Welcome to the course!

EXPERIMENTAL DESIGN IN PYTHON



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Experimental design

Data

Allows us to answer questions

How do we get answers?

Need rigorous methods

Approach

- Build hypotheses with exploratory data analysis
- Test hypotheses with statistical tests

Mapping variables

Variable types

- Discrete: Finite set of possible values (Ex: True or False)
- Continuous: Any value (Ex: Measurement)

Mapping

- X or Y axes
- Change color with fill or color arguments

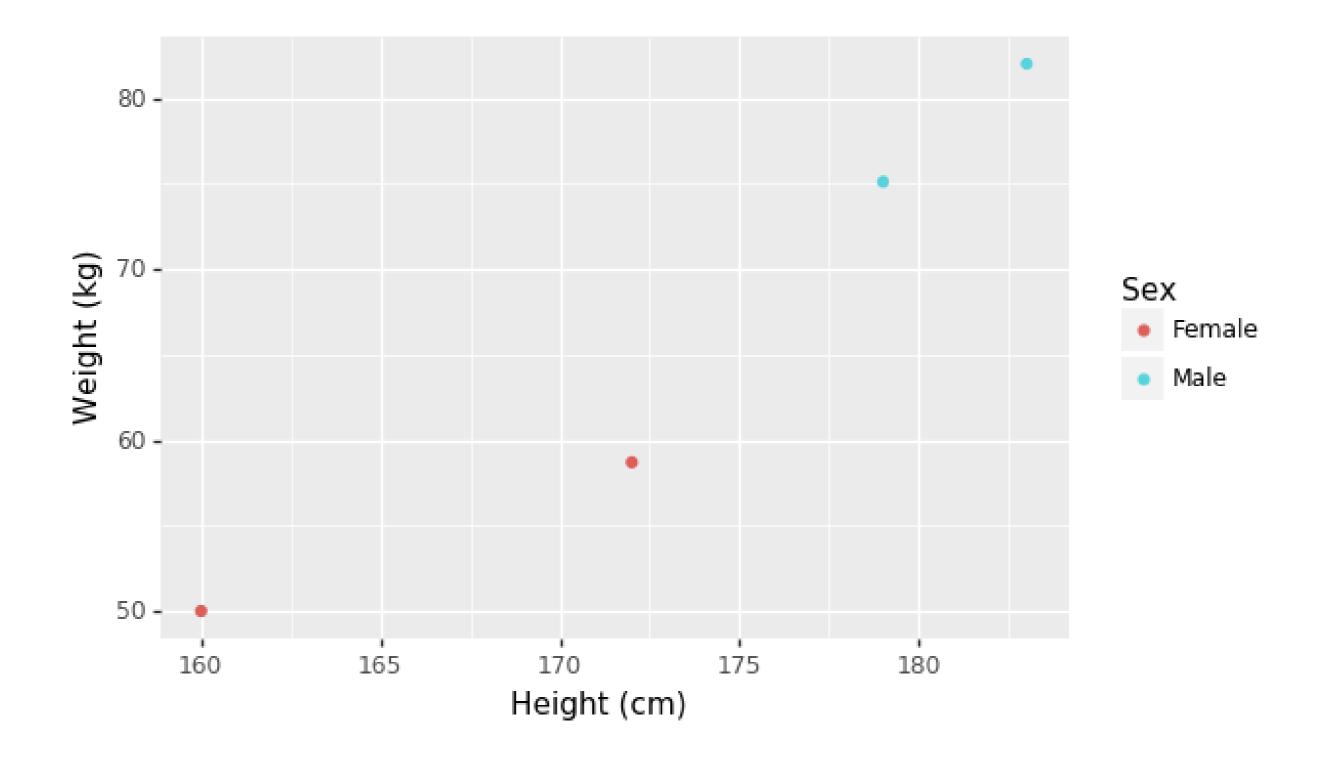
Making plots with plotnine

- Call ggplot() function and give it a
 DataFrame
- 2. Assign mapping of variables with aes()
- 3. Specify a geometry

```
import plotnine as p9
(p9.ggplot([pandas DataFrame])+
p9.aes(
    x='variable to put on X-axis',
    y='variable to put on Y-axis',
    color='variable ')+
p9.geom_point()
```

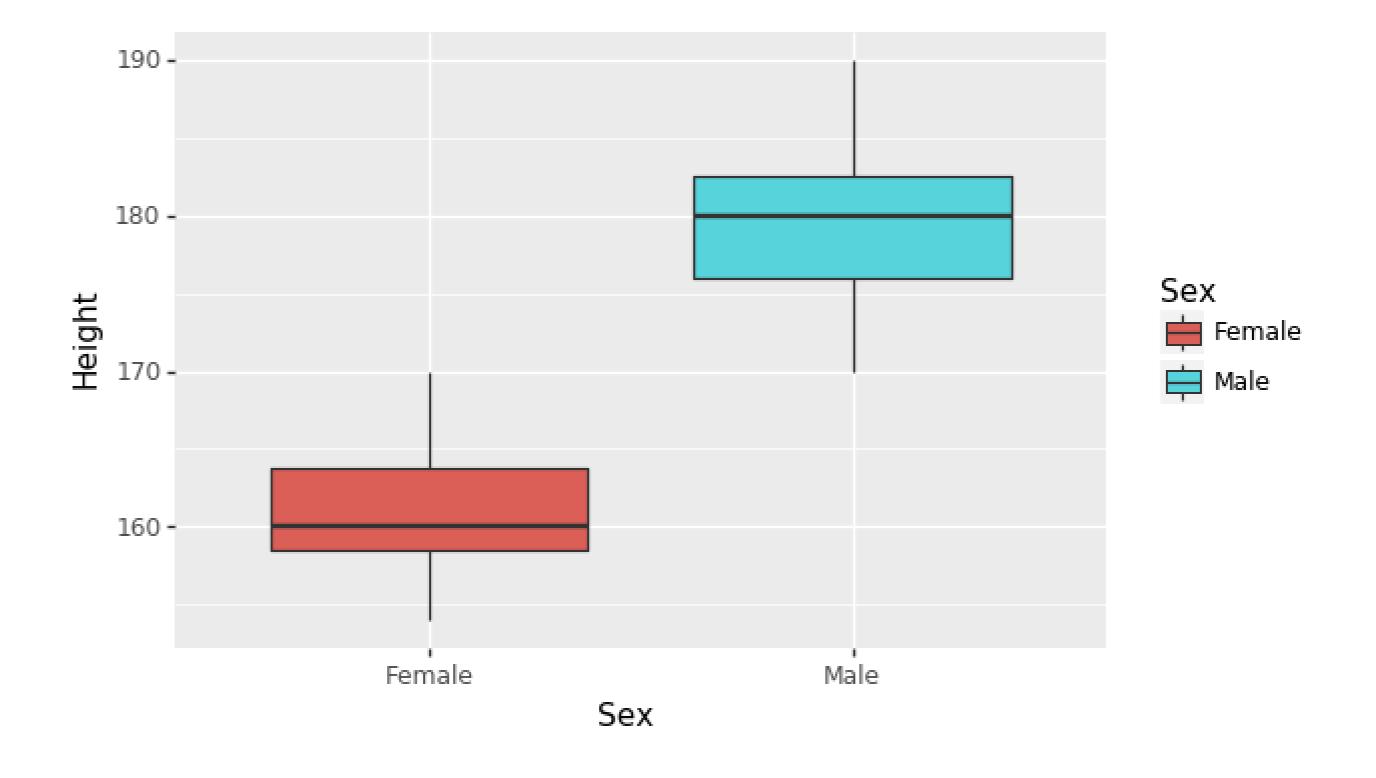
Scatter plot

geom_point()



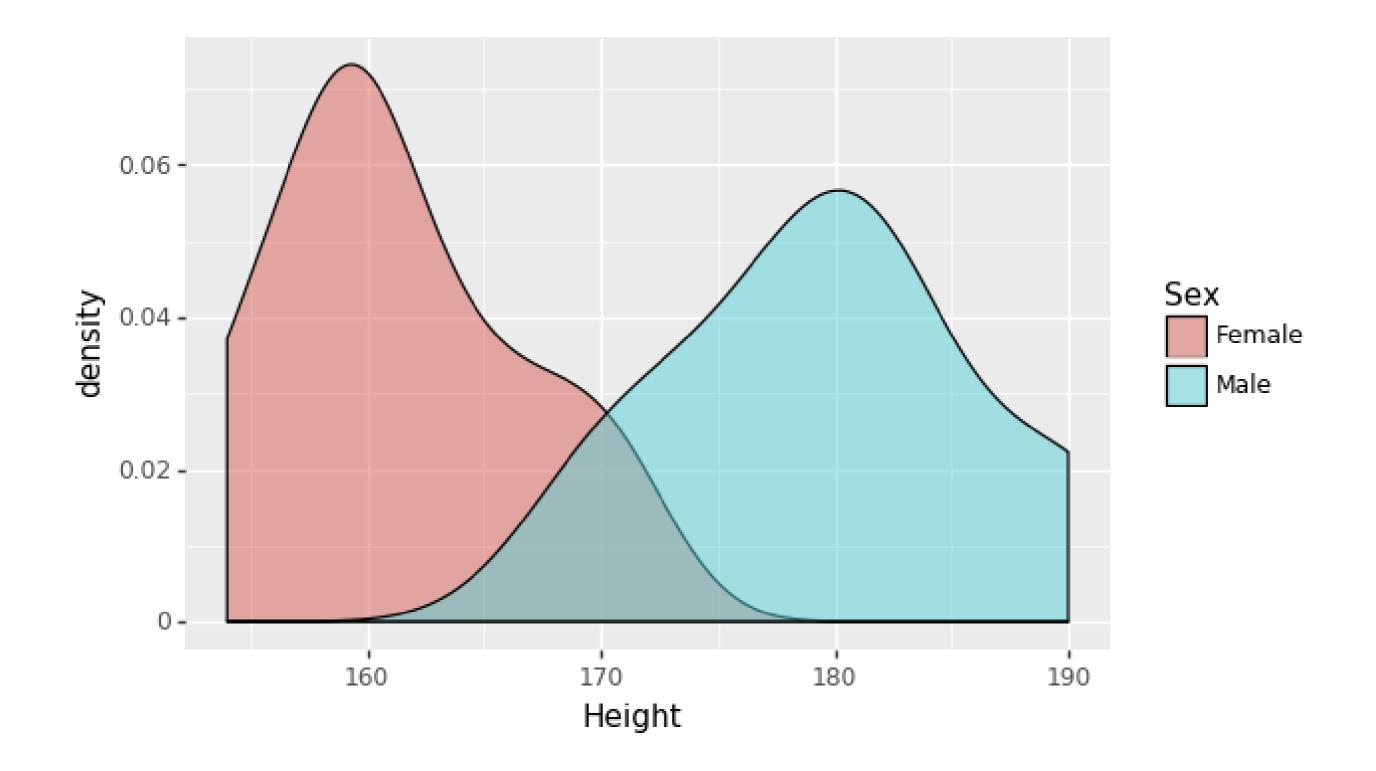
Boxplot

geom_boxplot()



Density plot

geom_density()



Let's practice!

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Our first hypothesis test - Student's t-test

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From observed pattern to reliable result

Data contains patterns

- Some expected
- Others surprising
- Random variation also

Dealing with this

How do we go from observation to result?

Are these groups different?

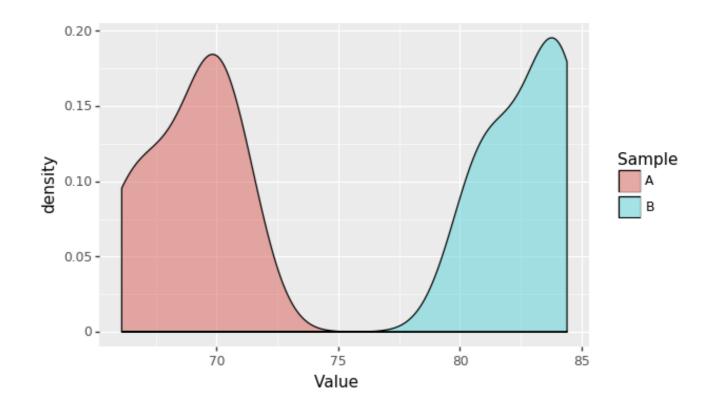
Weights of two groups of adults

Sample A:

Sample B:

```
[83.7,81.5, 80.6, 83.9, 84.4]
```

```
(p9.ggplot(df)+
p9.aes('Value', fill='Sample')+
p9.geom_density(alpha=0.5))
```



Two hypotheses

Null hypothesis

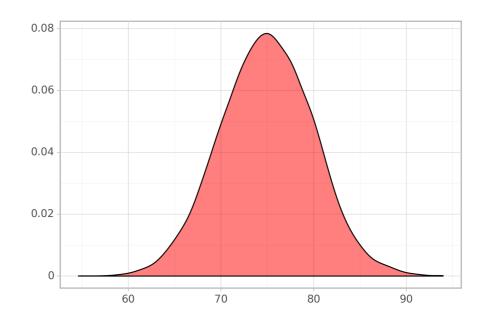
$$A = B$$

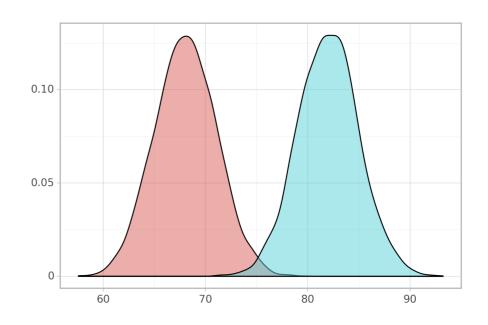
 Observed patterns are the product of random chance

Alternative hypothesis

$$A != B$$

 Difference between samples represents a real difference between the populations





Some statistical terms

p-value

• Likelihood of pattern under null hypothesis

alpha

Crucial threshold of p-value

• Usually alpha < 0.05: reject null hypothesis
below a 5 / Pubchility that random chance would produce
the pattern observed, it's usually size to reject the
null Hypothesis.

Student's t-test

- Invented by William Sealy Gosset
- Two basic types:

One-sample: Mean of population different

from a given value?

Two-sample: Two means equal?

Coding a t-test

```
from scipy import stats
```

```
stats.ttest_ind(Sample_A, Sample_B)
```

Implementing a one-sample t-test

```
from scipy import stats
Sample_A = df[df.Sample == "A"]
t_result = stats.ttest_1sample(Sample_A, 65)
alpha = 0.05
                                 it P < 0.05
if (t_result[1] < alpha):</pre>
    print("mean(A) != 65")
```

```
mean(A) != 65
```



Implementing a two-sample t-test

```
from scipy import stats
Sample_A = df[df.Sample == "A"]
Sample_B = df[df.Sample == "B"]
t_result = stats.ttest_ind(Sample_A, Sample_B)
alpha = 0.05
if (t_result[1] < alpha):</pre>
    print("A and B are different!")
```

A and B are different!



Now let's try it out!

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Testing proportion and correlation

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Hypothesis tests

t-test:

Compare means of continuous variables

Chi-square:

• Examine proportions of discrete categories

Fisher exact test:

• Examine proportions of discrete categories

Pearson test:

Examine if continuous variables are correlated

Chi-square

Test distinguishes between:

Null hypothesis:

- Observed outcomes fit distribution
- coin is not biased

Alternative hypothesis:

- Observed outcomes doesn't fit distribution
- coin is biased

Example

Coin flipped 30 times

Expected: 15 heads, 15 tails

Observed: 24 heads, 6 tails

Expected outcomes significantly different

from expected?

Implementing a simple Chi-square test

```
from scipy import stats

coins = df['Flip'].value_counts()

chi = stats.chisquare(coins)

print(chi)
```

Power_divergenceResult(statistic=10.8, pvalue=0.0010150009471130682)

Fisher exact test

Two-sample version of Chi-square test

Test distinguishes between:

Null hypothesis:

Two samples have same distribution of outcomes

Alternative hypothesis:

Two samples have different distribution of outcomes

Example

Two coins each flipped 30 times

Expected outcomes significantly differ?

Are these two discrete variables related?

Implementing a Fisher exact test

```
from scipy import stats
import pandas as pd
table = pd.crosstab(df.Coin,df.Flip)
print(table)
```

```
Flip heads tails
Coin
1 22 8
2 17 13
```

Implementing a Fisher exact test

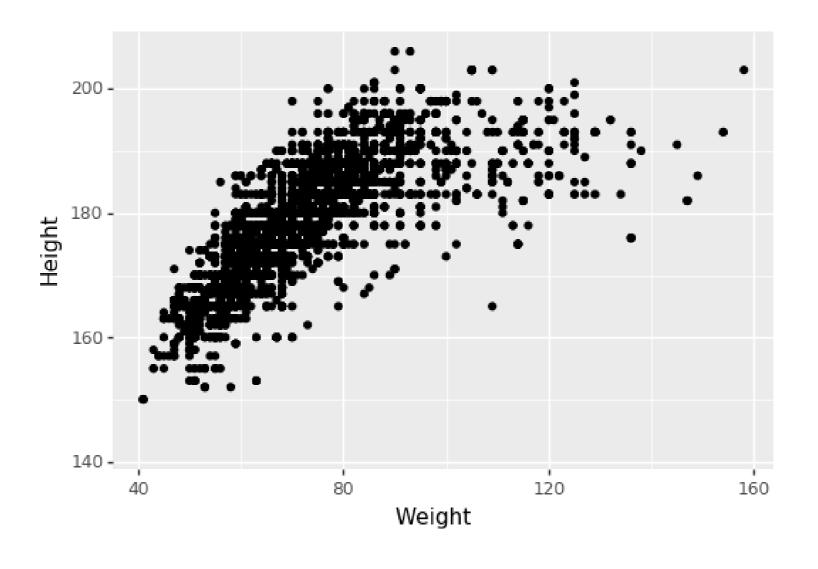
```
chi = stats.fisher_exact(table, alternative='two-sided')
print(chi[1])
```

0.421975381019902



Correlation

```
import plotnine as p9
(p9.ggplot(olyAmericans)+ p9.aes(x='Weight',y='Height')+ p9.geom_point())
```





Pearson test for correlation

```
from scipy import stats
import pandas as pd

pearson = stats.pearsonr(df.Weight, df.Height)

print(pearson)
```

(0.7922545330545416, 0.0)

(Correlation coefficient, p-value)

Let's practice!

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