DATA_301_Assignment_3_Ishaan_Sathaye_and_Sreshta_Talluri

November 3, 2023

This assignment is in four parts. Read the notebook from the beginning and answer the questions as you go. You can add as many cells as you want. Submission instructions are at the end. See Canvas for general rules about Assignments and collaboration.

0.1 Part 1: The 2000 U.S. Presidential Election

The 2000 presidential election—between Republican George W. Bush, Democrat Al Gore, and other third-party candidates—was one of the closest in American history. The election came down to one state, Florida, which Bush won by just 537 votes (out of nearly 6,000,000 votes cast in the state).

After Election Day, Democrats claimed that the "butterfly ballot" that was used in Palm Beach County confused Gore voters into voting for Reform Party candidate Pat Buchanan. To vote for Gore, who is listed second on the left, a voter actually had to punch the third hole (because the second hole is actually a vote for Buchanan, who is listed first on the right).

In this exercise, you will evaluate this claim. The data file `https://dlsun.github.io/pods/data/florida.csv` contains county-level information about:

- the number of votes for Gore, Bush, Buchanan, and a few other candidates in the 2000 presidential election
- the number of votes for Clinton (Democrat), Dole (Republican), and Perot (Reform) in the 1996 presidential election
- the number of votes for Buchanan in the 1996 primary
- the number of registered Reform voters and the total number of registered voters

Using this data, evaluate the claim that many voters in Palm Beach County voted for Buchanan when they intended to vote for Gore. You should check whether Palm Beach County fits the general pattern of the other counties in Florida, but you need to decide how to measure/visualize the "general pattern". Visualizations will likely be more helpful than summary statistics. Then, craft a story that guides the reader through your discoveries. Your story should contain both figures and explanations.

There are many ways to approach this problem. You don't have to explore every possibility, but you should include at least more than one perspective. That is, you should include several plots/summaries.

Hint: you can add new columns to the data frame. For example, the current columns contain counts, but you might also want to consider proportions. Also, you have the 1996 data for a reason, so you should make some comparisons between 2000 and 1996 (e.g., you might want to compute changes from 1996 to 2000.)

[2]:
```python
# ENTER YOUR CODE HERE. ADD AS MANY CELLS AS YOU WANT.
import pandas as pd
import numpy as np

df_2000 = pd.read_csv('https://dlsun.github.io/pods/data/florida.csv')

df_2000.head()
```

[2]:
```
      county buchanan2000 gore2000 bush2000 nader2000 browne2000 total2000  \
0    ALACHUA          262   47,300   34,062     3,215        658    85,235
1      BAKER           73    2,392    5,610        53         17     8,072
2        BAY          248   18,850   38,637       828        171    58,486
3   BRADFORD           65    3,072    5,413        84         28     8,597
4    BREVARD          570   97,318  115,185     4,470        643   217,616

  clinton96  dole96 perot96 buchanan96p  reform.reg total.reg
0    40,144  25,303   8,072       2,151          91   120,867
1     2,273   3,684     667          73           4    12,352
2    17,020  28,290   5,922       1,816          55    92,749
3     3,356   4,038     819         155           3    13,547
4    80,416  87,980  25,249       7,927         148   283,680
```

[3]:
```python
# remove commas from numbers
df_2000 = df_2000.replace(',','', regex=True)

# convert all columns to numeric except for first column
df_2000.iloc[:,1:] = df_2000.iloc[:,1:].apply(pd.to_numeric)

df_2000.head()
```

[3]:
```
      county buchanan2000 gore2000 bush2000 nader2000 browne2000 total2000  \
0    ALACHUA          262    47300    34062      3215        658     85235
1      BAKER           73     2392     5610        53         17      8072
2        BAY          248    18850    38637       828        171     58486
3   BRADFORD           65     3072     5413        84         28      8597
4    BREVARD          570    97318   115185      4470        643    217616

  clinton96 dole96 perot96 buchanan96p  reform.reg total.reg
0     40144  25303    8072        2151          91    120867
1      2273   3684     667          73           4     12352
2     17020  28290    5922        1816          55     92749
3      3356   4038     819         155           3     13547
4     80416  87980   25249        7927         148    283680
```

[4]:
```python
df_2000['buchanan2000_prop'] = df_2000['buchanan2000'] / df_2000['total2000']
df_2000["gore2000_prop"] = df_2000["gore2000"] / df_2000["total2000"]
df_2000["bush2000_prop"] = df_2000["bush2000"] / df_2000["total2000"]
df_2000["buchanan1996_prop"] = df_2000["buchanan96p"] / df_2000["total.reg"]
df_2000["buchanan change"] = df_2000["buchanan2000_prop"] -
 ↪df_2000["buchanan1996_prop"]
df_2000["buchanan2000_96_prop"] = (df_2000["buchanan2000"] -
 ↪df_2000["buchanan96p"]) / (df_2000["buchanan2000"] + df_2000["buchanan96p"])
df_2000["buchanan_vs_gore"] = df_2000["buchanan2000"] / df_2000["gore2000"]

df_2000.head()
```

[4]:
```
     county  buchanan2000  gore2000  bush2000  nader2000  browne2000  total2000  \
0   ALACHUA           262     47300     34062       3215         658      85235
1     BAKER            73      2392      5610         53          17       8072
2       BAY           248     18850     38637        828         171      58486
3  BRADFORD            65      3072      5413         84          28       8597
4   BREVARD           570     97318    115185       4470         643     217616

  clinton96 dole96 perot96 buchanan96p  reform.reg total.reg  \
0     40144  25303    8072        2151          91    120867
1      2273   3684     667          73           4     12352
2     17020  28290    5922        1816          55     92749
3      3356   4038     819         155           3     13547
4     80416  87980   25249        7927         148    283680

  buchanan2000_prop gore2000_prop bush2000_prop buchanan1996_prop  \
0          0.003074      0.554936      0.399625          0.017796
1          0.009044      0.296333      0.694995           0.00591
2           0.00424      0.322299       0.66062           0.01958
3          0.007561      0.357334      0.629638          0.011442
4          0.002619      0.447201      0.529304          0.027943

  buchanan change buchanan2000_96_prop buchanan_vs_gore
0       -0.014723            -0.782843         0.005539
1        0.003134                  0.0         0.030518
2       -0.015339             -0.75969         0.013156
3       -0.003881            -0.409091         0.021159
4       -0.025324            -0.865835         0.005857
```

[5]:
```python
# see all county names in data in a list
palm_beach = df_2000[df_2000['county'] == 'PALM BEACH']

palm_beach
```

[5]:
```
        county  buchanan2000  gore2000  bush2000  nader2000  browne2000  total2000  \
49  PALM BEACH          3407    268945    152846       5564         743     428098
```

```
   clinton96  dole96 perot96 buchanan96p  reform.reg total.reg
49    230621  133762   30739        8788         337    656694  \

   buchanan2000_prop gore2000_prop bush2000_prop buchanan1996_prop
49          0.007958      0.628232      0.357035          0.013382  \

   buchanan change buchanan2000_96_prop buchanan_vs_gore
49       -0.005424            -0.441246         0.012668
```

[6]:
```python
import plotly.express as px
```

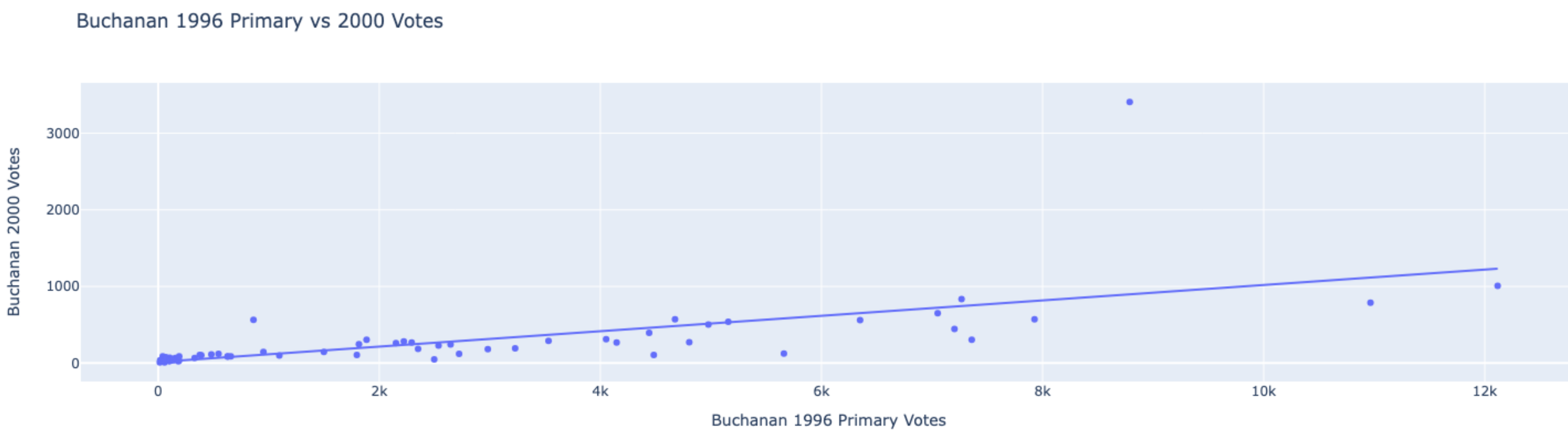
[7]:
```python
fig = px.scatter(df_2000,
                 x="buchanan96p",
                 y="buchanan2000",
                 hover_name="county",
                 labels={
                     "buchanan96p": "Buchanan 1996 Primary Votes",
                     "buchanan2000": "Buchanan 2000 Votes"
                 },
                 title="Buchanan 1996 Primary vs 2000 Votes",
                 # add a trendline
                 trendline="ols")
fig.show()
```

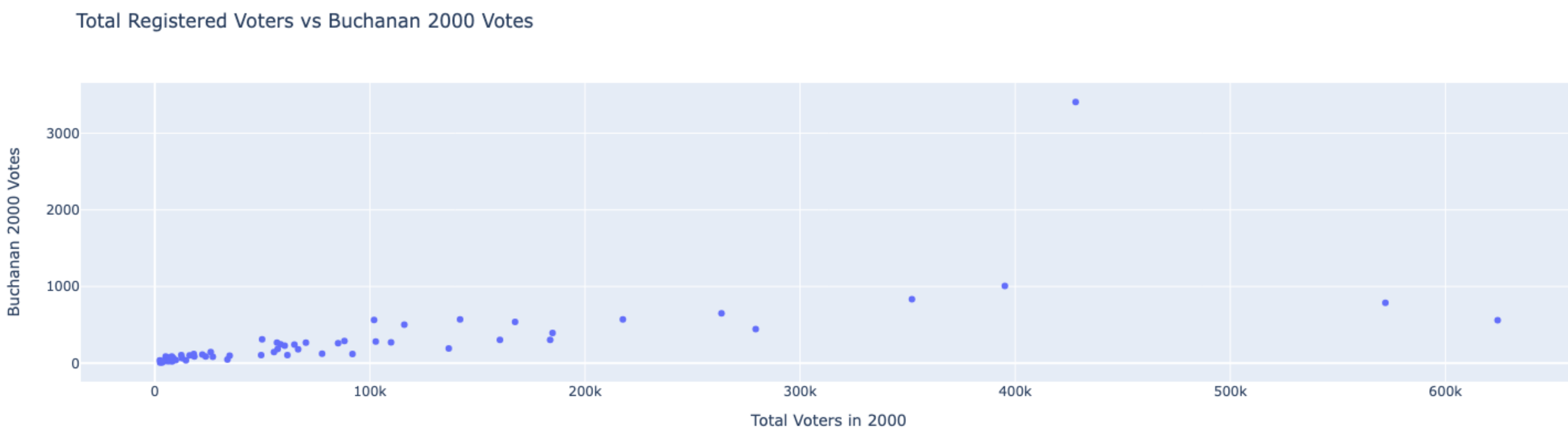
Looking at the graph above, we plotted the graph of votes for Buchanan in the 1996 Primary versus votes for Buchanan in the 2000 election. If we see the general trendline and compare the Palm Beach point, Palm Beach is a major outlier. Many more people voted for Buchanan in the 2000 election compared to the 1996 primary.

[8]:
```python
fig2 = px.scatter(df_2000,
                  x="total2000",
                  y="buchanan2000",
                  hover_name="county",
                  labels={
                      "total2000": "Total Voters in 2000",
                      "buchanan2000": "Buchanan 2000 Votes"
                  },
                  title="Total Registered Voters vs Buchanan 2000 Votes",)

fig2.show()
```

This graph/visualization shows a similar story as the previous graph, however, this graph compares the votes for Buchanan against the total votes in the 2000 election. Looking at this graph, we can see that Palm Beach is an outlier again. The number of people who voted for Buchanan is well above the general trendline for how many votes Buchanan should be getting compared to the total 2000 election votes.


Buchanan 1996 Primary vs 2000 Votes
Buchanan 2000 Votes
Buchanan 1996 Primary Votes
0
1000
2000
3000
0
2k
4k
6k
8k
10k
12k


Total Registered Voters vs Buchanan 2000 Votes
Buchanan 2000 Votes
3000
2000
1000
0
0
100k
200k
300k
400k
500k
600k
Total Voters in 2000

[9]:
```python
fig3 = px.scatter(df_2000,
                  x="total2000",
                  y="gore2000",
                  hover_name="county",
                  labels={
                      "total2000": "Total Voters in 2000",
                      "gore2000": "Gore 2000 Votes"
                  },
                  title="Total Voters in 2000 vs Gore 2000 Votes",
                  trendline="ols")

fig3.show()
```

Previously, we checked the values regarding the votes for Buchanan, however, this visualization compares the votes that Gore got to check if Gore had less votes in Palm Beach. According to the graph, Gore did not have less votes than the general trend for votes. This is interesting because if Buchanan had significantly more votes than the trend, we would expect Gore to have less as they would balance out, however, that is not the case. So, maybe the votes that Buchanan got are not from Gore and someone else instead. Therefore, we can't fully conclude anything and probably have to get more information.

0.2 Part 2: 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 (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 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:

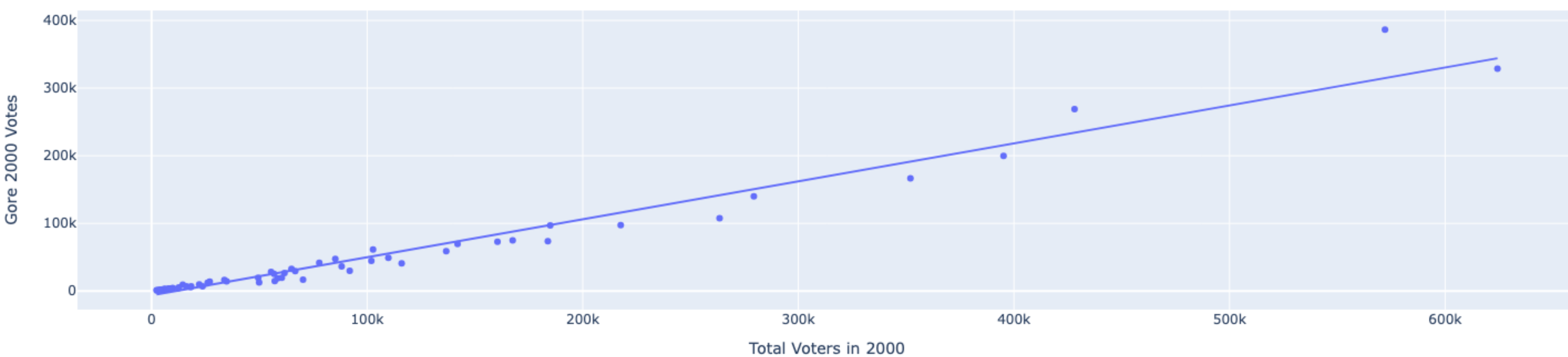
1. each subject's score on a follow-up learning test one week later
2. each subject's *prediction* of how well they would do on that test

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 here: https://dlsun.github.io/pods/data/KarpickeBlunt2011Replication/data.csv. - The codebook (explaining what the variables mean) is here: https://dlsun.github.io/pods/data/KarpickeBlunt2011Replication/codebook.csv.

For all of the following parts, your code should be as short and simple as possible. Use `groupby` whenever possible.

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/summary

Total Voters in 2000 vs Gore 2000 Votes



and describe the results in context.

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

[10]:
```python
# ENTER YOUR CODE HERE. ADD AS MANY CELLS AS YOU WANT.
url = 'https://dlsun.github.io/pods/data/KarpickeBlunt2011Replication/data.csv'
df_learning = pd.read_csv(url)

df_learning.head()
```

[10]:
```
    ID  Age  Gender  Date.P1  Date.P2 Condition  IC.1  IC.2  Comp.1  Comp.2  \
0  KB1   18  Female 11/21/16 11/28/16   Concept     1     1       1       1
1  KB2   18    Male 11/21/16 11/28/16   Concept     1     1       1       1
2  KB3   18    Male 11/21/16 11/28/16   Concept     1     1       1       1
3  KB4   19  Female 11/21/16 11/28/16   Concept     1     1       1       1
4  KB5   19  Female 11/22/16 11/29/16   Concept     1     1       1       1

   … Scorer.2.2 R2CS.avg TS.1 Scorer.1.3 TS.2 Scorer.2.3 TS.avg Exc.1  \
0  …        NaN      NaN 0.36         NK 0.42         MS   0.39     0
1  …        NaN      NaN 0.48         MS 0.36         NK   0.42     0
2  …        NaN      NaN 0.08         NK 0.08         MS   0.08     0
3  …        NaN      NaN 0.44         MS 0.42         NK   0.43     0
4  …        NaN      NaN 0.26         NK 0.28         MS   0.27     0

  Exc.2  Collection
0     0           1
1     0           1
2     0           1
3     0           1
4     0           1

[5 rows x 35 columns]
```

[11]:
```python
df_codebook = pd.read_csv('https://dlsun.github.io/pods/data/
↪KarpickeBlunt2011Replication/codebook.csv')
df_codebook
```

[11]:
```
         Name                    Variable full label
0          ID                         Participant ID  \
1       netID                              UVA netID
2     Date.P1                            Date part 1
3     Date.P2                            Date part 2
4   Condition                     Condition assigned
5        IC.1                    Informed consent 1
6        IC.2                    Informed consent 2
7      Comp.1                        Compensation 1
8      Comp.2                        Compensation 2
```

```
9          PR.1                  Prediction response 1
10         PR.2                  Prediction response 2
11        MCS.1                Map completion score 1
12     Scorer.1                               Scorer 1
13        MCS.2                Map completion score 2
14     Scorer.2                               Scorer 2
15      MCS.avg          Map completion score average
16       R1CS.1       Retrieval #1 completion score 1
17     Scorer.1                               Scorer 1
18       R1CS.2       Retrieval #1 completion score 2
19     Scorer.2                               Scorer 2
20     R1CS.avg  Retrieval #1 average completion score
21       R2CS.1       Retrieval #2 completion score 1
22     Scorer.1                               Scorer 1
23       R2CS.2       Retrieval #2 completion score 2
24     Scorer.2                               Scorer 2
25     R2CS.avg  Retrieval #2 average completion score
26         TS.1                           Test score 1
27     Scorer.1                               Scorer 1
28         TS.2                           Test score 2
29     Scorer.2                               Scorer 2
30       TS.avg                     Test score average
31        Exc.1                     Exclusion part 1
32        Exc.2                     Exclusion part 2
33   Collection                     Collection round

                                  Variable description          Valid range
0            Participant's study number/identifier           KB1 - KB52  \
1                      Student's UVA netID identifier                  NaN
2                              Date of part 1 session             00/00/00
3            Date of part 2 session (1 week later)             00/00/00
4   Participant's assigned study condition (block …  Retrieval OR Concept
5     Informed consent administered for part 1 session                 0-1
6     Informed consent administered for part 2 session                 0-1
7   Compensation (SONA credit) awarded for part 1 …                 0-1
8   Compensation (SONA credit) awarded for part 2 …                 0-1
9                                          Q1 response                 0-1
10                                         Q2 response           0.0 - 1.0
11               Concept map completion single score           0.0 - 1.0
12  First scorer for the concept map completion sc…           AA - ZZ
13                Concept map completion double score           0.0 - 1.0
14  Second scorer for the concept map completion s…           AA - ZZ
15  Average of the first and second scorers' conce…         0.0 - 1.0
16     Retrieval practice #1 completion single score           0.0 - 1.0
17  First scorer for the retrieval practice #1 com…           AA - ZZ
18      Retrieval practice #1 completion double score           0.0 - 1.0
19  Second scorer for the retrieval practice #1 co…           AA - ZZ
```

```
20  Average of the first and second scorers' retri…           0.0 - 1.0
21  Retrieval practice #2 completion single score …          0.0 - 1.0
22  First scorer for the retrieval practice #2 com…             AA - ZZ
23      Retrieval practice #2 completion double score          0.0 - 1.0
24  Second scorer for the retrieval practice #2 co…             AA - ZZ
25  Average of the first and second scorers' retri…           0.0 - 1.0
26               Follow-up learning test single score          0.0 - 1.0
27       First scorer of the follow-up learning test             AA - ZZ
28               Follow-up learning test double score          0.0 - 1.0
29       Second scorer of the follow-up learning test            AA - ZZ
30  Average of the first and second scorers' test …           0.0 - 1.0
31                      Exclusions for part 1 session                0-1
32                      Exclusions for part 2 session                0-1
33  Round of SSRP collection (1st round (90% confi…                  1-2

                                              Scoring
0                                                 NaN  \
1                                                 NaN
2                                                 NaN
3                                                 NaN
4                                                 NaN
5                                                 NaN
6                                                 NaN
7                                                 NaN
8                                                 NaN
9                         (responses: 1 = yes, 0 = no)
10                                                NaN
11  (score = number of idea units mapped divided b…
12                                                NaN
13  (score = number of idea units mapped divided b…
14                                                NaN
15                         (score = (MCS.1 + MCS.2)/2)
16  (score = number of idea units listed divided b…
17                                                NaN
18  (score = number of idea units listed divided b…
19                                                NaN
20                       (score = (R1CS.1 + R1CS.2)/2)
21  (score = number of idea units listed divided b…
22                                                NaN
23  (score = number of idea units listed divided b…
24                                                NaN
25                       (score = (R2CS.1 + R2CS.2)/2)
26  (score = number of earned points/25 possible p…
27                                                NaN
28  (score = number of earned points/25 possible p…
29                                                NaN
30                           (score = (TS.1 + TS.2)/2)
```

```
31                  1 = exclusion, 0 = no exclusion
32                  1 = exclusion, 0 = no exclusion
33                                              NaN

    Value indicating missing data  Value indicating inapplicable data  \
0                               0                                 NaN
1                               0                                 NaN
2                               0                                 NaN
3                               0                                 NaN
4                               0                                 NaN
5                               0                                 NaN
6                               0                                 NaN
7                               0                                 NaN
8                               0                                 NaN
9                               0                                 NaN
10                              0                                 NaN
11                              0                                 NaN
12                              0                                 NaN
13                              0                                 NaN
14                              0                                 NaN
15                              0                                 NaN
16                              0                                 NaN
17                              0                                 NaN
18                              0                                 NaN
19                              0                                 NaN
20                              0                                 NaN
21                              0                                 NaN
22                              0                                 NaN
23                              0                                 NaN
24                              0                                 NaN
25                              0                                 NaN
26                              0                                 NaN
27                              0                                 NaN
28                              0                                 NaN
29                              0                                 NaN
30                              0                                 NaN
31                              0                                 NaN
32                              0                                 NaN
33                              0                                 NaN

                               Experiment file used
0                                               NaN
1                                               NaN
2                                               NaN
3                                               NaN
4                                               NaN
5   "Karpicke & Blunt (2011) - informed consent (c…
```

```
6   "Karpicke & Blunt (2011) - informed consent (c…
7                                  0.5 SONA credit
8                                  0.5 SONA credit
9   "Karpicke & Blunt (2011) - Prediction question…
10  "Karpicke & Blunt (2011) - Prediction question…
11  "Karpicke & Blunt (2011) - Concept map templat…
12  "Karpicke & Blunt (2011) - Original idea units…
13  "Karpicke & Blunt (2011) - Concept map templat…
14  "Karpicke & Blunt (2011) - Original idea units…
15                                             NaN
16  "Karpicke & Blunt (2011) - Retrieval practice …
17  "Karpicke & Blunt (2011) - Original idea units…
18  "Karpicke & Blunt (2011) - Retrieval practice …
19  "Karpicke & Blunt (2011) - Original idea units…
20                                             NaN
21  "Karpicke & Blunt (2011) - Retrieval practice …
22  "Karpicke & Blunt (2011) - Original idea units…
23  "Karpicke & Blunt (2011) - Retrieval practice …
24  "Karpicke & Blunt (2011) - Original idea units…
25                                             NaN
26  "Karpicke & Blunt (2011) - Original learning t…
27  "Karpicke & Blunt (2011) - Original learning t…
28  "Karpicke & Blunt (2011) - Original learning t…
29  "Karpicke & Blunt (2011) - Original learning t…
30                                             NaN
31                                             NaN
32                                             NaN
33                                             NaN
```

[12]:
```
df_codebook = df_codebook[['Name', 'Variable full label', 'Variable description', 'Valid range', 'Scoring']]
df_codebook
```

[12]:
```
         Name                     Variable full label
0          ID                          Participant ID  \
1       netID                               UVA netID
2     Date.P1                             Date part 1
3     Date.P2                             Date part 2
4   Condition                      Condition assigned
5        IC.1                      Informed consent 1
6        IC.2                      Informed consent 2
7      Comp.1                          Compensation 1
8      Comp.2                          Compensation 2
9        PR.1                   Prediction response 1
10       PR.2                   Prediction response 2
11      MCS.1                   Map completion score 1
12   Scorer.1                                Scorer 1
```

```
13       MCS.2                Map completion score 2
14    Scorer.2                              Scorer 2
15     MCS.avg          Map completion score average
16      R1CS.1       Retrieval #1 completion score 1
17    Scorer.1                              Scorer 1
18      R1CS.2       Retrieval #1 completion score 2
19    Scorer.2                              Scorer 2
20    R1CS.avg  Retrieval #1 average completion score
21      R2CS.1       Retrieval #2 completion score 1
22    Scorer.1                              Scorer 1
23      R2CS.2       Retrieval #2 completion score 2
24    Scorer.2                              Scorer 2
25    R2CS.avg  Retrieval #2 average completion score
26        TS.1                          Test score 1
27    Scorer.1                              Scorer 1
28        TS.2                          Test score 2
29    Scorer.2                              Scorer 2
30      TS.avg                    Test score average
31       Exc.1                    Exclusion part 1
32       Exc.2                    Exclusion part 2
33  Collection                    Collection round

                                Variable description          Valid range
0             Participant's study number/identifier           KB1 - KB52  \
1                    Student's UVA netID identifier                  NaN
2                            Date of part 1 session             00/00/00
3             Date of part 2 session (1 week later)             00/00/00
4   Participant's assigned study condition (block …  Retrieval OR Concept
5    Informed consent administered for part 1 session                 0-1
6    Informed consent administered for part 2 session                 0-1
7   Compensation (SONA credit) awarded for part 1 …                  0-1
8   Compensation (SONA credit) awarded for part 2 …                  0-1
9                                       Q1 response                  0-1
10                                      Q2 response            0.0 - 1.0
11               Concept map completion single score           0.0 - 1.0
12  First scorer for the concept map completion sc…            AA - ZZ
13                Concept map completion double score           0.0 - 1.0
14  Second scorer for the concept map completion s…            AA - ZZ
15  Average of the first and second scorers' conce…          0.0 - 1.0
16     Retrieval practice #1 completion single score            0.0 - 1.0
17  First scorer for the retrieval practice #1 com…            AA - ZZ
18      Retrieval practice #1 completion double score           0.0 - 1.0
19  Second scorer for the retrieval practice #1 co…            AA - ZZ
20  Average of the first and second scorers' retri…          0.0 - 1.0
21  Retrieval practice #2 completion single score …         0.0 - 1.0
22  First scorer for the retrieval practice #2 com…            AA - ZZ
23      Retrieval practice #2 completion double score           0.0 - 1.0
```

24	Second scorer for the retrieval practice #2 co…	AA - ZZ
25	Average of the first and second scorers' retri…	0.0 - 1.0
26	Follow-up learning test single score	0.0 - 1.0
27	First scorer of the follow-up learning test	AA - ZZ
28	Follow-up learning test double score	0.0 - 1.0
29	Second scorer of the follow-up learning test	AA - ZZ
30	Average of the first and second scorers' test …	0.0 - 1.0
31	Exclusions for part 1 session	0-1
32	Exclusions for part 2 session	0-1
33	Round of SSRP collection (1st round (90% confi…	1-2

	Scoring
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	NaN
8	NaN
9	(responses: 1 = yes, 0 = no)
10	NaN
11	(score = number of idea units mapped divided b…
12	NaN
13	(score = number of idea units mapped divided b…
14	NaN
15	(score = (MCS.1 + MCS.2)/2)
16	(score = number of idea units listed divided b…
17	NaN
18	(score = number of idea units listed divided b…
19	NaN
20	(score = (R1CS.1 + R1CS.2)/2)
21	(score = number of idea units listed divided b…
22	NaN
23	(score = number of idea units listed divided b…
24	NaN
25	(score = (R2CS.1 + R2CS.2)/2)
26	(score = number of earned points/25 possible p…
27	NaN
28	(score = number of earned points/25 possible p…
29	NaN
30	(score = (TS.1 + TS.2)/2)
31	1 = exclusion, 0 = no exclusion
32	1 = exclusion, 0 = no exclusion
33	NaN

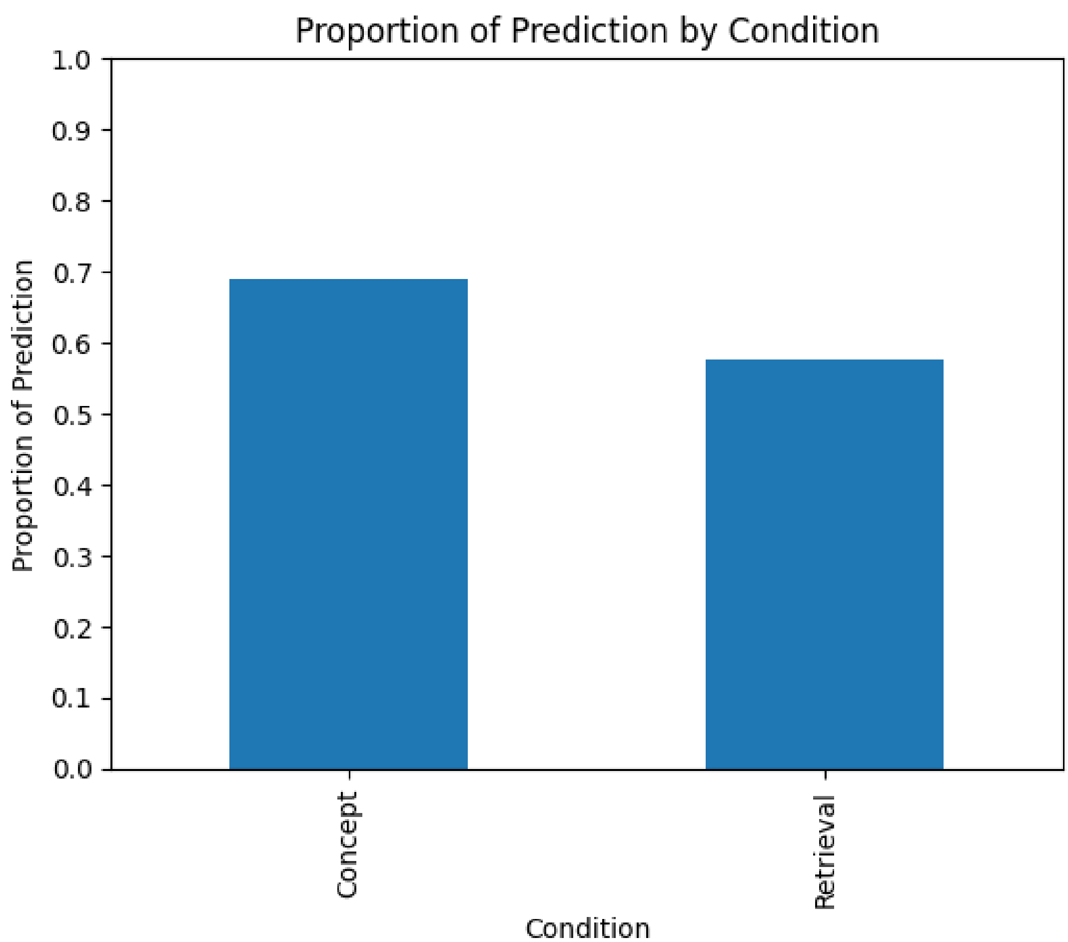
[13]:
```
p1 = df_learning.groupby('Condition')['PR.2'].mean().reset_index()
p1
```

[13]:

	Condition	PR.2
0	Concept	0.690385
1	Retrieval	0.576471

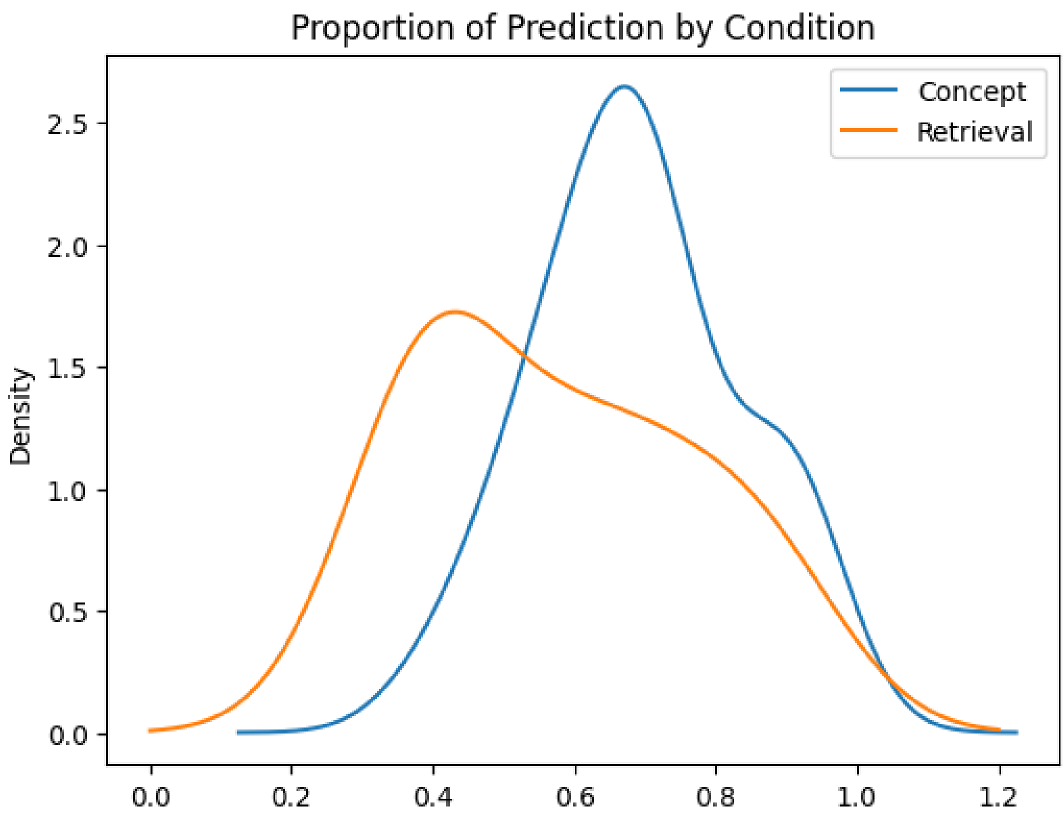
[14]:
```
p1.plot.bar(
    title='Proportion of Prediction by Condition',
    x = 'Condition',
    y = 'PR.2',
    legend=False,
    ylabel='Proportion of Prediction',
    ylim=(0, 1),
    yticks=np.arange(0, 1.1, .1)
)
```

[14]:
```
<Axes: title={'center': 'Proportion of Prediction by Condition'},
xlabel='Condition', ylabel='Proportion of Prediction'>
```



[18]:
```
p2 = df_learning.groupby('Condition')['PR.2'].plot.density(
    title='Proportion of Prediction by Condition',
    legend=True,
)
p2
```

[18]:
```
Condition
Concept      Axes(0.125,0.11;0.775x0.77)
Retrieval    Axes(0.125,0.11;0.775x0.77)
Name: PR.2, dtype: object
```



YOUR RESPONSE HERE

It seems that more of those who practiced the concept map predicted that they would do well on a test one week later than the group that practiced retrieval.

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

Read the codebook carefully to figure out which variable to use (consulting the original paper, if necessary), make an informed decision, and *explain your choice*.

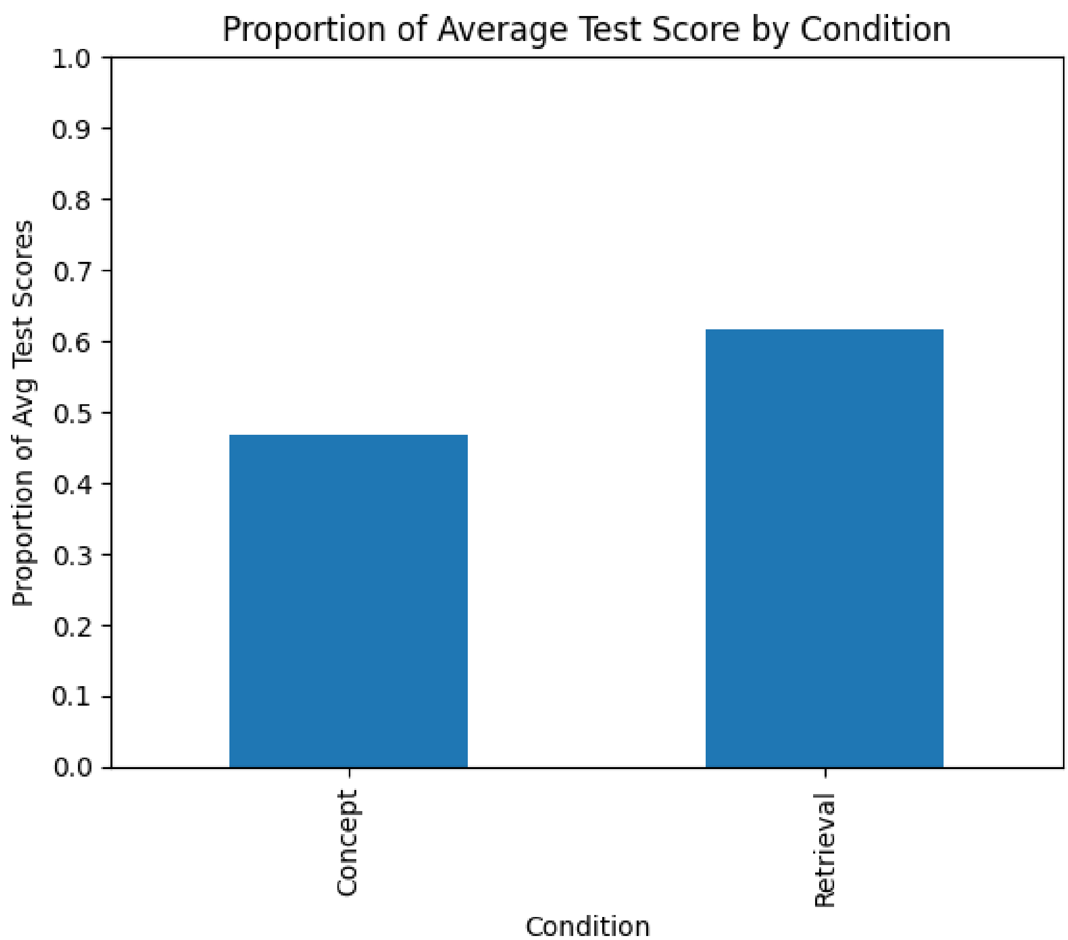
Hint: check out "TSAvg"

[ ]:
```
# ENTER YOUR CODE HERE. ADD AS MANY CELLS AS YOU WANT.
p2 = df_learning.groupby('Condition')['TS.avg'].mean().reset_index()
p2
```

[ ]:
```
   Condition    TS.avg
0    Concept  0.468846
1  Retrieval  0.616471
```

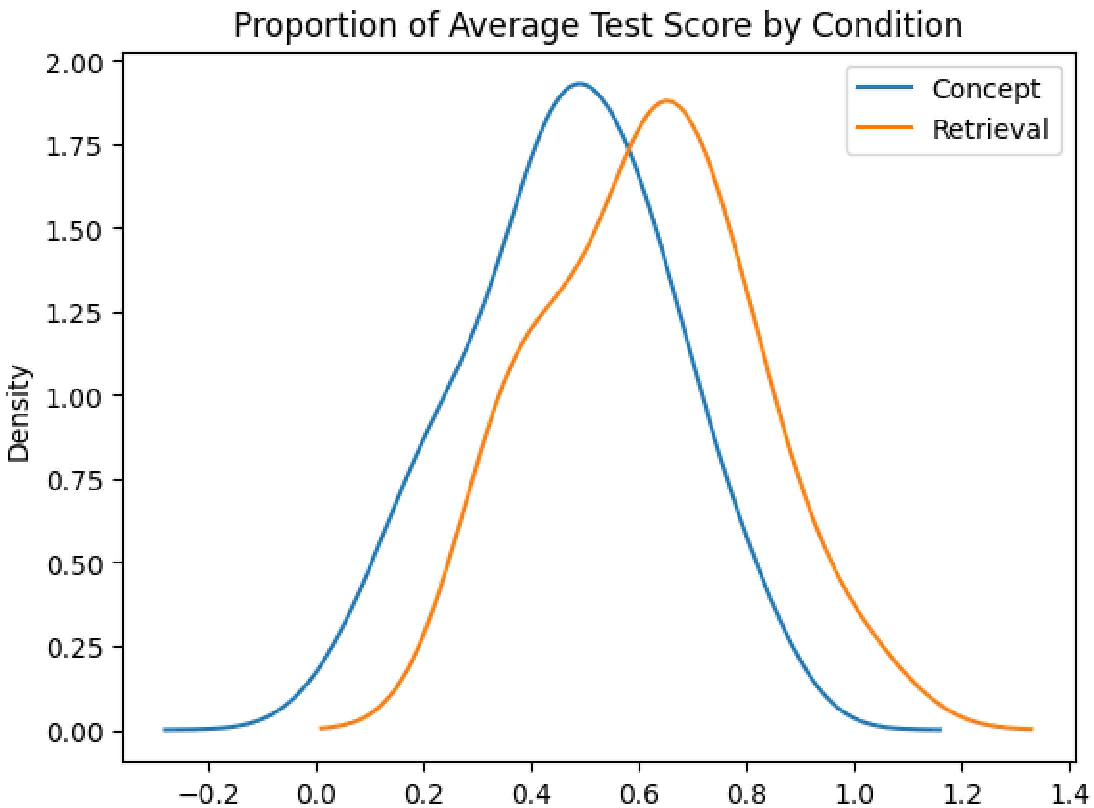
[ ]:
```
p2.plot.bar(
    title='Proportion of Average Test Score by Condition',
    ylabel='Proportion of Avg Test Scores',
    x = 'Condition',
    legend=False,
    ylim=(0, 1),
    yticks=np.arange(0, 1.1, .1)
)
```

[ ]:
```
<Axes: title={'center': 'Proportion of Average Test Score by Condition'},
xlabel='Condition', ylabel='Proportion of Avg Test Scores'>
```



[21]:
```
p3 = df_learning.groupby('Condition')['TS.avg'].plot.density(
    title='Proportion of Average Test Score by Condition',
    legend=True,
)
p3
```

[21]:
```
Condition
Concept      Axes(0.125,0.11;0.775x0.77)
Retrieval    Axes(0.125,0.11;0.775x0.77)
Name: TS.avg, dtype: object
```



YOUR RESPONSE HERE

It seems that the retrieval group did better since the proportion of their average test scores is higher than the concept map group. We stuck with the TS.avg variable since it measures the average of the first and second scorer's test scores.

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, make an appropriate visualization/summary, and describe the results in context.

[ ]:
```
# ENTER YOUR CODE HERE. ADD AS MANY CELLS AS YOU WANT.
df_learning['Prediction Error'] = abs(df_learning['TS.avg'] - df_learning['PR.
↪2'])
prediction_accuracy = df_learning.groupby('Condition')['Prediction Error'].
↪mean().reset_index()

prediction_accuracy
```

[ ]:
```
    Condition  Prediction Error
0     Concept          0.275385
1   Retrieval          0.191765
```

[ ]:
```python
import altair as alt

alt.Chart(prediction_accuracy).mark_bar().encode(
    x='Condition',
    y='Prediction Error'
).properties(
    title='Prediction Accuracy by Condition'
)
```

[ ]: alt.Chart(…)

[28]:
```python
fig2 = px.scatter(df_learning,
                    x="PR.2",
                    y="TS.avg",
                    color="Condition",
                    title="Average Test Score vs Prediction",
                    trendline="ols")
fig2.show()
```

YOUR RESPONSE HERE

From the bar graph, the group with the retrieval practice had a lower prediction error compared to the concept group. Essentially, those who practiced retrieval were better at predicting their performance on the follow-up test than those who utilized concept maps. This is also reinforced by the chart above where the retrieval group more accurately predicted their score on the follow-up test.

4. Write a paragraph summarizing the conclusions of your analysis. Based on this study alone, what would you tell other students about study strategies?

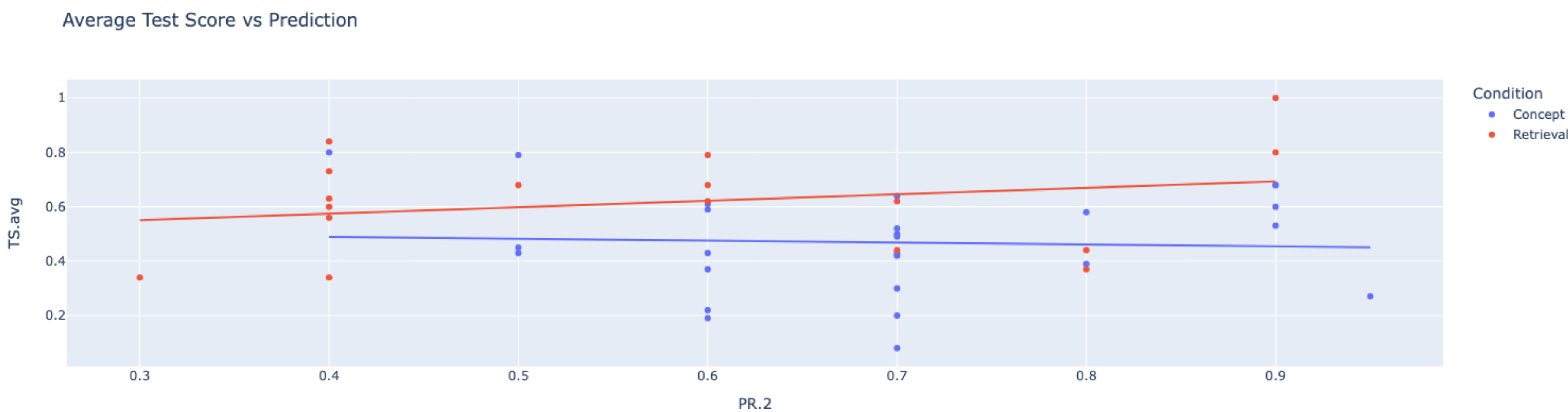
YOUR RESPONSE HERE

Based on this study alone, we would tell other students that retrieval practice is a better study strategy than concept mapping. This is because the retrieval group did better on the follow-up test than the concept group. When it comes to predicting how well they would do on the follow-up test, the retrieval group was still better at predicting their performance than the concept group, so in the end I would tell the other students that retrieval practice is a better study strategy than concept mapping.

0.3 Part 3: Data Visualization

In the in class notebook for Day 06, you played with two activities: "Graph Gallery" and "Copy the Masters". Choose one graph that you created — using either Altair or Plotly — for these activities and reproduce it here. Your graph doesn't have to be perfect, but you should definitely do some tailoring beyond what you did in class to make it as clean as possible.

Remember: just because you can produce a graph doesn't necessarily mean it's an effective visual in context. If you choose the "graph gallery" activity, select a graph that most effectively conveys the story in the data. If you choose the "copy the masters" activity, you don't necessarily have to "copy" them; maybe you can find a way to improve the graphic!


Average Test Score vs Prediction
TS.avg
1
0.8
0.6
0.4
0.2
PR.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Condition
Concept
Retrieval

Include all the code necessary to produce the graphic. Then write two paragraphs:

- one that describes the story that the graphic tells in context
- one that describes why you chose this graphic and your process for recreating it. What was the hardest part to implement?

1. Provide your code and reproduce your graphic here

[ ]:
```
df_penguins = pd.read_csv("https://raw.githubusercontent.com/kevindavisross/
↪data301/main/data/penguins.csv")

px.scatter(df_penguins,
           x="bill_length_mm",
           y="bill_depth_mm",
           color="species",
           marginal_y="box",
           marginal_x="box",
           trendline="ols",
           template="simple_white",
           title="Bill Length vs Bill Depth by Species",
           labels={
                "bill_length_mm": "Bill Length (mm)",
                "bill_depth_mm": "Bill Depth (mm)"
           })
```

2. Write a paragraph that describes the story the graphic tells in context.

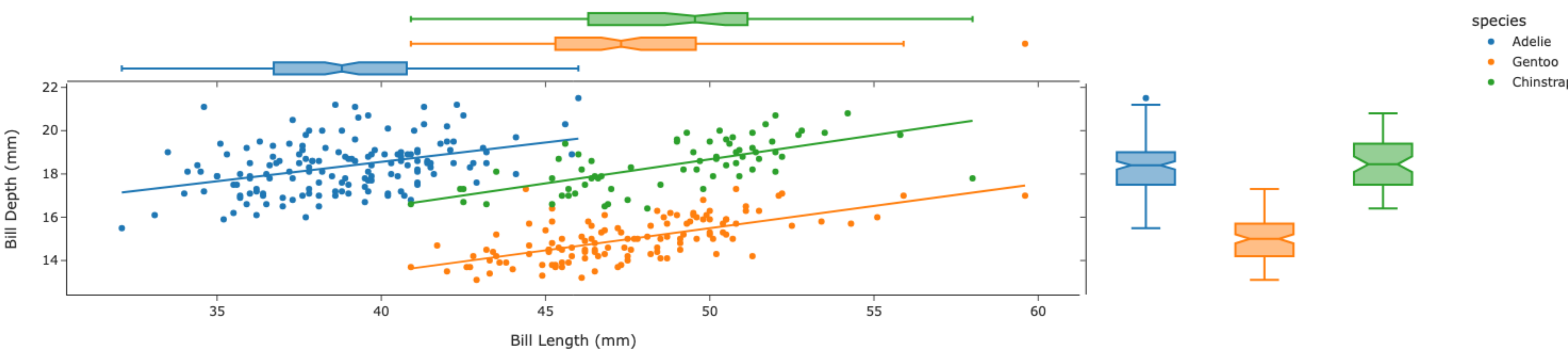
This graph displays the bill length versus the bill depth for the penguins. If we do not split up the graph based on the species, then we actually see a negative correlation meaning that penguins with longer bills have smaller bill depths. However, if we put the data in context with the species (as shown in the above graph), we see that for each species there is actually a positive correlation (can see with the trendline as well). Also, each species has its own range for bill lengths or bill depths, most likely due to evolution and them adapting to their surroundings.

On the side of the scatter plot, there are also box plots that we can compare for each species regarding specifically bill length or bill depth. We can see that Adelie and Chinstrap have a similar distribution for bill depths, while Gentoo and Chinstrap have similar distribution/spread for bil lengths.

3. Write a paragraph that describes why you chose this graphic and your process for recreating it. What was the hardest part to implement?

A scatter plot is the best way to visualize the bill length vs bill depth for the penguins as each penguin is an observation and we are able to see the general trend visually. We are also able to split the observations by their species, so we can see the trend of all the penguins/observations and specifically for each species as well. A bar graph or line graph would not be able to show the data in the same way where it is easy for the audience to visually see what the general trend is. I saw something similar in the Plotly Graph Gallery that had observations graphed on a scatter plot, colored by a certain variable, and then had a box plot for each axis. I thought that this would be

Bill Length vs Bill Depth by Species



perfect for our penguin data as we want to see how bill depth is related to bill length, but we can also compare each independently. The hardest part was finding out about the marginalx and the marginaly to create the boxplots specific to each axis.

0.4 Part 4: House Recommendations

In the "Activity" from the Day 07 notebook you recommended some houses that were similar to, but cheaper than, house 0 in the Ames data set. You will recreate your recommendation here. Provide a list of your top recommendations — including the number of the house and its main features — and explain why you're recommending these houses. Your explanation should include

- Which variables you included, and why
- Which scaling you used, and why
- Which distance metric you used, and why
- How sensitive your recommendations were to different choices (of variables, scaling, distance metric). You should at least compare to what you did in the previous parts (where you considered the 3 quantitative variables and 1 categorical variable).

Hint: be careful about how you are treating the categorical variables.

1. Provide all the code to reproduce your recommendations here.

[ ]:
```
# ENTER YOUR CODE HERE. ADD AS MANY CELLS AS YOU WANT.
df_housing = pd.read_csv("https://raw.githubusercontent.com/kevindavisross/
    ↪data301/main/data/AmesHousing.txt", sep="\t")
df_housing["Bathrooms"] = df_housing["Full Bath"] + 0.5 * df_housing["Half␣
    ↪Bath"]

df_housing
```

[ ]:
```
      Order        PID  MS SubClass MS Zoning  Lot Frontage  Lot Area Street  \
0         1  526301100           20        RL         141.0     31770   Pave
1         2  526350040           20        RH          80.0     11622   Pave
2         3  526351010           20        RL          81.0     14267   Pave
3         4  526353030           20        RL          93.0     11160   Pave
4         5  527105010           60        RL          74.0     13830   Pave
…       …          …          …       …           …       …  …
2925   2926  923275080           80        RL          37.0      7937   Pave
2926   2927  923276100           20        RL           NaN      8885   Pave
2927   2928  923400125           85        RL          62.0     10441   Pave
2928   2929  924100070           20        RL          77.0     10010   Pave
2929   2930  924151050           60        RL          74.0      9627   Pave

     Alley Lot Shape Land Contour  … Pool QC  Fence Misc Feature Misc Val  \
0      NaN       IR1          Lvl  …     NaN    NaN          NaN        0
1      NaN       Reg          Lvl  …     NaN  MnPrv          NaN        0
2      NaN       IR1          Lvl  …     NaN    NaN         Gar2    12500
3      NaN       Reg          Lvl  …     NaN    NaN          NaN        0
4      NaN       IR1          Lvl  …     NaN  MnPrv          NaN        0
```

```
...    ...       ...          ...   ...      ...     ...         ...       ...
2925   NaN       IR1          Lvl  ...       NaN  GdPrv          NaN         0
2926   NaN       IR1          Low  ...       NaN  MnPrv          NaN         0
2927   NaN       Reg          Lvl  ...       NaN  MnPrv         Shed       700
2928   NaN       Reg          Lvl  ...       NaN    NaN          NaN         0
2929   NaN       Reg          Lvl  ...       NaN    NaN          NaN         0

     Mo Sold Yr Sold Sale Type Sale Condition  SalePrice  Bathrooms
0          5    2010       WD            Normal     215000        1.0
1          6    2010       WD            Normal     105000        1.0
2          6    2010       WD            Normal     172000        1.5
3          4    2010       WD            Normal     244000        2.5
4          3    2010       WD            Normal     189900        2.5
...      ...     ...      ...              ...        ...        ...
2925       3    2006       WD            Normal     142500        1.0
2926       6    2006       WD            Normal     131000        1.0
2927       7    2006       WD            Normal     132000        1.0
2928       4    2006       WD            Normal     170000        1.0
2929      11    2006       WD            Normal     188000        2.5

[2930 rows x 83 columns]
```

[ ]:
```python
df_housing.columns
# Interested in: Bedroom AbvGr, Gr Liv Area, Lot Area, Bldg Type, House Style,␣
↪Year Built, Garage Area, Bathrooms
```

[ ]:
```
Index(['Order', 'PID', 'MS SubClass', 'MS Zoning', 'Lot Frontage', 'Lot Area',
       'Street', 'Alley', 'Lot Shape', 'Land Contour', 'Utilities',
       'Lot Config', 'Land Slope', 'Neighborhood', 'Condition 1',
       'Condition 2', 'Bldg Type', 'House Style', 'Overall Qual',
       'Overall Cond', 'Year Built', 'Year Remod/Add', 'Roof Style',
       'Roof Matl', 'Exterior 1st', 'Exterior 2nd', 'Mas Vnr Type',
       'Mas Vnr Area', 'Exter Qual', 'Exter Cond', 'Foundation', 'Bsmt Qual',
       'Bsmt Cond', 'Bsmt Exposure', 'BsmtFin Type 1', 'BsmtFin SF 1',
       'BsmtFin Type 2', 'BsmtFin SF 2', 'Bsmt Unf SF', 'Total Bsmt SF',
       'Heating', 'Heating QC', 'Central Air', 'Electrical', '1st Flr SF',
       '2nd Flr SF', 'Low Qual Fin SF', 'Gr Liv Area', 'Bsmt Full Bath',
       'Bsmt Half Bath', 'Full Bath', 'Half Bath', 'Bedroom AbvGr',
       'Kitchen AbvGr', 'Kitchen Qual', 'TotRms AbvGrd', 'Functional',
       'Fireplaces', 'Fireplace Qu', 'Garage Type', 'Garage Yr Blt',
       'Garage Finish', 'Garage Cars', 'Garage Area', 'Garage Qual',
       'Garage Cond', 'Paved Drive', 'Wood Deck SF', 'Open Porch SF',
       'Enclosed Porch', '3Ssn Porch', 'Screen Porch', 'Pool Area', 'Pool QC',
       'Fence', 'Misc Feature', 'Misc Val', 'Mo Sold', 'Yr Sold', 'Sale Type',
       'Sale Condition', 'SalePrice', 'Bathrooms'],
      dtype='object')
```

[ ]:
```python
df_housing_subset = df_housing[["Bedroom AbvGr", "Gr Liv Area", "Lot Area",␣
↪"Bldg Type", "House Style", "Year Built", "Garage Area", "Bathrooms"]]

df_housing_subset
```

[ ]:
```
      Bedroom AbvGr  Gr Liv Area  Lot Area Bldg Type House Style  Year Built
0                 3         1656     31770      1Fam      1Story        1960  \
1                 2          896     11622      1Fam      1Story        1961
2                 3         1329     14267      1Fam      1Story        1958
3                 3         2110     11160      1Fam      1Story        1968
4                 3         1629     13830      1Fam      2Story        1997
…             …          …        …       …         …          …
2925              3         1003      7937      1Fam        SLvl        1984
2926              2          902      8885      1Fam      1Story        1983
2927              3          970     10441      1Fam      SFoyer        1992
2928              2         1389     10010      1Fam      1Story        1974
2929              3         2000      9627      1Fam      2Story        1993

      Garage Area  Bathrooms
0           528.0        1.0
1           730.0        1.0
2           312.0        1.5
3           522.0        2.5
4           482.0        2.5
…             …         …
2925        588.0        1.0
2926        484.0        1.0
2927          0.0        1.0
2928        418.0        1.0
2929        650.0        2.5

[2930 rows x 8 columns]
```

[ ]:
```python
# find any missing values
df_housing_subset.isnull().sum()
```

[ ]:
```
Bedroom AbvGr    0
Gr Liv Area      0
Lot Area         0
Bldg Type        0
House Style      0
Year Built       0
Garage Area      1
Bathrooms        0
dtype: int64
```

[ ]:
```
df_housing_subset[df_housing_subset["Garage Area"].isnull()]
df_housing_subset.loc[df_housing_subset["Garage Area"].isnull(), "Garage Area"]␣
↪= 0

df_housing_subset.isnull().sum()
```

[ ]:
```
Bedroom AbvGr    0
Gr Liv Area      0
Lot Area         0
Bldg Type        0
House Style      0
Year Built       0
Garage Area      0
Bathrooms        0
dtype: int64
```

[ ]:
```
df_housing_dummies = pd.get_dummies(df_housing_subset, columns=["Bldg Type",␣
↪"House Style"])
df_housing_dummies
```

[ ]:
```
      Bedroom AbvGr  Gr Liv Area  Lot Area  Year Built  Garage Area
0                 3         1656     31770        1960        528.0  \
1                 2          896     11622        1961        730.0
2                 3         1329     14267        1958        312.0
3                 3         2110     11160        1968        522.0
4                 3         1629     13830        1997        482.0
…               …           …         …           …           …
2925              3         1003      7937        1984        588.0
2926              2          902      8885        1983        484.0
2927              3          970     10441        1992          0.0
2928              2         1389     10010        1974        418.0
2929              3         2000      9627        1993        650.0

      Bathrooms  Bldg Type_1Fam  Bldg Type_2fmCon  Bldg Type_Duplex
0           1.0            True             False             False  \
1           1.0            True             False             False
2           1.5            True             False             False
3           2.5            True             False             False
4           2.5            True             False             False
…           …              …                 …                 …
2925        1.0            True             False             False
2926        1.0            True             False             False
2927        1.0            True             False             False
2928        1.0            True             False             False
2929        2.5            True             False             False

      Bldg Type_Twnhs  Bldg Type_TwnhsE  House Style_1.5Fin
```

```
0             False          False             False  \
1             False          False             False
2             False          False             False
3             False          False             False
4             False          False             False
…             …              …                 …
2925          False          False             False
2926          False          False             False
2927          False          False             False
2928          False          False             False
2929          False          False             False

      House Style_1.5Unf  House Style_1Story  House Style_2.5Fin
0                  False                True               False  \
1                  False                True               False
2                  False                True               False
3                  False                True               False
4                  False               False               False
…                  …                  …                  …
2925               False               False               False
2926               False                True               False
2927               False               False               False
2928               False                True               False
2929               False               False               False

      House Style_2.5Unf  House Style_2Story  House Style_SFoyer
0                  False               False               False  \
1                  False               False               False
2                  False               False               False
3                  False               False               False
4                  False                True               False
…                  …                  …                  …
2925               False               False               False
2926               False               False               False
2927               False               False                True
2928               False               False               False
2929               False                True               False

      House Style_SLvl
0                False
1                False
2                False
3                False
4                False
…                …
2925              True
2926             False
```

```
2927             False
2928             False
2929             False

[2930 rows x 19 columns]
```

[ ]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(df_housing_dummies)
df_housing_scaled = scaler.transform(df_housing_dummies)

df_housing_scaled
```

[ ]:
```
array([[ 0.17609421,  0.30926506,  2.74438073, …, -0.65146333,
        -0.17074395, -0.21373267],
       [-1.03223376, -1.19442705,  0.18709726, …, -0.65146333,
        -0.17074395, -0.21373267],
       [ 0.17609421, -0.33771825,  0.5228137 , …, -0.65146333,
        -0.17074395, -0.21373267],
       …,
       [ 0.17609421, -1.04801492,  0.03719892, …, -0.65146333,
         5.85672304, -0.21373267],
       [-1.03223376, -0.21900572, -0.01750572, …, -0.65146333,
        -0.17074395, -0.21373267],
       [ 0.17609421,  0.9898836 , -0.06611797, …,  1.53500581,
        -0.17074395, -0.21373267]])
```

[ ]:
```
from sklearn.metrics.pairwise import euclidean_distances

eu_dist = euclidean_distances(df_housing_scaled, df_housing_scaled[0, :].
 ↪reshape(1, -1))
eu_dist
```

[ ]:
```
array([[0.        ],
       [3.33817768],
       [2.6403318 ],
       …,
       [7.52623689],
       [3.13733521],
       [4.90935057]])
```

[ ]:
```
df_housing["eu_distances"] = eu_dist
df_recommend = df_housing.sort_values(by = "eu_distances").head(10).
 ↪sort_values(by = "SalePrice")
df_recommend
```

```
[ ]:       Order        PID  MS SubClass MS Zoning  Lot Frontage  Lot Area Street
2298   2299  923251160           20        RL         124.0     27697   Pave  \
2903   2904  923125030           20   A (agr)         125.0     31250   Pave
1013   1014  527226020           20        RL           NaN     31220   Pave
970     971  923202060           20        RL         100.0     21750   Pave
2700   2701  904100170           20        RL         100.0     21370   Pave
334     335  923251080           20        RL           NaN     26142   Pave
2294   2295  923229140           20        RL          61.0     33983   Pave
1895   1896  534425015           20        RL           NaN     22002   Pave
2223   2224  909428180           20        RL           NaN     25485   Pave
0         1  526301100           20        RL         141.0     31770   Pave

     Alley Lot Shape Land Contour  …  Fence Misc Feature Misc Val Mo Sold
2298   NaN       Reg          Lvl  …    NaN          NaN        0      11  \
2903   NaN       Reg          Lvl  …    NaN          NaN        0       5
1013   NaN       IR1          Bnk  …    NaN         Shed      750       5
970    NaN       Reg          Lvl  …  GdPrv          NaN        0      11
2700   NaN       Reg          Lvl  …    NaN         Shed      600       6
334    NaN       IR1          Lvl  …    NaN          NaN        0       4
2294   NaN       IR1          Lvl  …  GdPrv          NaN        0       5
1895   NaN       Reg          Lvl  …    NaN          NaN        0       7
2223   NaN       IR1          Lvl  …    NaN          NaN        0       5
0      NaN       IR1          Lvl  …    NaN          NaN        0       5

     Yr Sold Sale Type Sale Condition SalePrice  Bathrooms  eu_distances
2298    2007       COD        Abnorml     80000        1.0      0.655589
2903    2006       WD          Normal     81500        1.5      1.465712
1013    2008       WD          Normal    115000        1.0      0.477549
970     2009       WD          Normal    115000        1.0      1.570220
2700    2006       WD          Normal    131000        1.0      1.496900
334     2010       WD          Normal    157900        1.0      1.542711
2294    2007       WD          Normal    196000        1.5      1.203981
1895    2007       WD          Normal    200000        1.5      1.466419
2223    2007       WD          Normal    201000        1.5      1.155843
0       2010       WD          Normal    215000        1.0      0.000000

[10 rows x 84 columns]
```

2. Provide the list of your top recommendations here, including the number of the house and its main features

```
[ ]: # ENTER YOUR CODE HERE. ADD AS MANY CELLS AS YOU WANT.
df_recommend[["Bedroom AbvGr", "Gr Liv Area", "Lot Area", "Bldg Type", "House␣
 ↪Style", "Year Built", "Garage Area", "Bathrooms", "SalePrice"]].head(5)
```

```
[ ]:       Bedroom AbvGr  Gr Liv Area  Lot Area Bldg Type House Style  Year Built
2298              3         1608     27697      1Fam      1Story        1961  \
2903              3         1600     31250      1Fam      1Story        1951
```

```
1013                  3          1474     31220      1Fam      1Story          1952
970                   3          1771     21750      1Fam      1Story          1960
2700                  3          1640     21370      1Fam      1Story          1950

      Garage Area  Bathrooms  SalePrice
2298        444.0        1.0      80000
2903        270.0        1.5      81500
1013        495.0        1.0     115000
970         336.0        1.0     115000
2700        394.0        1.0     131000
```

[ ]:
```python
# get house number 0
df_recommend[df_recommend["Order"] == 1][["Bedroom AbvGr", "Gr Liv Area", "Lot Area", "Bldg Type", "House Style", "Year Built", "Garage Area", "Bathrooms", "SalePrice"]]
```

[ ]:
```
   Bedroom AbvGr  Gr Liv Area  Lot Area Bldg Type House Style  Year Built  \
0              3         1656     31770      1Fam      1Story        1960

   Garage Area  Bathrooms  SalePrice
0        528.0        1.0     215000
```

3. Explain your choices here. Your explanation should include

- Which variables you included, and why
- Which scaling you used, and why
- Which distance metric you used, and why
- How sensitive your recommendations were to different choices (of variables, scaling, distance metric). You should at least compare to what you did in the previous parts (where you considered the 3 quantitative variables and 1 categorical variable).

YOUR RESPONSE HERE

- **Which variables you included, and why**
  - Variables I included in my analysis are the bedrooms above ground, living area, lot area, building type, house style, year built, garage area, and bathrooms. The reason I chose these variables because they are the most common aspects that people look for when buying a house.
- **Which scaling you used, and why**
  - The scaling I used was the Standard Scaler because it is the most common scaling method used in data science and it is the default scaling method in sklearn. Standardizing the data is important because it allows us to compare the data on the same scale.
- **Which distance metric you used, and why**
  - The distance metric I used was the Euclidean distance because it allows us to measure the distance between two points in space.
- **How sensitive your recommendations were to different choices (of variables, scaling, distance metric). You should at least compare to what you did in the previous parts (where you considered the 3 quantitative variables and 1 categorical variable).**

– My recommendations were not very sensitive to different choices of distance metrics, since when I used Euclidean and Manhattan the top 5 recommendations were the same. However, from the previous part from day 7 lecture when we considered 3 quant and 1 categorical var, the recommendations differed. The number 1 choice of house 2298 remained the same however then ext 4 recommendations changed due to the effect of the various variables used in this analysis.

[ ]:
```
# ENTER YOUR CODE HERE. ADD AS MANY CELLS AS YOU WANT.
from sklearn.metrics.pairwise import manhattan_distances

man_dist = manhattan_distances(df_housing_scaled, df_housing_scaled[0, :].
 ↪reshape(1, -1))
man_dist
```

[ ]:
```
array([[ 0.        ],
       [ 6.24124991],
       [ 4.71652916],
       …,
       [15.60433858],
       [ 5.47271521],
       [11.66969279]])
```

[ ]:
```
df_housing["man_distances"] = eu_dist
df_recommend2 = df_housing.sort_values(by = "man_distances").head(10).
 ↪sort_values(by = "SalePrice")
df_recommend2
```

[ ]:
```
      Order        PID  MS SubClass MS Zoning  Lot Frontage  Lot Area Street  
2298   2299  923251160           20        RL         124.0     27697   Pave   \
2903   2904  923125030           20   A (agr)         125.0     31250   Pave
1013   1014  527226020           20        RL           NaN     31220   Pave
970     971  923202060           20        RL         100.0     21750   Pave
2700   2701  904100170           20        RL         100.0     21370   Pave
334     335  923251080           20        RL           NaN     26142   Pave
2294   2295  923229140           20        RL          61.0     33983   Pave
1895   1896  534425015           20        RL           NaN     22002   Pave
2223   2224  909428180           20        RL           NaN     25485   Pave
0         1  526301100           20        RL         141.0     31770   Pave

     Alley Lot Shape Land Contour  … Misc Feature Misc Val Mo Sold Yr Sold  
2298   NaN       Reg          Lvl  …          NaN        0      11    2007  \
2903   NaN       Reg          Lvl  …          NaN        0       5    2006
1013   NaN       IR1          Bnk  …         Shed      750       5    2008
970    NaN       Reg          Lvl  …          NaN        0      11    2009
2700   NaN       Reg          Lvl  …         Shed      600       6    2006
334    NaN       IR1          Lvl  …          NaN        0       4    2010
2294   NaN       IR1          Lvl  …          NaN        0       5    2007
```

```
1895    NaN        Reg          Lvl  ...          NaN          0        7    2007
2223    NaN        IR1          Lvl  ...          NaN          0        5    2007
0       NaN        IR1          Lvl  ...          NaN          0        5    2010

     Sale Type Sale Condition SalePrice Bathrooms  eu_distances  man_distances
2298       COD        Abnorml     80000       1.0      0.655589       0.655589
2903        WD         Normal     81500       1.5      1.465712       1.465712
1013        WD         Normal    115000       1.0      0.477549       0.477549
970         WD         Normal    115000       1.0      1.570220       1.570220
2700        WD         Normal    131000       1.0      1.496900       1.496900
334         WD         Normal    157900       1.0      1.542711       1.542711
2294        WD         Normal    196000       1.5      1.203981       1.203981
1895        WD         Normal    200000       1.5      1.466419       1.466419
2223        WD         Normal    201000       1.5      1.155843       1.155843
0           WD         Normal    215000       1.0      0.000000       0.000000

[10 rows x 85 columns]
```

[ ]:
```python
df_recommend[["Bedroom AbvGr", "Gr Liv Area", "Lot Area", "Bldg Type", "House Style", "Year Built", "Garage Area", "Bathrooms", "SalePrice"]].head(5)
```

[ ]:
```
      Bedroom AbvGr  Gr Liv Area  Lot Area Bldg Type House Style  Year Built  \
2298              3         1608     27697      1Fam      1Story        1961
2903              3         1600     31250      1Fam      1Story        1951
1013              3         1474     31220      1Fam      1Story        1952
970               3         1771     21750      1Fam      1Story        1960
2700              3         1640     21370      1Fam      1Story        1950

      Garage Area  Bathrooms  SalePrice
2298        444.0        1.0      80000
2903        270.0        1.5      81500
1013        495.0        1.0     115000
970         336.0        1.0     115000
2700        394.0        1.0     131000
```

0.5 Submission Instructions

- After you have completed the notebook, select **Runtime > Restart and run all**
- After the notebook finishes rerunning check to make sure that you have no errors and everything runs properly. Fix any problems and redo this step until it works.
- Rename this notebook by clicking on "DATA 301 Assigment - YOUR NAMES HERE" at the very top of this page. Replace "YOUR NAMES HERE" with the first and last names of ALL partners who collaborated on this assignment.
- Expand all cells with View > Expand Sections
- Save a PDF version: File > Print > Save as PDF
  - Under "More Settings" make sure "Background graphics" is checked
  - Printing to PDF doesn't always work so well and some of your output might get cutoff.

That's ok.
  - It's not necessary, but if you want a more nicely formatted PDF you can uncomment and run the code in the following cell. (Here's a video with other options.)
- Download the notebook: File > Download .ipynb
- **Submit the notebook and PDF in Canvas**. If you worked in a team, only one person should submit in Canvas. Add the names of all team members in the comments in the submission in Canvas.

[ ]:
```
# !wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
# from colab_pdf import colab_pdf
# colab_pdf('DATA 301 Lab1B - YOUR NAMES HERE.ipynb')
```