Retrieval Practice and Learning

What is the most effective way to learn a subject? Many students focus exclusively on the *encoding* process---that is, how to get the knowledge into memory in the first place. For example, taking notes is an activity for encoding knowledge.

Retrieval, on the other hand, is the process of reconstructing that knowledge from memory. [Karpicke and Blunt (http://science.sciencemag.org/content/331/6018/772)](http://science.sciencemag.org/content/331/6018/772) (2011) demonstrated that *retrieval* is more effective for learning than activites designed to promote effective encoding. They conducted an experiment in which subjects had to learn about sea otters by reading a passage. Subjects were randomly assigned to one of two conditions: some were instructed to create a [concept map (https://en.wikipedia.org/wiki/Concept_map)](https://en.wikipedia.org/wiki/Concept_map) as they read the passage, while others were instructed to practice retrieval (i.e., read the passage, recall as much as they could, read the text again, and recall again). The two main measurements they recorded were:

1. each subject's score on a follow-up learning test one week later
2. each subject's *prediction* of how well they would do on that test

In this lab, you will analyze data from a *replication* of Karpicke and Blunt's experiment, conducted by Buttrick *et al*.

- The data file is : data.csv.
- The codebook (explaining what the variables mean) is : codebook.csv.

In [33]:
```
# READ IN THE DATA SET HERE
%matplotlib inline
import pandas as pd

#df = pd.read_csv("codebook.csv")
df = pd.read_csv("data.csv")
df

#counts = pd.crosstab(df['Condition'], df['TS.1'])
#counts

#table = pd.pivot_table(data = df , values = 'TS.2' , index = df['Conc
#table.loc [ [ 'Concept', 'Retrieval'  ] ]
```

Out[33]:

	ID	Age	Gender	Date.P1	Date.P2	Condition	IC.1	IC.2	Comp.1	Comp.2	...	Score

0	KB1	18	Female	11/21/16	11/28/16	Concept	1	1	1	1	...	I
1	KB2	18	Male	11/21/16	11/28/16	Concept	1	1	1	1	...	I
2	KB3	18	Male	11/21/16	11/28/16	Concept	1	1	1	1	...	I
3	KB4	19	Female	11/21/16	11/28/16	Concept	1	1	1	1	...	I
4	KB5	19	Female	11/22/16	11/29/16	Concept	1	1	1	1	...	I
5	KB6	19	Male	11/22/16	11/29/16	Concept	1	1	1	1	...	I
6	KB7	18	Male	11/22/16	12/6/16	Concept	1	1	1	1	...	I
7	KB8	20	Male	11/22/16	11/29/16	Concept	1	1	1	1	...	I
8	KB9	20	Male	11/22/16	11/28/16	Concept	1	1	1	1	...	I
9	KB10	20	Female	11/29/16	12/6/16	Concept	1	1	1	1	...	I
10	KB11	21	Female	11/21/16	11/28/16	Retrieval	1	1	1	1	...	
11	KB12	18	Female	11/21/16	11/29/16	Retrieval	1	1	1	1	...	
12	KB13	20	Female	11/21/16	11/28/16	Retrieval	1	1	1	1	...	
13	KB14	19	Female	11/21/16	11/28/16	Retrieval	1	1	1	1	...	
14	KB15	18	Female	11/22/16	11/29/16	Retrieval	1	1	1	1	...	
15	KB16	19	Male	11/22/16	11/29/16	Retrieval	1	1	1	1	...	
16	KB18	20	Male	11/22/16	11/29/16	Retrieval	1	1	1	1	...	
17	KB19	21	Female	11/29/16	12/6/16	Retrieval	1	1	1	1	...	
18	KB20	17	Male	11/29/16	12/6/16	Retrieval	1	1	1	1	...	
19	KB21	20	Male	11/29/16	12/6/16	Concept	1	1	1	1	...	I
20	KB22	18	Male	11/29/16	12/6/16	Concept	1	1	1	1	...	I
21	KB23	21	Male	11/29/16	12/6/16	Concept	1	1	1	1	...	I
22	KB24	18	Male	11/29/16	12/6/16	Concept	1	1	1	1	...	I
23	KB25	19	Male	11/29/16	12/6/16	Concept	1	1	1	1	...	I
24	KB26	18	Female	11/29/16	12/6/16	Concept	1	1	1	1	...	I
25	KB27	18	Male	11/29/16	12/6/16	Concept	1	1	1	1	...	I
26	KB28	18	Male	11/29/16	12/2/16	Concept	1	1	1	1	...	I
27	KB29	19	Male	1/23/17	1/31/17	Concept	1	1	1	1	...	I
28	KB30	18	Female	1/23/17	1/31/17	Concept	1	1	1	1	...	I
29	KB31	19	Female	1/23/17	2/1/17	Concept	1	1	1	1	...	I
30	KB32	18	Male	1/23/17	1/31/17	Concept	1	1	1	1	...	I
31	KB33	21	Male	1/24/17	1/31/17	Concept	1	1	1	1	...	I

32	KB34	22	Female	1/24/17	1/31/17	Retrieval	1	1	1	1	...	
33	KB35	19	Male	1/24/17	2/2/17	Retrieval	1	1	1	1	...	
34	KB37	20	Male	1/24/17	1/31/17	Retrieval	1	1	1	1	...	
35	KB38	19	Female	1/24/17	1/31/17	Concept	1	1	1	1	...	l
36	KB39	19	Female	1/25/17	2/1/17	Concept	1	1	1	1	...	l
37	KB40	20	Female	1/25/17	2/2/17	Retrieval	1	1	1	1	...	
38	KB41	19	Female	1/25/17	2/1/17	Retrieval	1	1	1	1	...	
39	KB42	19	Female	1/25/17	2/1/17	Retrieval	1	1	1	1	...	
40	KB43	18	Female	1/25/17	2/1/17	Retrieval	1	1	1	1	...	
41	KB44	20	Male	1/25/17	2/1/17	Concept	1	1	1	1	...	l
42	KB45	19	Female	1/26/17	2/2/17	Retrieval	1	1	1	1	...	

43 rows × 35 columns

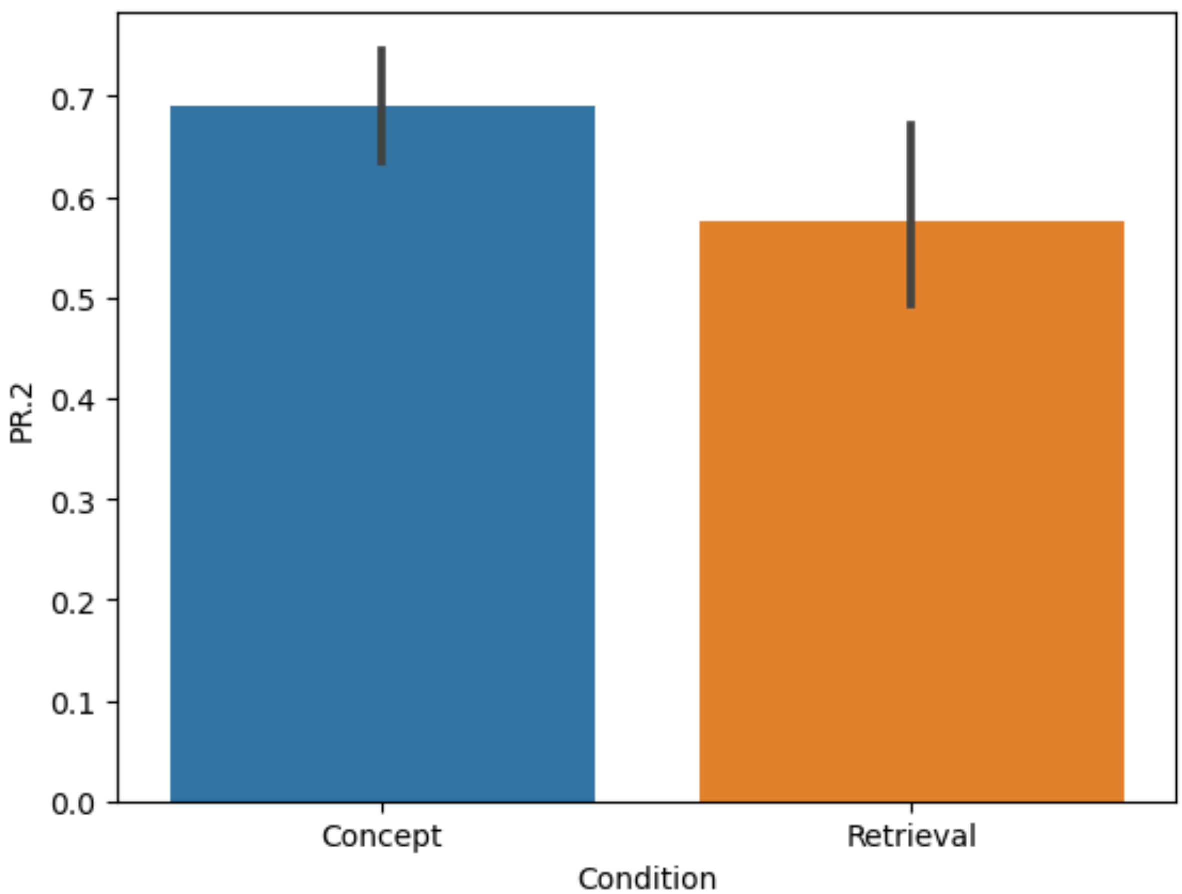
Question 1

Which group felt like they learned more: the subjects who made concept maps or the ones who practiced retrieval? (Or are they about the same?) Make an appropriate visualization and explain what you see.

Hint: Use the variable `PR.2` , which contains the participants' predictions of how well they would do on a test one week later.

In [34]:
```
# YOUR CODE HERE
import seaborn as sns
%matplotlib inline
import pandas as pd

df = pd.read_csv("data.csv")

test = df.pivot_table(
    index= df['Condition'], columns= df['PR.2'],
    values= 'ID',  # We can pretty much count any column, as long as t
    aggfunc="count" # The count function will count the number of non-
)
test

#sns.heatmap(test)
sns.barplot(x='Condition', y='PR.2', data=df)
```

Out[34]: <AxesSubplot:xlabel='Condition', ylabel='PR.2'>



Represented by Heatmap The group who made the concept maps felt they learned because more of the concept group predicted scores that were higher than the scores predicted by the retrieval group. The retrieval group predicted lower scores.

Represented by barplot On average the concept group predicted they would score higher. On average the retrieval group predicted they would score lower.

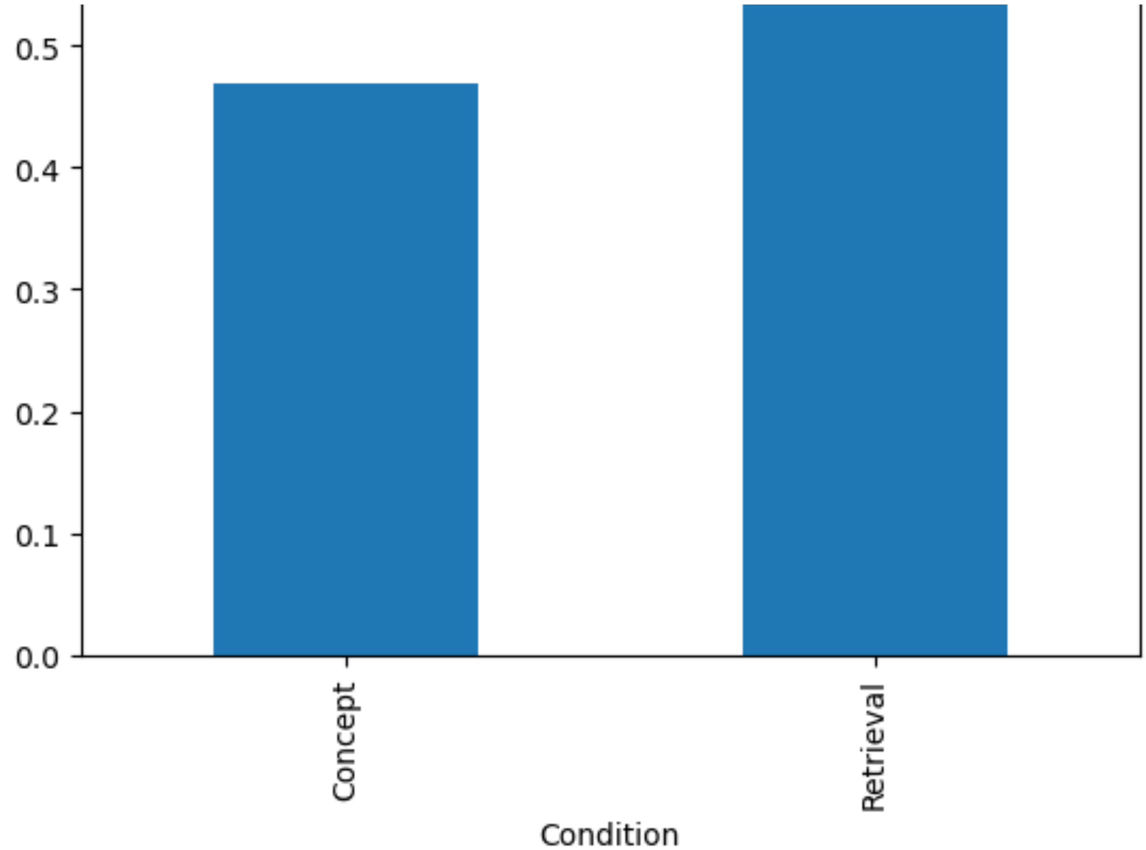
Question 2

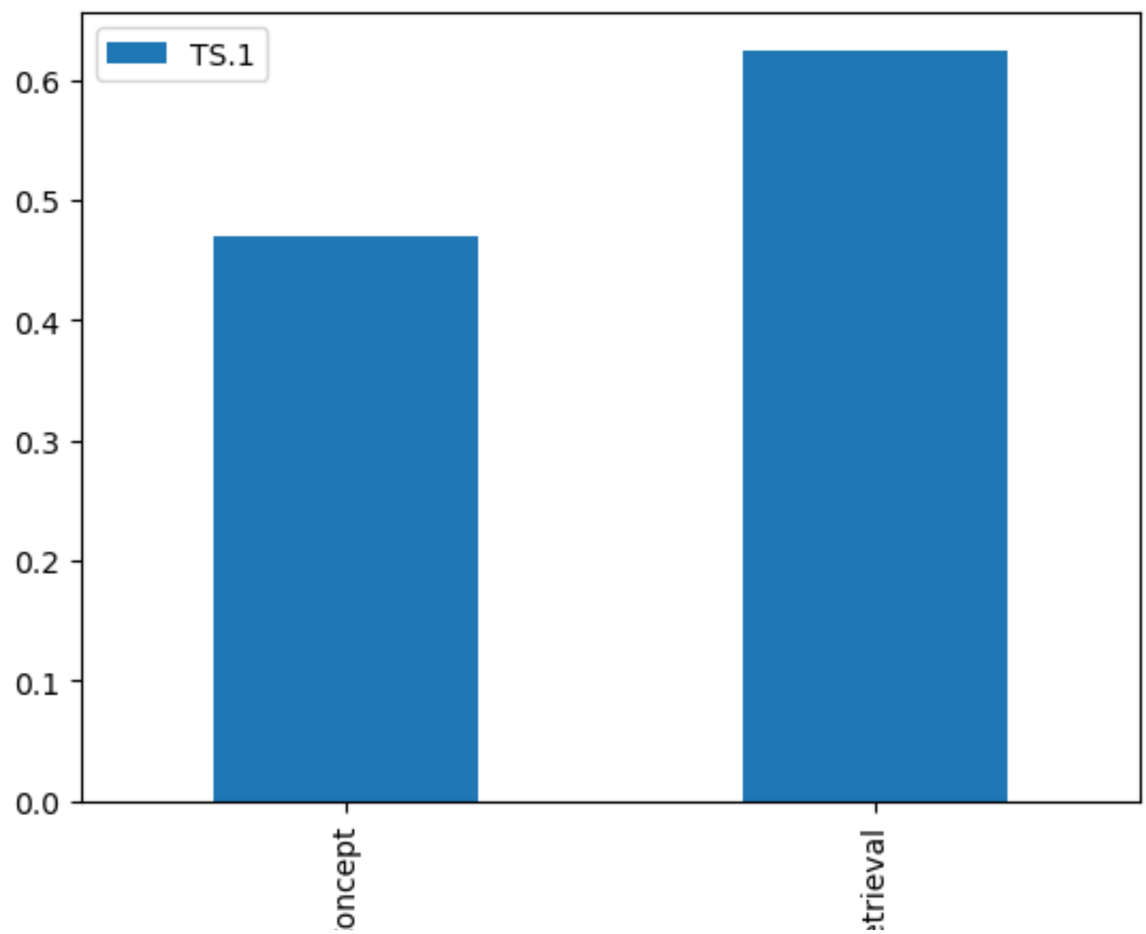
Which group actually did better on the follow-up learning test one week later? Make an appropriate visualization and explain what you see.

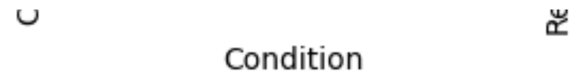
Hint: Don't ask which variable you should use. That is for you to figure out. Read the codebook carefully (consulting the [original paper (http://science.sciencemag.org/content/331/6018/772)](http://science.sciencemag.org/content/331/6018/772), if necessary), make an informed decision, and explain your choice.

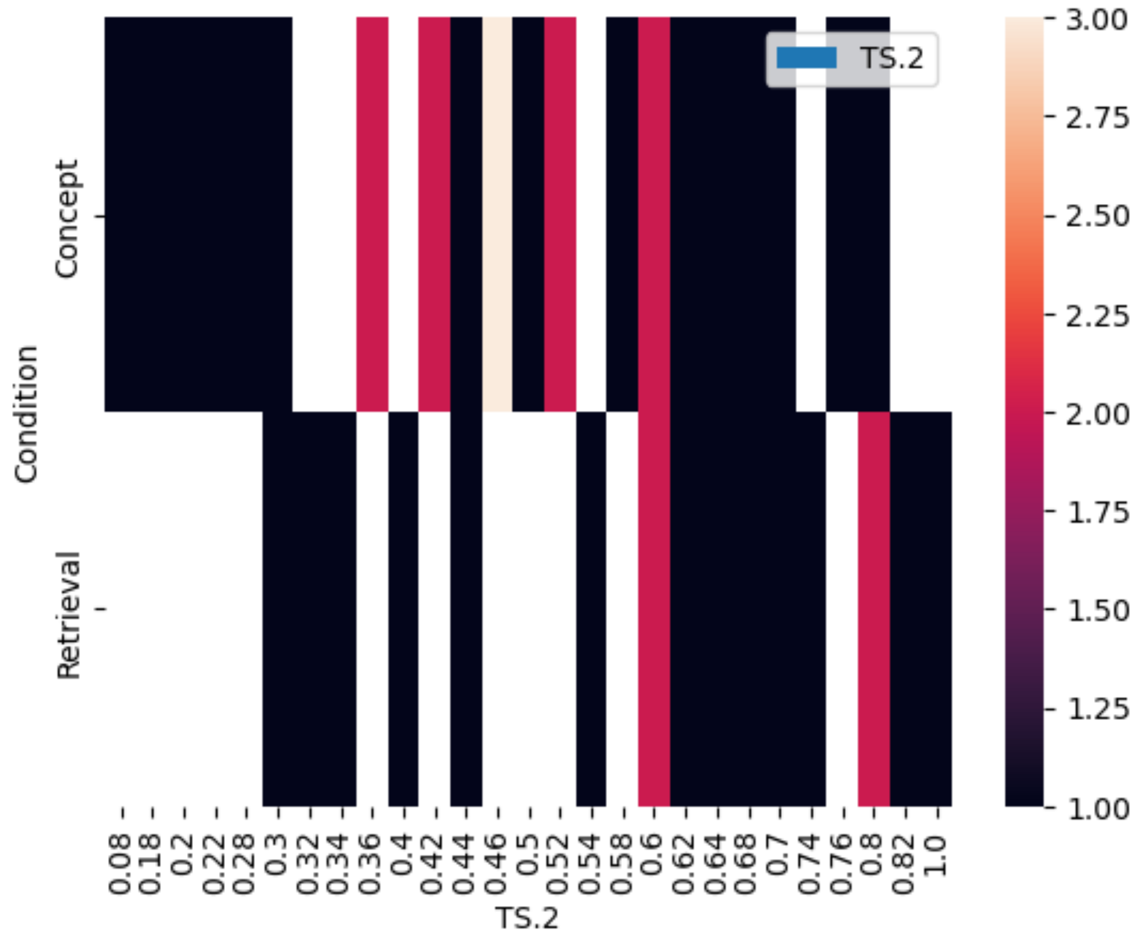
In [11]:
```
# YOUR CODE HERE

test2 = df.pivot_table(
    index= df['Condition'], columns= df['TS.2'],
    values= 'ID',  # We can pretty much count any column, as long as t
    aggfunc="count" # The count function will count the number of non-
)
test

test2
#sns.barplot(data=test2)

table1 = pd.pivot_table(data = df , values = 'TS.avg' , index = df['Co
table1.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )

table2 = pd.pivot_table(data = df , values = 'TS.1' , index = df['Conc
table2.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )

table3 = pd.pivot_table(data = df , values = 'TS.2' , index = df['Conc
table3.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )

sns.heatmap(test2)
```

Out[11]:
```
<AxesSubplot:xlabel='TS.2', ylabel='Condition'>
```


0.5
0.4
0.3
0.2
0.1
0.0
Concept
Retrieval
Condition


TS.1
0.6
0.5
0.4
0.3
0.2
0.1
0.0





After comparing all 3 variables; TS.1, TS.2, and TS.avg, the retrieval group performed better than the concept group on average.

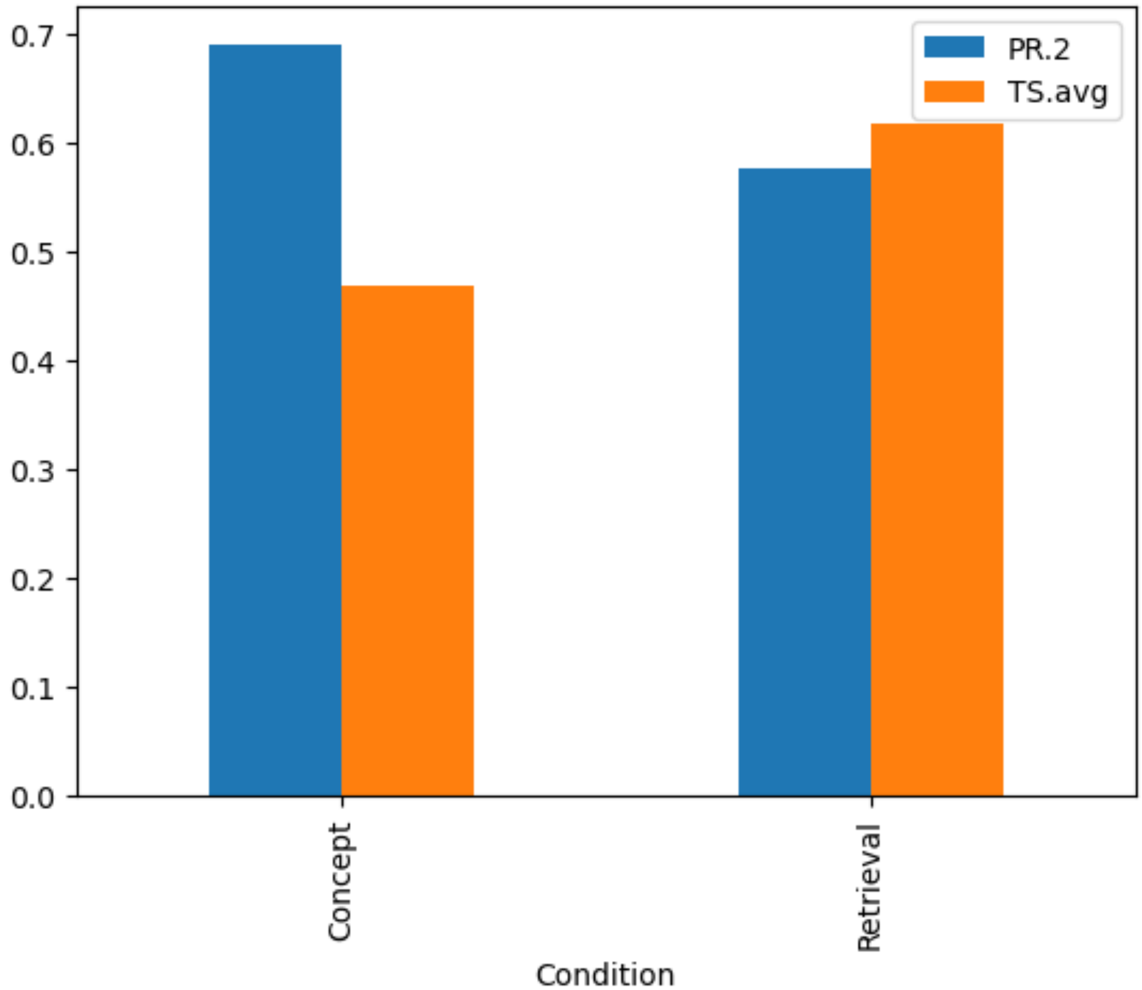
Question 3

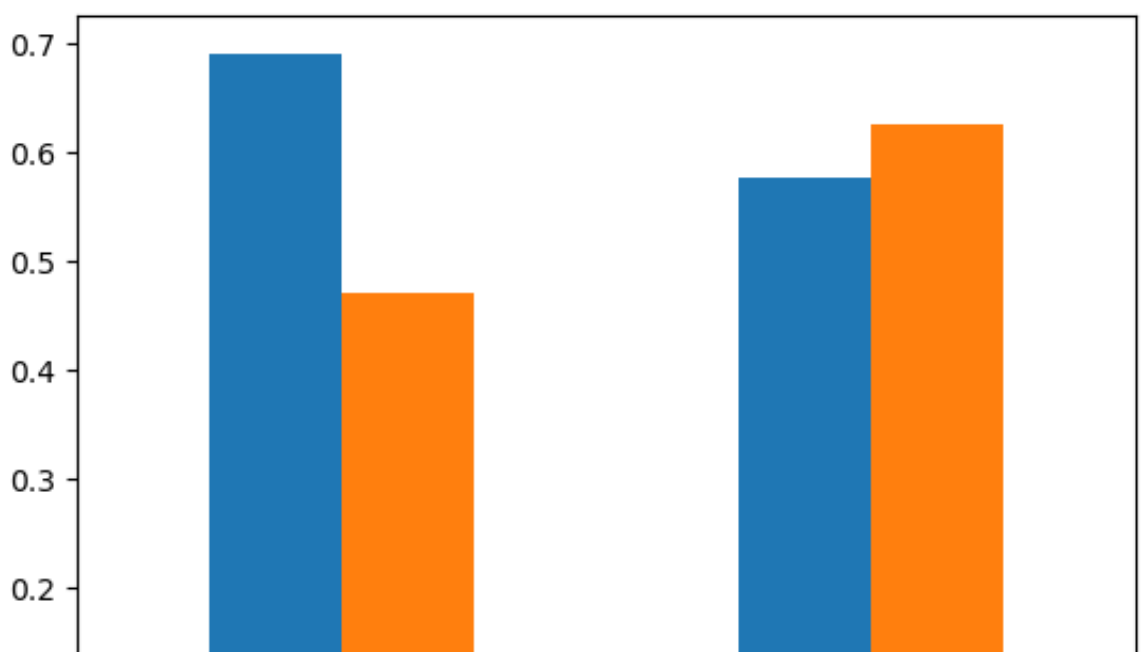
How good were subjects at predicting how well they would do on the follow-up learning test? Calculate a measure of how well subjects predicted their performance and interpret the value in context. (Optionally, you may want to include a visualization as well.)

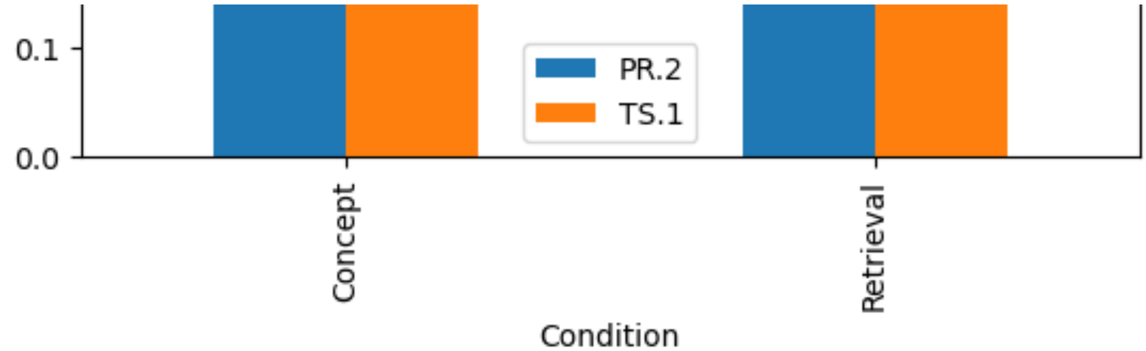
In [129]:
```
table4 = pd.pivot_table(data = df , values = ['TS.avg','PR.2'] , index
table4.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )

table5 = pd.pivot_table(data = df , values = ['TS.1','PR.2'] , index =
table5.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )

table6 = pd.pivot_table(data = df , values = ['TS.2','PR.2'] , index =
```

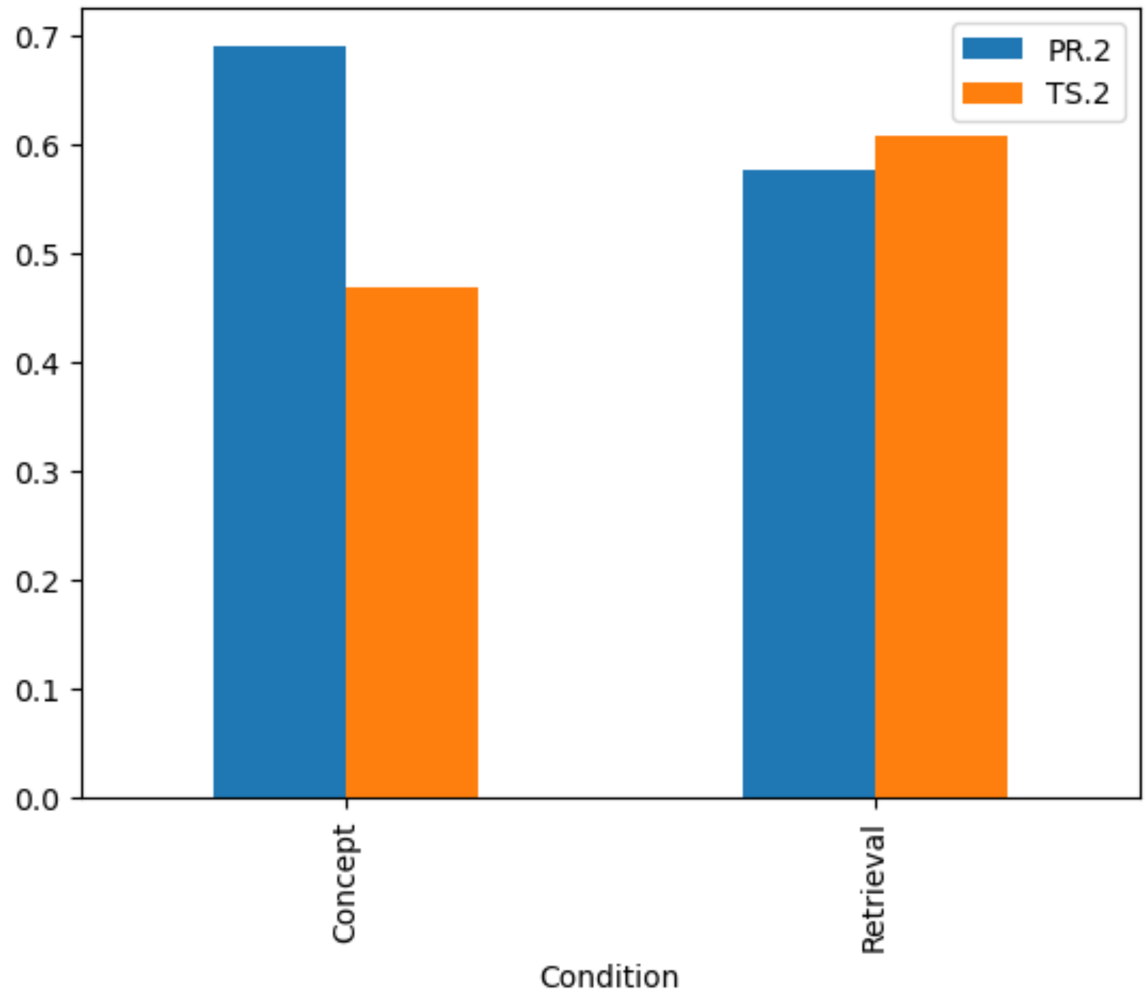
```
table6.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )
```

Out[129]: <AxesSubplot:xlabel='Condition'>









The retrieval group was close to predicting the actual scores they would have received on the test.

The concept group seemed pretty confident and predicted to achieve high scores. However, they ended scoring lower than expected.

Question 4

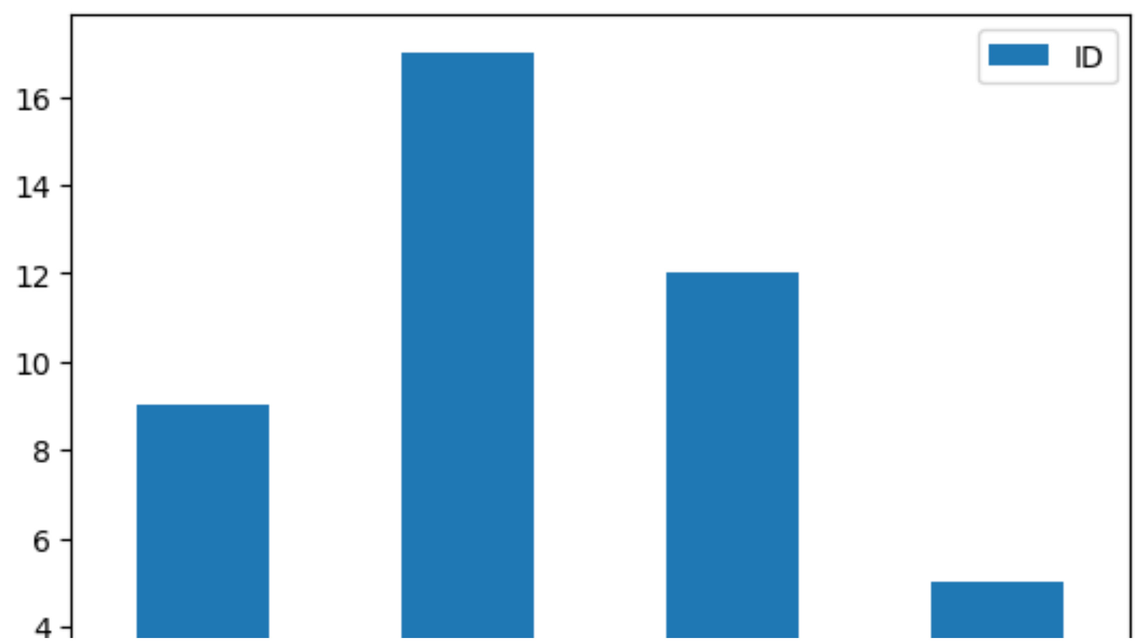
This was a completely randomized experiment. This means that the condition that each subject was assigned to should be independent of their gender, age, and any other subject characteristics. Does that seem to be true in this case? Calculate a summary measure and/or make a visualization, and explain what you see.

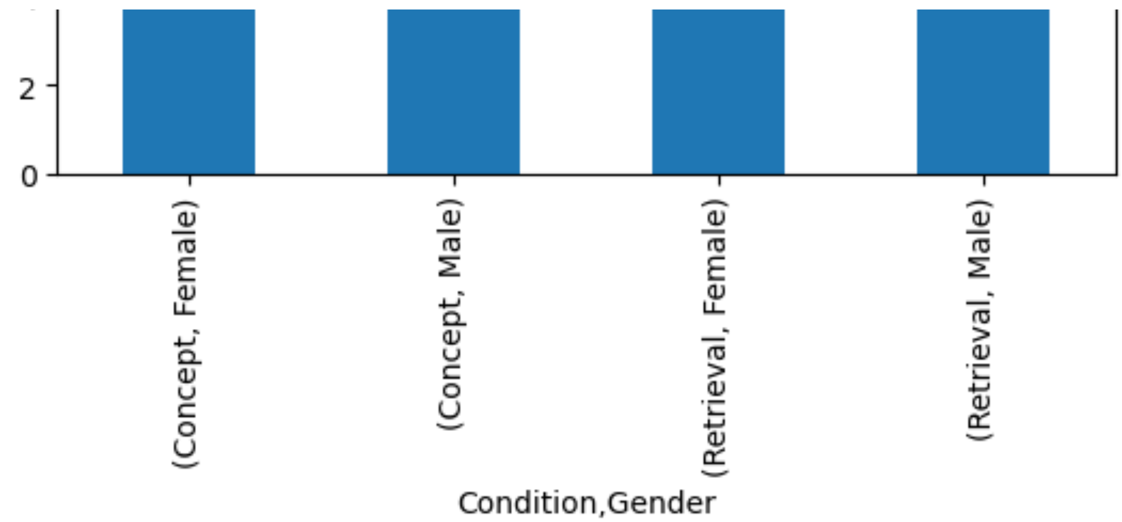
In [168]:

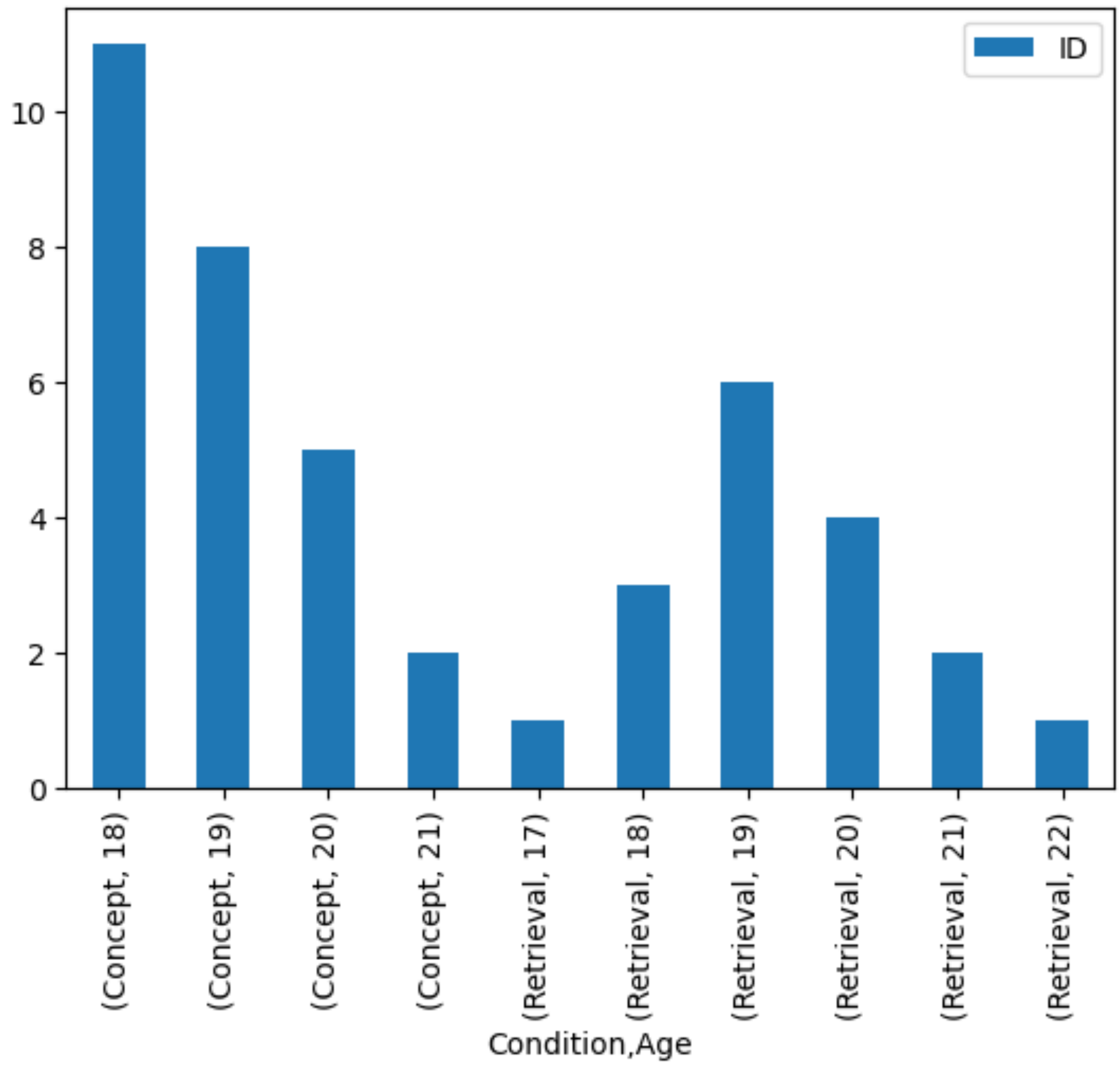
```
# YOUR CODE HERE


table1 = pd.pivot_table(data = df , values = 'ID', index =  [df['Condi
table1.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )

table2 = pd.pivot_table(data = df , values = 'ID', index =  [df['Condi
table2.loc [ [ 'Concept', 'Retrieval'  ] ].plot( kind = 'bar' )

table3 = pd.pivot_table(data = df , values = 'ID' , index = ['Gender',
table3.loc [ [ 'Male', 'Female'  ] ].plot( kind = 'bar' )

pd.crosstab(df['Condition'], df['Gender'])
pd.crosstab(df['Condition'], df['Age'])
```

Out[168]:

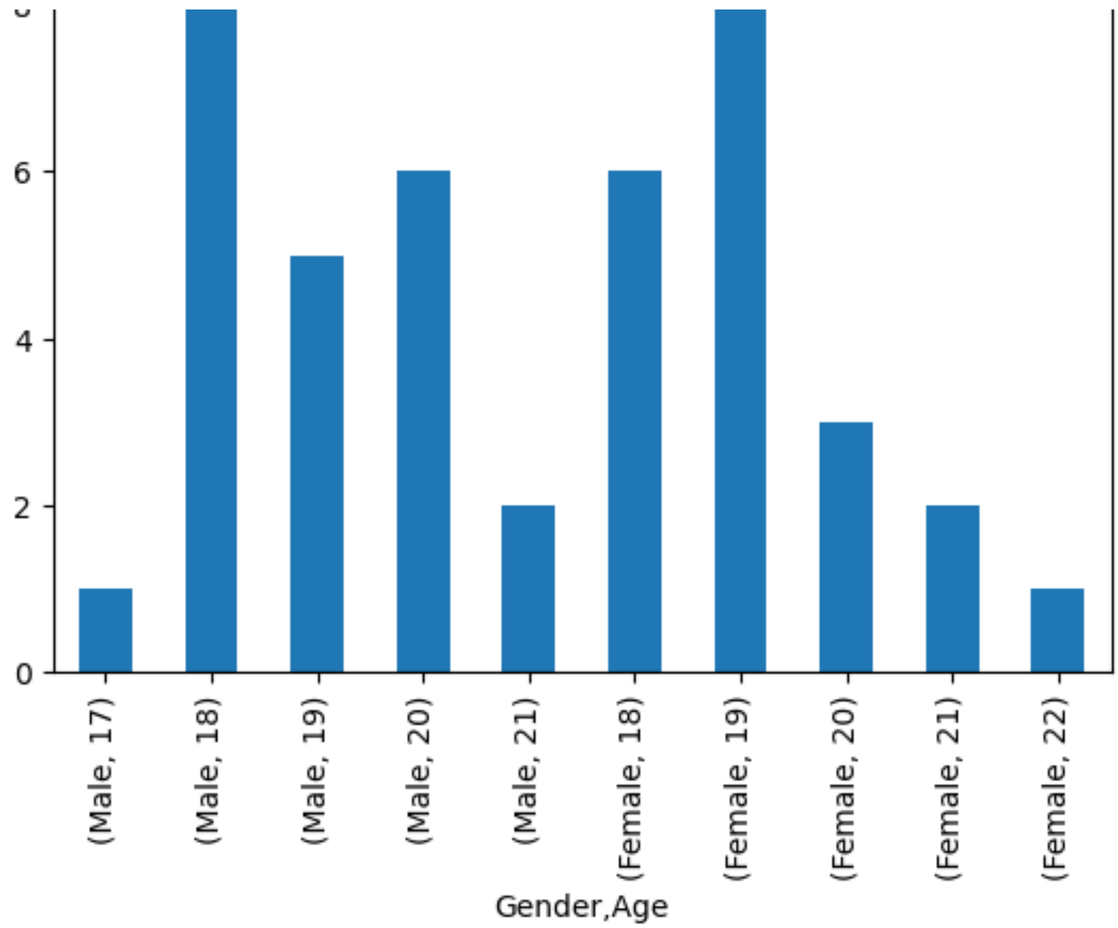
Age	17	18	19	20	21	22
Condition						
Concept	0	11	8	5	2	0
Retrieval	1	3	6	4	2	1




2
0
(Concept, Female)
(Concept, Male)
(Retrieval, Female)
(Retrieval, Male)
Condition,Gender


ID
10
8
6
4
2
0
(Concept, 18)
(Concept, 19)
(Concept, 20)
(Concept, 21)
(Retrieval, 17)
(Retrieval, 18)
(Retrieval, 19)
(Retrieval, 20)
(Retrieval, 21)
(Retrieval, 22)
Condition,Age


ID



Even though this is specified as a randomized experiment, it seems somewhat unfair in terms of how the age groups and gender groups were distributed. Gender and age can could factor in an individual's, otherwise why would they be recored variables.

Age can play a factor in an individual's knowledge and experience. There are outliers in age where is only one 17 year-old and only 1 22 year-old.

Not sure how gender plays a factor in an individual's learning experience, but the distribution of male and female to each learning method is significantly uneven.

Submission Instructions

Once you are finished, follow these steps:

1. Restart the kernel and re-run this notebook from beginning to end by going to `Kernel > Restart Kernel and Run All Cells`.
2. If this process stops halfway through, that means there was an error. Correct the error and repeat Step 1 until the notebook runs from beginning to end.
3. Double check that there is a number next to each code cell and that these numbers are in order.
4. Upload the Notebook (ipynb) to canvas.