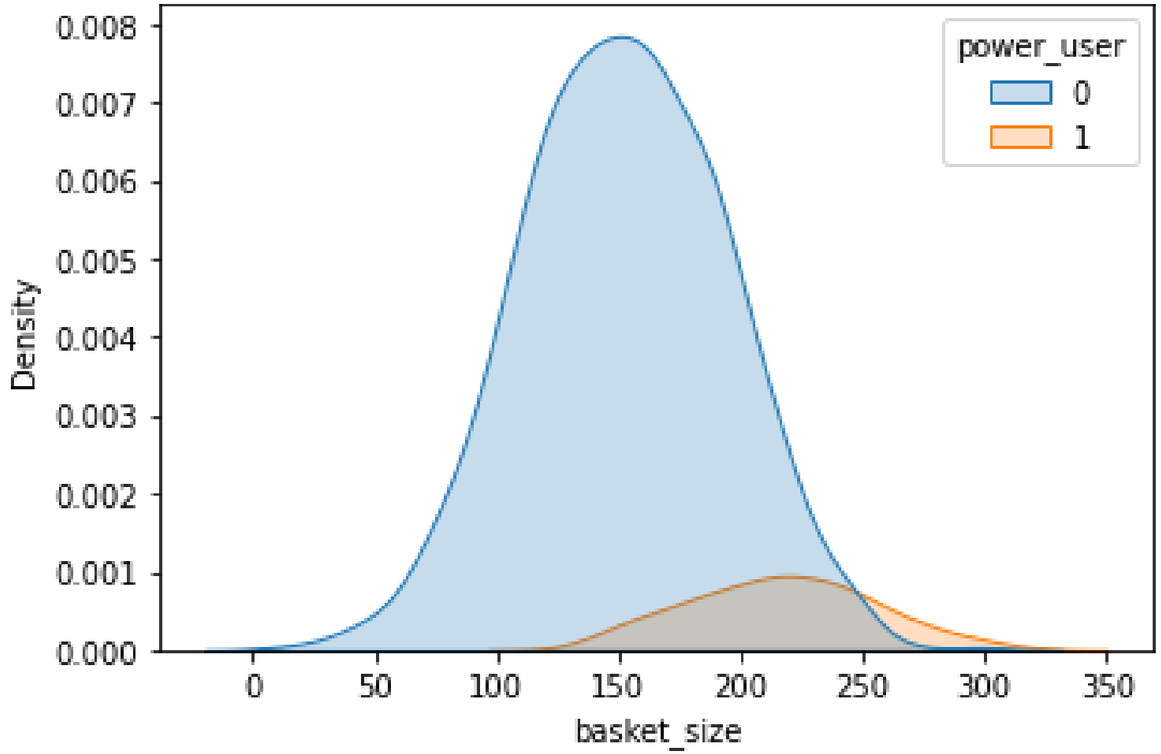
Block randomization in Python

```
group1 = ecom.sample(frac=0.5, random_state=42, replace=False)
group1['Block'] = 1
group2 = ecom.drop(group1.index)
group2['Block'] = 2
print(len(group1), len(group2))
```

```
500,500
```

Visualizing splits

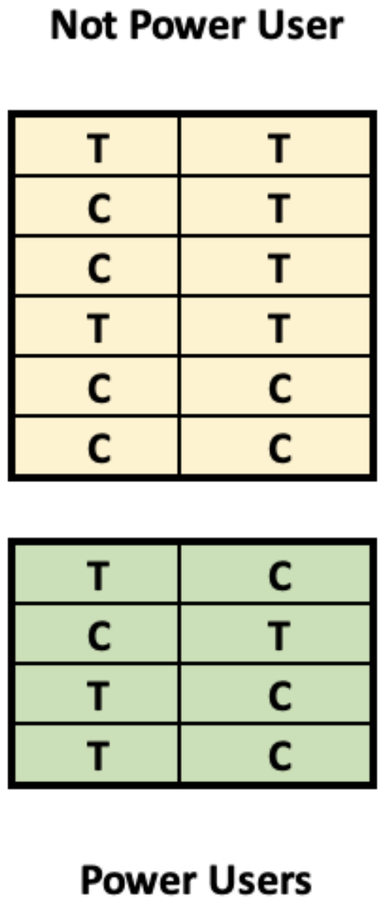
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.displot(data=ecom,
            x='basket_size',
            hue='power_user',
            fill=True,
            kind='kde')
plt.show()
```



Confounding = variable *might* cause the effect rather than treatment

Stratified randomization

- Splitting based on covariate(s) *first*
  - Then randomization
- Green = All power users (Yellow = Not power users)
  - Then split Treatment/Control
- Fixes covariate/confounding issue
- Can be done for multiple covariates - but gets complex!



Our first strata

- Separate power users
- Sample into Treatment/Control

```
strata_1 = ecom[ecom['power_user'] == 1]
strata_1['Block'] = 1
strata_1_g1 = strata_1.sample(frac=0.5, replace=False)
strata_1_g1['T_C'] = 'T'
strata_1_g2 = strata_1.drop(strata_1_g1.index)
strata_1_g2['T_C'] = 'C'
```

The second strata

- Separate not power users
- Sample into Treatment/Control

```
strata_2 = ecom.drop(strata_1.index)
strata_2['Block'] = 2
strata_2_g1 = strata_2.sample(frac=0.5, replace=False)
strata_2_g1['T_C'] = 'T'
strata_2_g2 = strata_2.drop(strata_2_g1.index)
strata_2_g2['T_C'] = 'C'
```

Confirming stratification

- Join blocks and groups
- Use groupby to check allocation

```
ecom_stratified = pd.concat([strata_1_g1, strata_1_g2, strata_2_g1, strata_2_g2])
ecom_stratified.groupby(['Block','T_C', 'power_user']).size()
```

```
Block  T_C  power_user
1      C    1             50
       T    1             50
2      C    0            450
       T    0            450
```

Let's practice!

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Normal data

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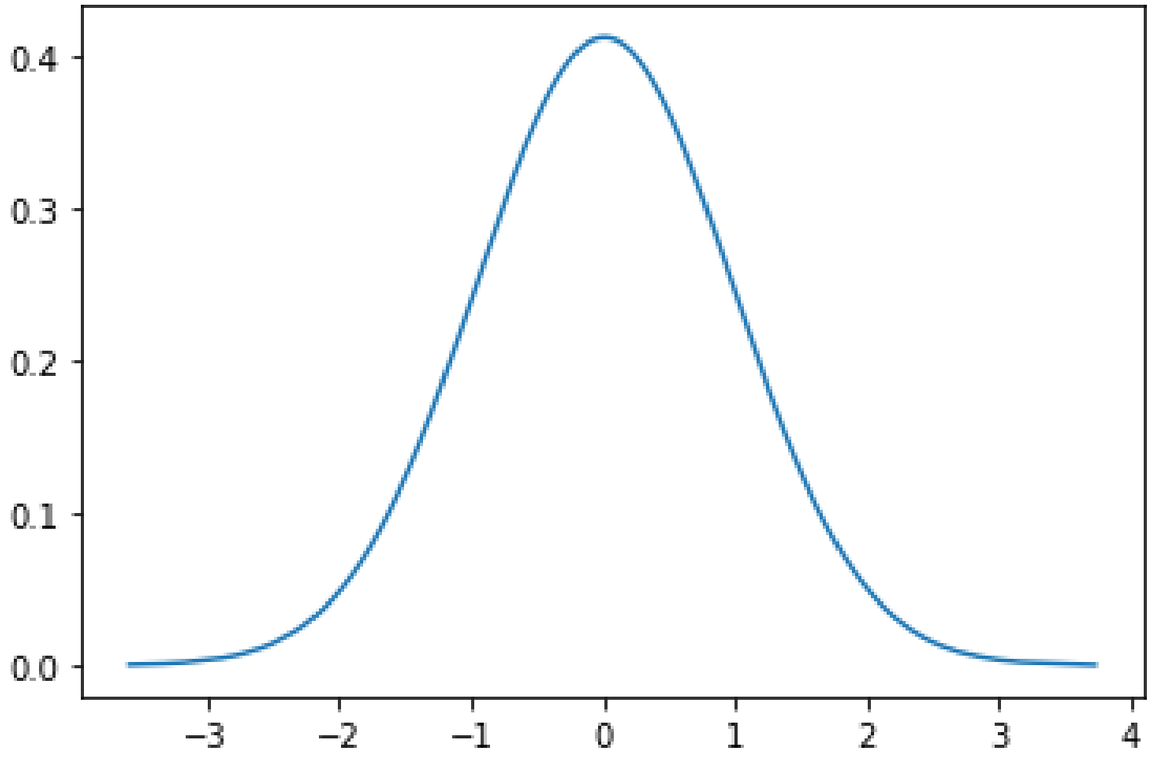
The normal distribution

- The familiar 'bell curve' shape
- Related to z-score work

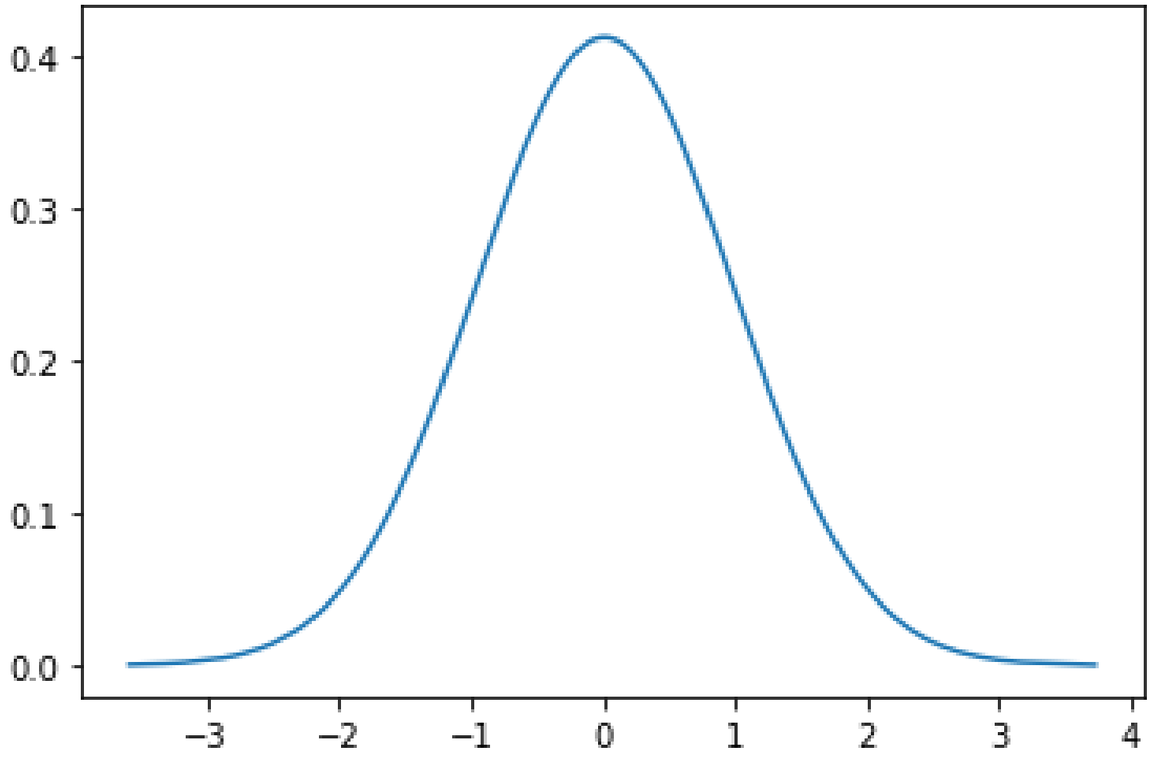
$$z = \frac{x - \mu}{\sigma}$$

- Mean = 0, std = 1
  - 'How many standard deviations is this point from the mean?'
  - 'What is the probability of obtaining this score?'



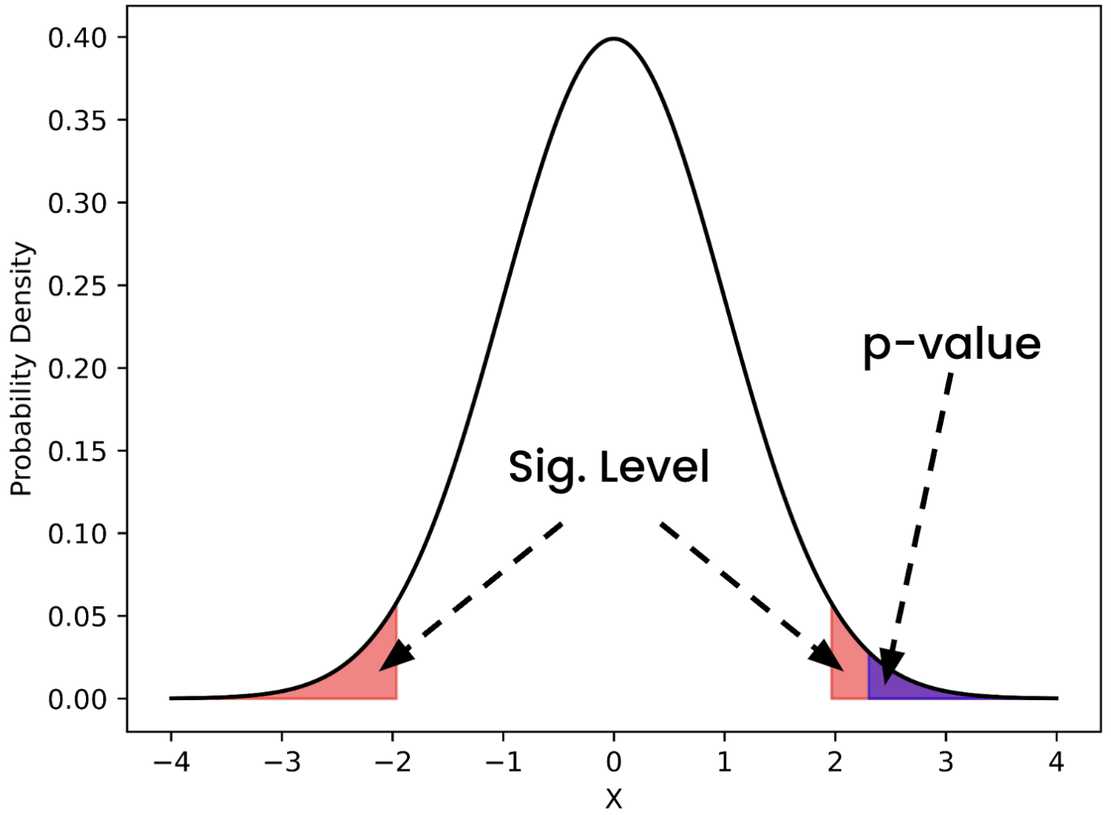
Normal data and statistical tests

- Required for **parametric** tests
- **Nonparametric tests:** don't assume normal data



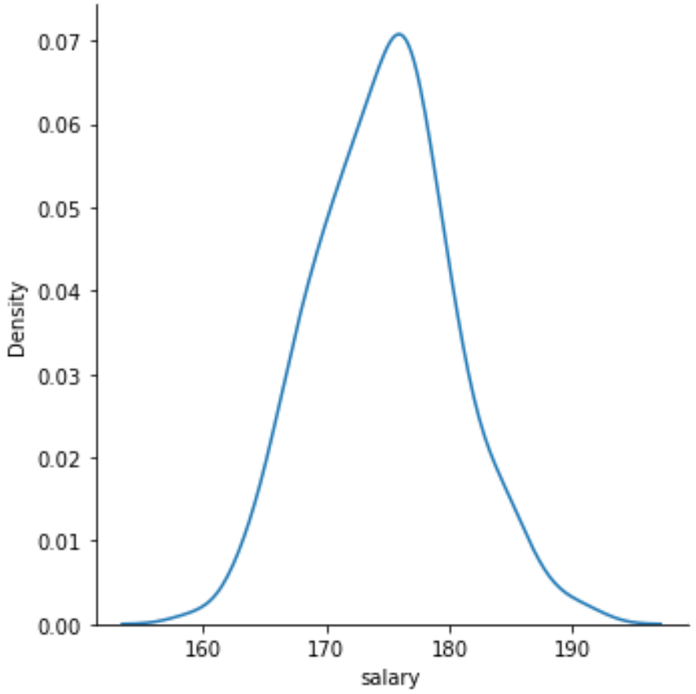
Normal, Z, and alpha

- Crucial link to significance level (α)
- Compare p-value to α
- Probability of a Type I error



Visualizing normal data

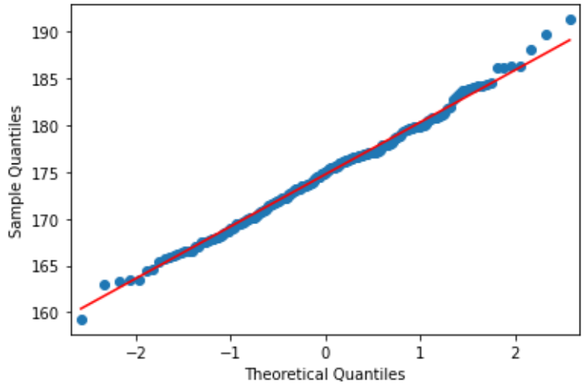
```
sns.displot(data=salaries,
            x='salary',
            kind="kde")
plt.show()
```

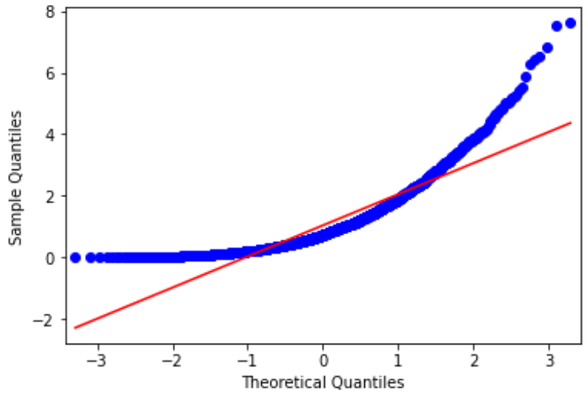


QQ plots

QQ plot: compare data to a particular distribution

```
from statsmodels.graphics.gofplots import qqplot
from scipy.stats.distributions import norm
qqplot(salaries['salary'],
       line='s',
       dist=norm)
plt.show()
```





- Ideal: dots hugging line
- Bad: bow out at ends

Tests for normality

- Shapiro-Wilk (good for smaller datasets)
- D'Agostino K^2 (uses **kurtosis** and **skewness**)
- Anderson-Darling (returns list of values)

H_0 = "Data is drawn from a Normal Distribution"

A Shapiro-Wilk test

```
from scipy.stats import shapiro
alpha = 0.05
stat, p = shapiro(salaries['salary'])
print(f"p: {round(p,4)} test stat: {round(stat,4)}")
```

```
p: 0.8293 test stat: 0.9956
```

- `p` > `alpha`
  - Fail to reject H_0 → likely normal

An Anderson-Darling test

```
from scipy.stats import anderson
result = anderson(x=salaries['salary'], dist="norm")
```

```
print(round(result.statistic,4))
print(result.significance_level)
print(result.critical_values)
```

```
0.2748
[15.  10.   5.   2.5  1. ]
[0.572 0.651 0.781 0.911 1.084]
```

- `0.2748` < `[0.572 0.651 0.781 0.911 1.084]`
  - Fail to reject H_0 → likely normal

Let's practice!

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