Week 4: Describing Relationships

Data Analysis for Psychology in R 1

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Course Overview

Exploratory Data Analysis	Research design and data
	Describing categorical data
	Describing continuous data
	Describing relationships
	Functions
Probability	Probability theory
	Probability rules
	Random variables (discrete)
	Random variables (continuous)
	Sampling

Foundations of inference	Confidence intervals
	Hypothesis testing (p-values)
	Hypothesis testing (critical values)
	Hypothesis testing and confidence intervals
	Errors, power, effect size, assumptions
Common hypothesis tests	One sample t-test
	Independent samples t-test
	Paired samples t-test
	Chi-square tests
	Correlation

Week's Learning Objectives

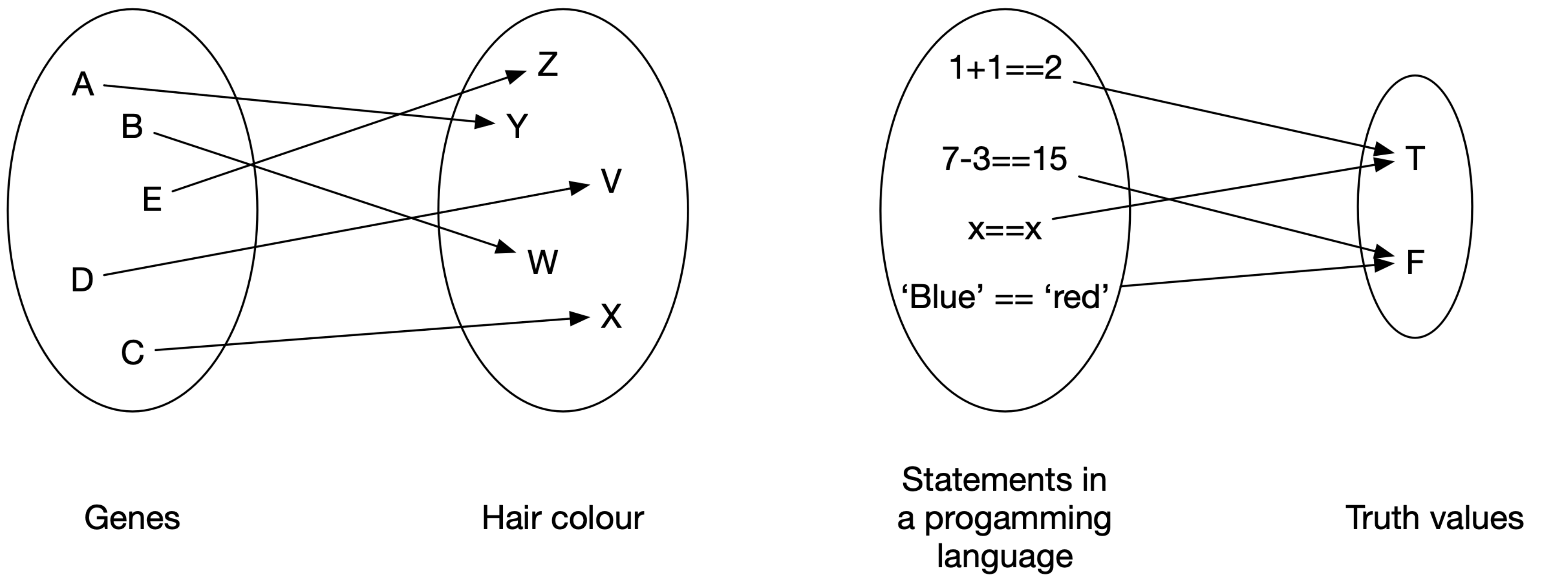
1. Understand the relation between X-Y (explanatory/outcome) specification and practical research questions.
2. Understand how to summarise and visualize categorical-categorical relationships.
3. Understand how to summarise and visualize numeric-categorical relationships.
4. Understand how to summarise and visualize numeric-numeric relationships.

Topics for today

- We have looked at how to describe individual variables.
  - Recall: A variable is a symbol specifying a value that may change or that we don't know yet.
- But we also need to describe the relationships between variables.
- These relationships are also the core of the statistical models we are going to move on to discuss.
- Today we will look at basic descriptions.

What is a relationship?

- A connection between two or more entities.
- In science, a connection between two things (or a relation between two things) is defined as a mapping between the elements of those two things.



- Aside: We will usually prefer to define the relationship using a function (we'll go over what those are next lecture...)

Why are relationships important?

- We typically have theories about relationships or predictions between variables.
- Our study designs distinguish between:
- **Dependent variables**: The thing we want to predict/understand.
  - Also referred to as the outcome.
  - or as y in stats notation
- **Independent variables**: The things we hypothesize influence the DV.
  - Also referred to as the predictor, explanatory variable.
  - or as x in stats notation
- **Covariates**: Things that will influence the outcome, but we may not have a hypothesis about.
  - Also called nuisance variables.
  - We typically try and control nuisance variables either statistically or by design, so as to minimize their effect.
  - These are also x's

Why are relationships important?

- So our questions are built on relationships.

- Before we statistically try to model these, it is important to describe them

    - Note: A model is a representation of a system in formal language.
    - In a model we try to represent the important aspects of a system and ignore anything extraneous.

- Today we will look at how to describe and summarise relationships.

Our data

- Recall our data:
  - `ID` = unique identifier
  - `Degree` = degree studied
  - `Year` = year of study
  - `Score1` = pre-summer school score
  - `Score2` = post-summer school score

ID	Degree	Year	Score1	Score2
ID101	Psych	2	71	74
ID102	Ling	2	65	72
ID103	Ling	2	64	72
ID104	Phil	1	69	74
ID105	Ling	3	62	69
ID106	Ling	1	68	72
ID107	Phil	3	66	75
ID108	Psych	1	64	71
ID109	Psych	3	65	73
ID110	Ling	1	64	72

Categorical-Categorical

- Let's look at the association between `Degree` and `Year`.

- When describing a single categorical variable, we used a frequency table.

- The equivalent for two categorical variables is called a **contingency table**

    - It shows the frequency of one level within levels of the other.
    - In our example, the number of students from each `Degree` in each `Year`

- We can then visualize this table as a **mosaic plot**

Contingency Tables

```
ex1 |>
  select(Degree, Year) |>
  table()
```

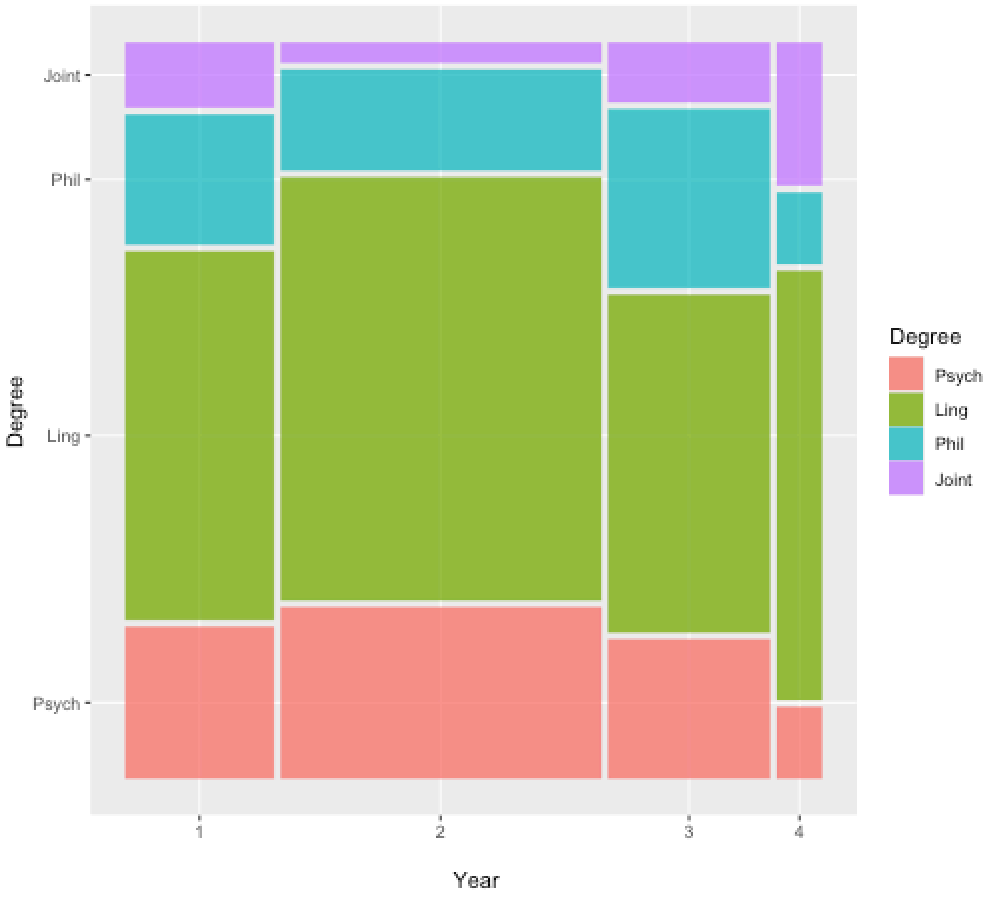
```
##          Year
## Degree    1  2  3  4
##    Psych  7 17  7  1
##    Ling  17 42 17  6
##    Phil   6 10  9  1
##    Joint  3  2  3  2
```

- `ex1` is our data set
- `select` is used to pick variables from the data set
  - `.` is used to indicate that the select function should use the data set passed by the `|>`
  - `Degree` and `Year` are names of variables in our data set
- `table()` produces the frequency table
  - when two variables are given, it produces a contingency table

Mosaic Plot

```
ggplot(data=ex1) +
geom_mosaic(aes(x = product(Degree, Year),
                fill=Degree)) +
labs(x = "\n Year")
```

- `geom_mosaic` is a add-on geom from the `ggmosaic()` library
  - It makes mosaic plots
- `product()` is used to indicate which variables to use.



Categorical-Continuous

- When describing continuous-categorical pairs, we typically look at grouped statistics.
- Specifically,...
    - the mean,
    - standard deviation, and
    - distribution shape
- ...of the continuous variable at each level of the categorical variable.
- In our example, what is the mean pre-test score for students from each degree.

Grouped summary statistics

```
ex1 |>
  group_by(Degree) |>
  summarise(
    Average = round(mean(Score1),2),
    SD = round(sd(Score1),2)
  )
```

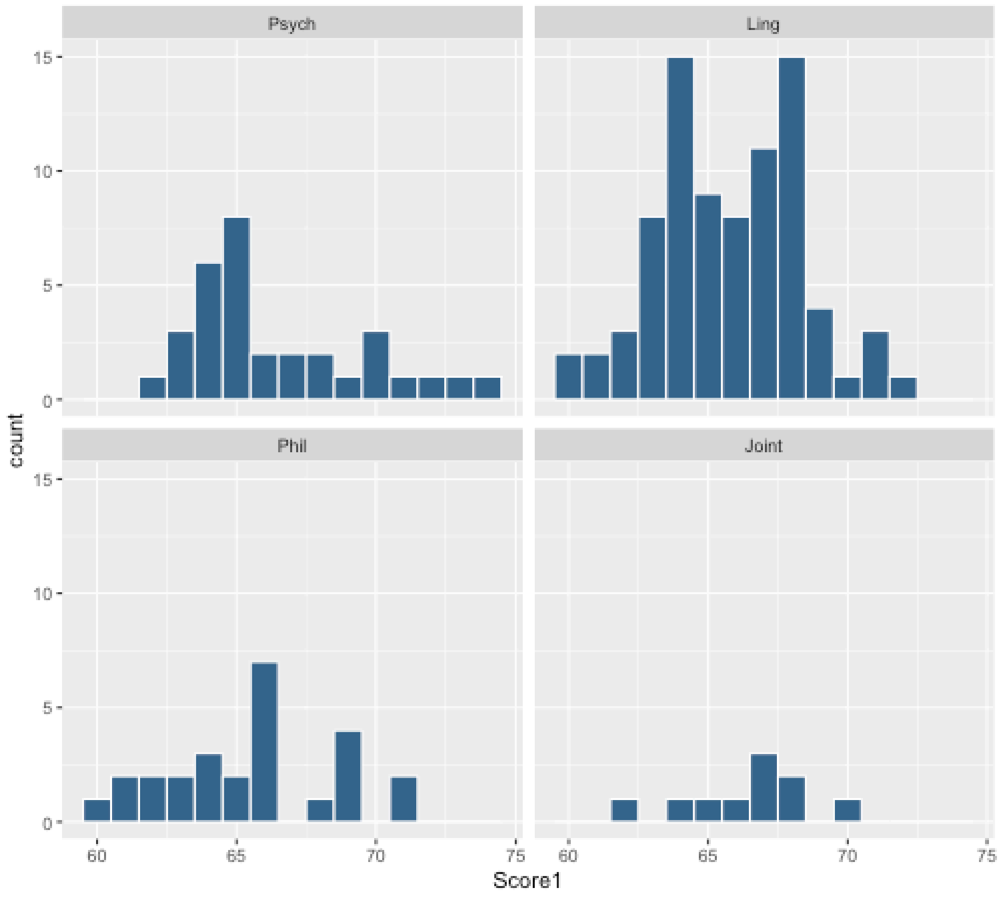
```
## # A tibble: 4 × 3
##   Degree Average    SD
##   <fct>    <dbl> <dbl>
## 1 Psych     66.4  3.16
## 2 Ling      65.8  2.58
## 3 Phil      65.5  3.05
## 4 Joint     66.4  2.27
```

- Key code here is `group_by`
- `group_by` splits the data by the categorical variable stated
    - It then does the next instructions for each level.

Grouped histograms

```
ggplot(data=ex1, aes(x=Score1)) +
geom_histogram(bins = 15,
               color = "white",
               fill = "steelblue4") +
facet_wrap(~Degree)
```

- The top section of code is identical to last week
- `facet_wrap` is used to produce a plot per value of the variable given.
- Notice how different these plots look.
  - But the mean and SD in each group are quite similar.
  - **What differs across the groups?**

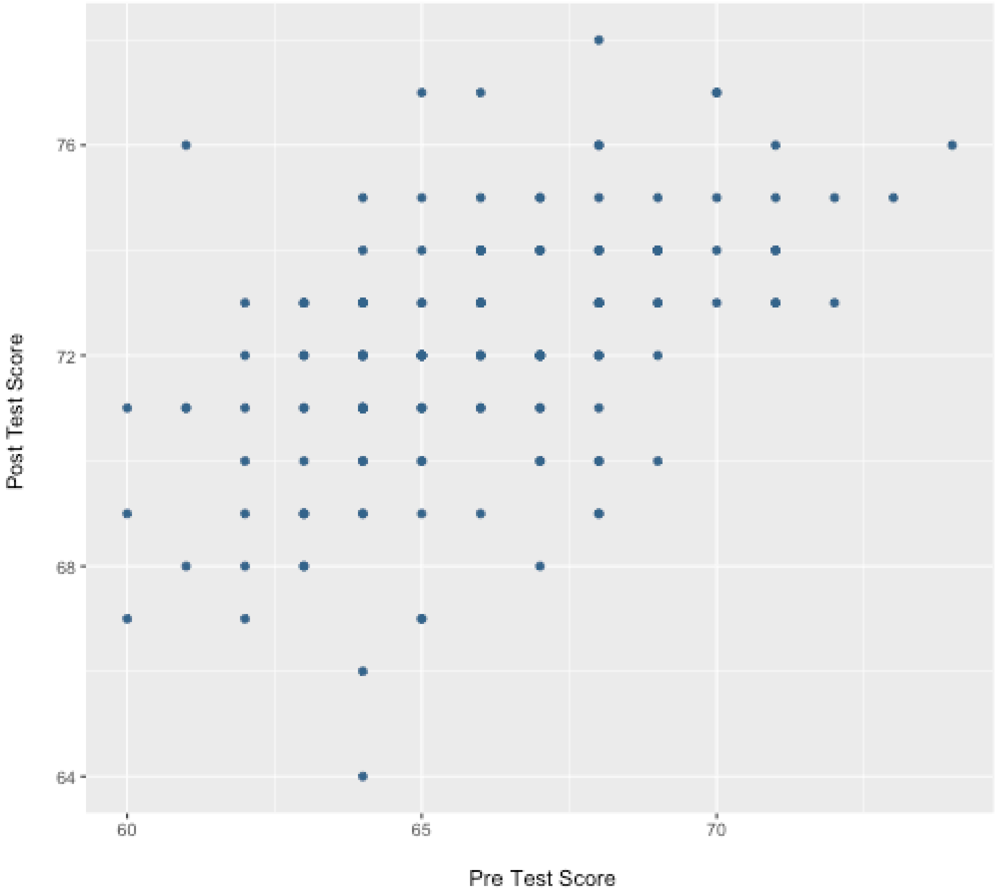


Continuous-Continuous

- When describing two continuous variables (`Score1` and `Score2`), we can not compute summary stats of one at each level of the other.
  - Far too many values!
- So we want a way to visually and numerically summarise the degree of relatedness.
- **Scatterplots**
  - lot points at the (x,y) co-ordinates for two measured variables.
  - We plot these points for each individual in our data set.
    - This produces the clouds of points.

Scatterplot of scores

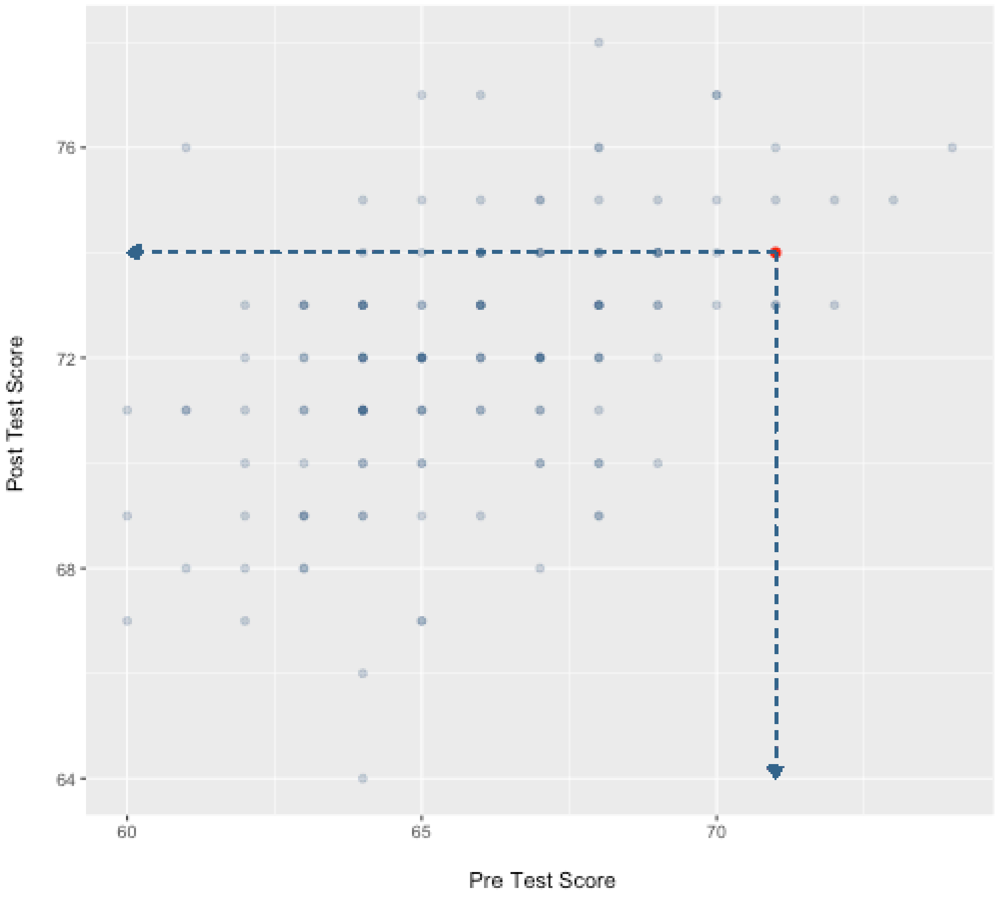
```
ggplot(data=ex1, aes(x=Score1, y=Score2)) +
geom_point(colour = "steelblue4") +
labs(x = "\n Pre Test Score",
     y = "Post Test Score \n")
```



Understanding a scatterplot

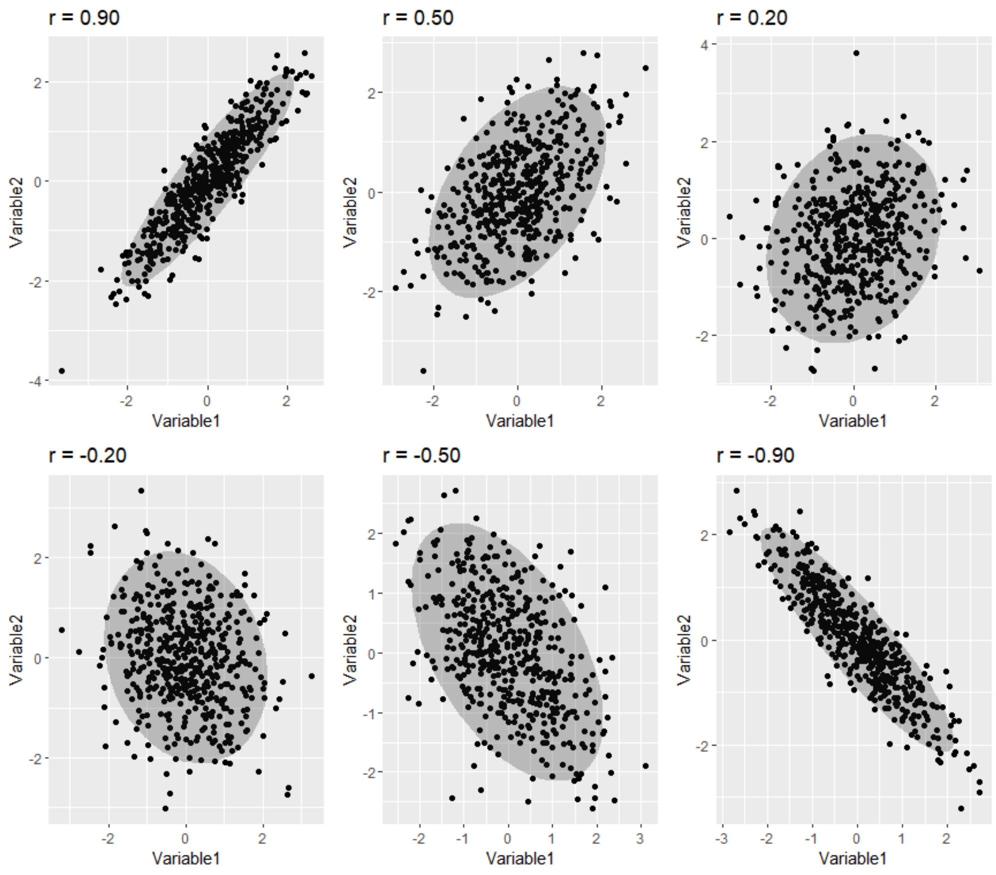
```
ex1 |>
  slice(1) |>
  select(Score1, Score2)
```

```
## # A tibble: 1 × 2
##   Score1 Score2
##    <dbl>  <dbl>
## 1     71     74
```



Understanding a scatterplot

- How do we read a scatterplot?
- If the cloud of points goes:
    - bottom left to top right, there is a positive relationship
    - Top left to bottom right, there is a negative relationship
    - no pattern = no relationship
    - the closer the points are to a straight line, the closer the relationship



Covariance

- **Covariance**
  - Numerical value representing the degree to which variables vary in the same way.
- To understand covariance, it is useful to briefly recap the idea of variance.

$$Var_x = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}$$

- So variance = deviation around the mean of a single variable.

Variance to covariance

- **Co**variance concerns variation in two variables.
- To think about the equation for covariance, suppose we re-write variance as follows:

$$Cov_{xx} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(x_i - \bar{x})}{n-1}$$

- We can then think about covariance of x and y as...

$$Cov_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{n-1}$$

- So our covariance is identical to our variance, with the exception that our summed termed is the combined deviance from the respective means of both x and y.

Calculating Covariance

- For our data:

```
cov(ex1$Score1, ex1$Score2)
```

```
## [1] 3.359732
```

- Interpreting covariance can be tricky.
- The scale is dependent on the scale of the original variables
- What is we multiply `Score1` by 100?

```
cov((ex1$Score1*100), ex1$Score2)
```

```
## [1] 335.9732
```

- Later in the course we will discuss correlation
  - A standardized covariance

Summary of today

- Categorical-categorical
    - Contingency tables
    - Mosaic plots
- Categorical-continuous
    - Grouped summary stats
    - Grouped histograms
- Continuous-Continuous
    - Scatterplots
    - Covariance

This week

Tasks

- Attend both lectures
- Attend your lab and work together on the lab tasks
- Complete the weekly quiz
    - Opens Monday at 9am
    - Closes Sunday at 5pm

Support

- **Office hours**: for one-to-one support on course materials or assessments
  (see LEARN > Course information > Course contacts)
- **Piazza**: help each other on this peer-to-peer discussion forum
- **Student Adviser**: for general support while you are at university
  (find your student adviser on MyEd/Euclid)