01_Intro

February 3, 2020

0.1 Introduction to Data and Python: Pew Data Example

We explore data from the Pew Research Center to illustrate statistical issues and data processing in Python. At this point it is not assumed that you are at all familar with Python. Instead, we will demonstrate some of the things you can do with it as a way to motivate going in more depth later.

The Pew Research Center conducts regular national surveys on issues of national concern. We use data from the February 2017 political survey. The data are publically available from the Pew Research Center website: https://www.people-press.org/dataset/february-2017-political-survey/ Downloading requires that you register with Pew.

0.1.1 Reading in the data from a csv file in a compressed folder

To get started I created an account and downloaded a compressed zip file with the data. In order to extract and view the data we need to import two Python modules:

- **pandas** - Python package for reading and processing flat data files
- **zipfile** - Python package for extracting compressed files

We'll be using **pandas** over and over throughout the course. We only need **zipfile** if we are dealing with compressed files, otherwise we don't need it.

[1]:
```
import pandas as pd    # main package for data frame structures and functions
import zipfile as zp   # package needed to read data from a zip compressed file
```

I put the zip file in a folder called "data" parallel with the current folder for these lecture notes. Let's read the file into a zipfile object and open the ".csv" file. CSV stands for "comma separated variables". Then we can use the pandas "read_csv" function to read the file into a pandas data frame (df). The "../" part of the path says to first move up to the parent folder that contains both the "data" folder and the folder containing this Jupyter notebook.

[2]:
```
zf = zp.ZipFile('../data/Feb17-public.zip')
df = pd.read_csv(zf.open('Feb17public.csv'))
```

Note: this example is complicated by the extraction from a zip file. If we simply had an uncompressed csv file exported from Excel, for example, we would have read the data simply as:

df = pd.read_csv('../data/Feb17public.csv')

0.1.2 Getting an idea of what's in the data

What can we find out about this data file? We can see the first few lines of data using the **head** function. Because there are so many columns, some of the middle columns are skipped.

[3]:
```
df.head()
```

[3]:
```
   psraid    sample  int_date   fcall          version  attempts refusal  \
0  100008  Landline     21017  170207   Client changes         4      No
1  100019  Landline     21217  170207   Client changes         4     Yes
2  100020  Landline     21217  170207   Client changes         4     Yes
3  100021  Landline     20717  170207  Initial version         1      No
4  100024  Landline     20717  170207  Initial version         1      No

     ilang    cregion           state  ... ql1a  qc1 money2  money3 iphoneuse  \
0  English    Midwest        Illinois  ...  NaN  NaN    NaN     NaN      Dual
1  English      South  North Carolina  ...  NaN  NaN    NaN     NaN      Dual
2  English  Northeast        New York  ...  NaN  NaN    NaN     NaN      Dual
3  English    Midwest       Minnesota  ...  NaN  NaN    NaN     NaN      Dual
4  English    Midwest        Illinois  ...  NaN  NaN    NaN     NaN      Dual

  hphoneuse ll cp cellweight    weight
0   Dual HH  1  1        NaN  1.733333
1   Dual HH  1  1        NaN  1.500000
2   Dual HH  1  1        NaN  1.533333
3   Dual HH  1  1        NaN  5.866667
4   Dual HH  1  1        NaN  1.700000

[5 rows x 130 columns]
```

What are all the variables in the data frame? We can extract this information using pandas as well.

[4]:
```
print(df.columns.values)
```

```
['psraid' 'sample' 'int_date' 'fcall' 'version' 'attempts' 'refusal'
 'ilang' 'cregion' 'state' 'density' 'sstate' 'form' 'stimes' 'igender'
 'irace' 'llitext0' 'susr' 'usr' 'scregion' 'qs1' 'q1' 'q1a' 'q2' 'q5af1'
 'q5bf1' 'q5cf1' 'q5df1' 'q6af2' 'q6bf2' 'q6cf2' 'q6df2' 'q10a' 'q10b'
 'q15af1' 'q15b' 'q15cf2' 'q15df1' 'q15ef1' 'q15ff1' 'q15gf2' 'q15hf2'
 'q15if2' 'q16' 'q19' 'q35' 'q36' 'q37' 'q39' 'q43' 'q44' 'q45' 'q45vb'
 'Q45VB0' 'Q45VB1' 'Q45VB2' 'q45oem1' 'q45oem2' 'q45oem3' 'q52' 'q53'
 'q54' 'q55' 'q61a' 'q61b' 'q61c' 'q61d' 'q61e' 'q62f1' 'q63f1' 'q64f2'
 'q65' 'q66' 'q68f1' 'q69f2' 'q70f1' 'q71f2' 'q74' 'q75' 'q81' 'q82'
 'q84a' 'q84bf1' 'q84cf1' 'q84df1' 'q84ef2' 'q84ff2' 'q84gf2' 'q88'
 'q90f1' 'q91f2' 'sex' 'age' 'gen5' 'educ2' 'hisp' 'adults' 'racethn'
 'racethn2' 'birth_hisp' 'citizen' 'child' 'relig' 'chr' 'born' 'attend'
 'q92' 'q92a' 'income' 'reg' 'party' 'partyln' 'partysum' 'partyideo'
 'q93' 'q94' 'ideo' 'hh1' 'hh3' 'ql1' 'ql1a' 'qc1' 'money2' 'money3'
 'iphoneuse' 'hphoneuse' 'll' 'cp' 'cellweight' 'weight']
```

How many rows and columns are there in the data frame? the **shape** attribute gives us this information.

[5]:
```
df.shape
```

[5]: (1503, 130)

Looking through the variable names we see a variable called 'sample' and the first few values are 'Landline'. We can get counts of the different values for this variable using the pandas function **.value_counts( )**

[6]:
```
df['sample'].value_counts()
```

[6]:
```
Cell        1126
Landline     377
Name: sample, dtype: int64
```

[7]:
```
df['sample'].shape
```

[7]: (1503,)

The row labels for this spreadsheet structure are in the "index" accessible as follows:

[8]:
```
df.index
```

[8]: RangeIndex(start=0, stop=1503, step=1)

Similarly, the column labels are accessed as:

[9]:
```
df.columns
```

[9]:
```
Index(['psraid', 'sample', 'int_date', 'fcall', 'version', 'attempts',
       'refusal', 'ilang', 'cregion', 'state',
       ...
       'ql1a', 'qc1', 'money2', 'money3', 'iphoneuse', 'hphoneuse', 'll', 'cp',
       'cellweight', 'weight'],
      dtype='object', length=130)
```

0.1.3 Visualizing categorical variables using barplots

In order to visualize the data we import two graphics modules that will be used frequently throughout the course:

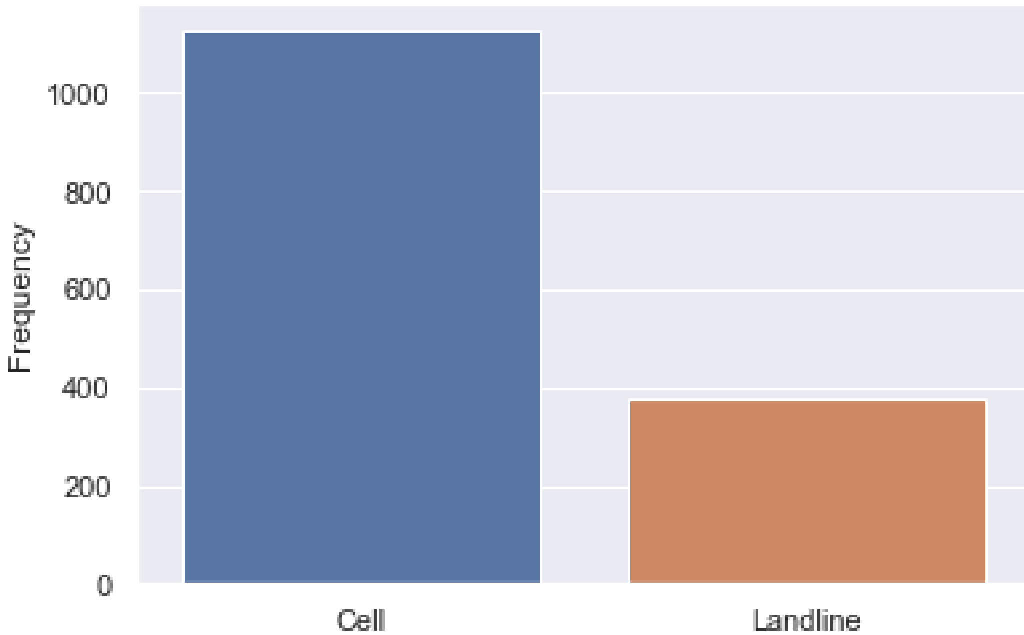
- **matplotlib.pyplot** - Basic python graphics functions
- **seaborn** - Enhanced graphics functions with additional styles and capabilities

[10]:
```
import matplotlib.pyplot as plt   # basic graphing package
import seaborn as sns; sns.set()  # enhanced graphing package
```

[11]:
```
counts = df['sample'].value_counts()
display(counts.shape, counts)
```

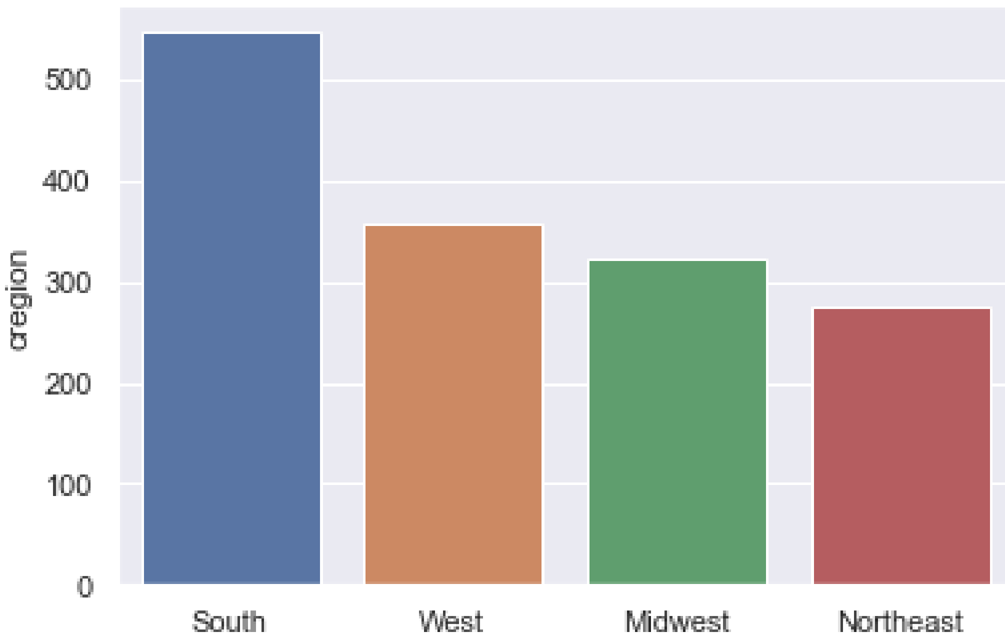
```
(2,)


Cell        1126
Landline     377
Name: sample, dtype: int64
```

[12]:
```
sns.barplot(x=counts.index, y=counts)
plt.ylabel('Frequency')
plt.show()
```



What is the regional distribution of respondants to the survey? There's a variable called 'cregion'. Let's investigate.

[13]:
```
temp = df['cregion'].value_counts()
sns.barplot(x=temp.index, y=temp)
plt.show()
```



How do the relative frequencies of cell phone and landline respondents vary across regions? Let's look at the **cross-tabulation** of the two variables.

[14]:
```
pd.crosstab(df['cregion'], df['sample'])
```

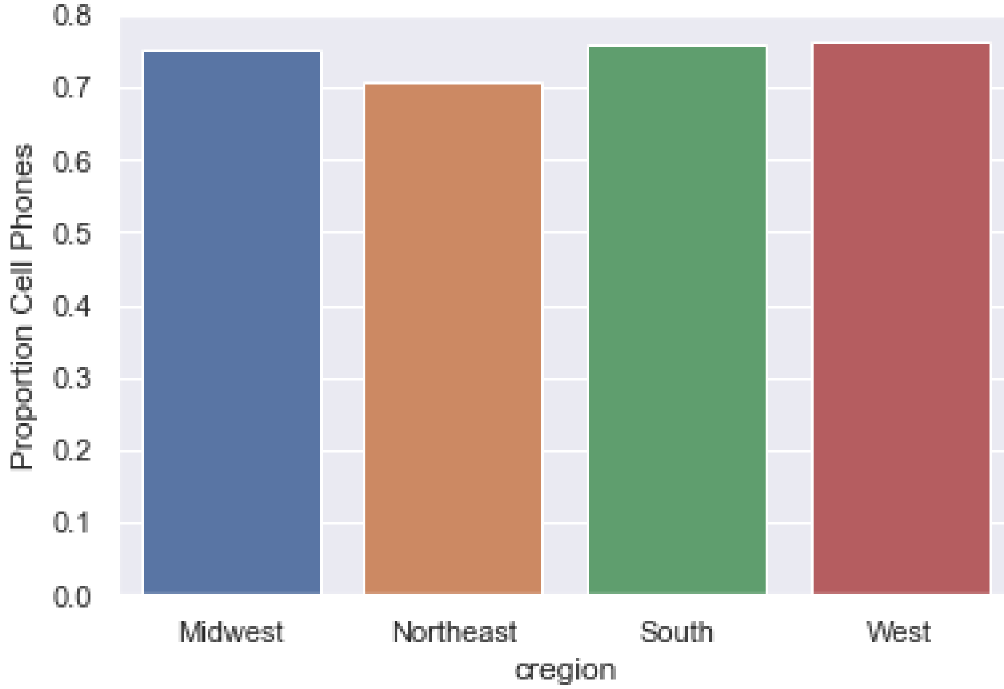
[14]:
```
sample     Cell  Landline
cregion
Midwest     244        80
Northeast   195        80
South       415       132
West        272        85
```

Those are the raw counts. Let's convert to row proportions to better compare across regions. Note that "index" here refers to rows. We devide each row by the row total to normalize it. If we wanted to normalize by columns we'd pass "columns" instead of "index" for the normalization.

[15]:
```
pd.crosstab(df['cregion'], df['sample'], normalize='index')
```

[15]:
```
sample         Cell  Landline
cregion
Midwest    0.753086  0.246914
Northeast  0.709091  0.290909
South      0.758684  0.241316
West       0.761905  0.238095
```

[16]:
```
# graph the normalized crosstabs
temp = pd.crosstab(df['cregion'], df['sample'], normalize='index')
sns.barplot(x=temp.index, y="Cell", data=temp)
plt.ylabel("Proportion Cell Phones")
plt.show()
```



Why did this work? Here are the row (index) and column names for the crosstab object we just created.

[17]:
```
display(temp.index, temp.columns)
```

```
Index(['Midwest', 'Northeast', 'South', 'West'], dtype='object', name='cregion')
```

```
Index(['Cell', 'Landline'], dtype='object', name='sample')
```

We only needed the first column - "Cell", which is equivalent to

```
temp['Cell']
```

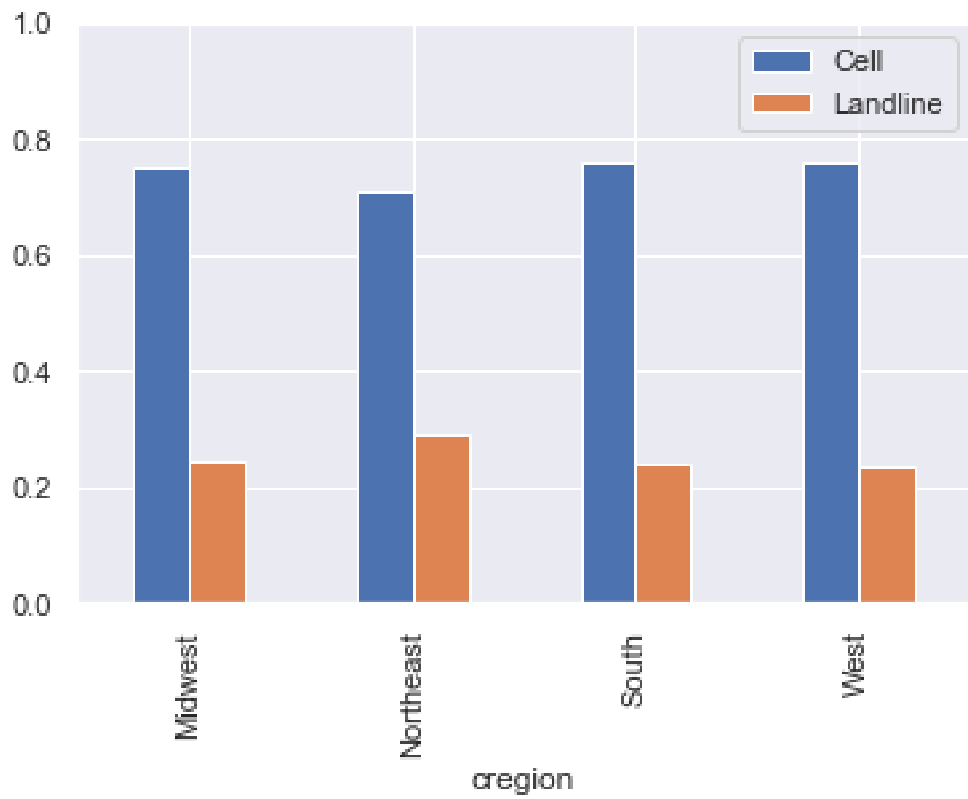
as follows.

[18]:
```
temp['Cell']
```

[18]:
```
cregion
Midwest      0.753086
Northeast    0.709091
South        0.758684
West         0.761905
Name: Cell, dtype: float64
```

Side-by-side bar plots Here's a way, using pandas, to see the proportions of both cell phones and landline across regions.

[19]:
```
temp.plot.bar()
plt.legend(loc='upper right')
plt.ylim([0,1])
plt.show()
```



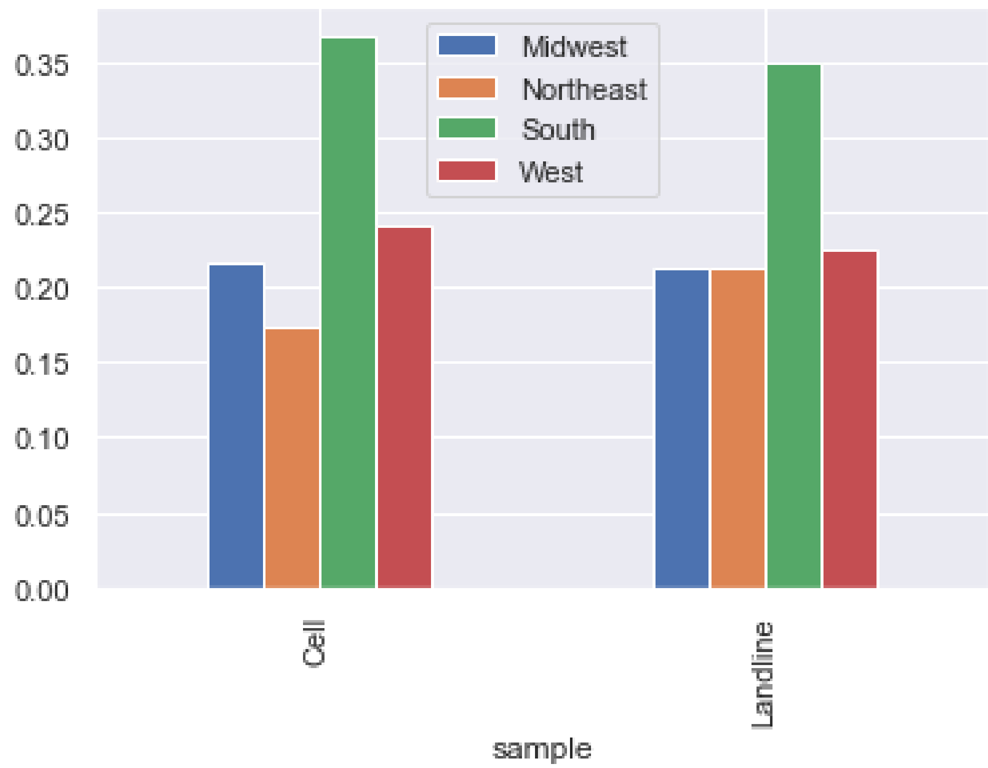
Remark on order of variables: If we had reversed the order of variables in the crosstab, the resulting data frame is transposed. Rows become columns and vice versa. We would then get a different presentation, showing the regional distribution within cell phone and landline users.

[20]:
```
temp2 = pd.crosstab(df['sample'], df['cregion'], normalize='index')
temp2
```

[20]:

cregion	Midwest	Northeast	South	West
sample				
Cell	0.216696	0.173179	0.368561	0.241563
Landline	0.212202	0.212202	0.350133	0.225464

[21]:
```
temp2.plot.bar()
plt.legend(loc="upper center")
plt.show()
```



0.1.4 Let's explore other variables!

Many of the columns in this data set are labeled by question number. To know what those are we have to look up the questions in a summary file included in the download. Here are two of the questions asked:

- q1 - Do you approve or disapprove of the way Donald Trump is handling his job as President?
- q52 - All in all, would you favor or oppose building a wall along the entire border with Mexico?

Use the methods we have seen so far to investigate the responses to these questions, and how they relate to each other or to geographic regions.

[ ]:
```

```

[ ]:
```

```

[ ]:
```

```

[ ]:
```

```

0.2 Summary

Using Pew Research center data we saw how to read in a comma separated file (and uncompress it if needed). Key ideas presented were:

- **data frames:** pandas objects with rows representing different observations and columns representing different variables for each observation
- **.head(), .shape, .columns.values** for getting a rough idea what kind information is in the data frame
- **counting and cross tabulation of categorical variables:** pandas functions .value_counts() and pandas.crosstab()
- **bar plots for visualizing categorical variable frequencies**
- **packages:** pandas, zipfile, matplotlib.pyplot, seaborn

0.2.1 Caution

To properly interpret results from the data we need to understand better how they were collected. Then we can better discuss the following questions:

- Based on how they were sampled, are the data representative of the general adult population?
- Are associations we find in the data causal? or are they merely associations?

STAT 207, Douglas Simpson, University of Illinois at Urbana-Champaign