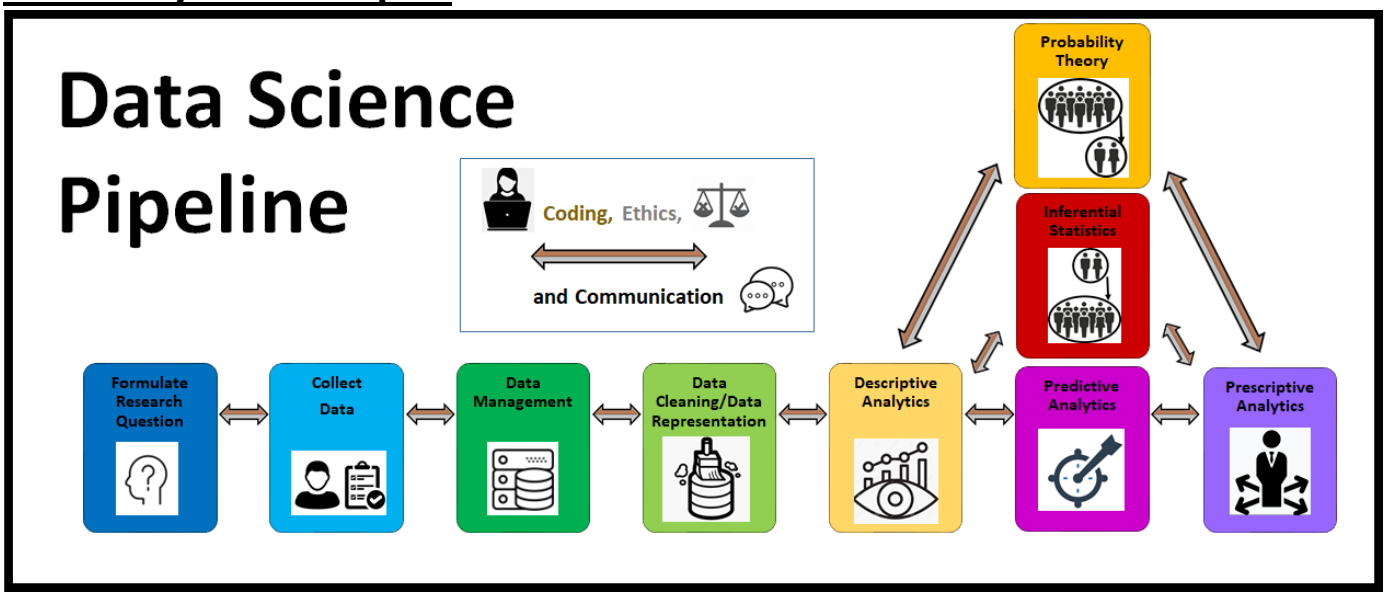
Unit 1: Introduction to Data and Python

Case Study: 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.

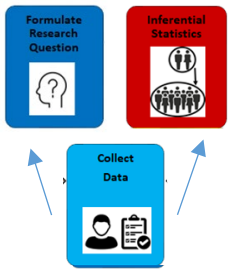
The Pew Research Center conducts regular national surveys on issues of national concern. We use data from the February 2017 political survey. The data are publically available from the Pew Research Center website: https://www.people-press.org/dataset/february-2017-political-survey/ Downloading requires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

Summary of Concepts:



Data Science Packages

- **import** to load packages
- **pandas** : for dataframe manipulation/data represention functions
- **zipfile**: for loading data
- **matplotlib.pyplot**: for visualizing data
- **seaborn**: for visualizing data



Inference Preliminaries

- How does the **way in which the data was collected** influence the types of **inferences** we can make and the **types of research questions we can ask**?

Different Ways to Represent Data in Python

- **Dataframes**
- *Dataframe.**head()***

BASICS: What's in the dataframe?

- *Dataframe.**head()***
- *Dataframe.**shape***
- *Dataframe.**columns.values***

BASICS: Descriptive Analytics for One or Two Categorical Variables

- ***Summary Statistics:***
  - **Counts**
    - *Dataframe.**value_counts()***
    -
    - ***pandas.crosstab()***
  - **Percentages/Proportions**
- ***Visualizations:***
  - **Barplots**
    - ***seaborn.barplot()***
    - *dataframe.**plot.bar()***

Types of Data

Definitions

_____ variable: can take a wide range of numerical values, and it is sensible to add, subtract, or take averages with

_____ variable: values represent categories, where each category is called a _____. It does *not* make sense to add, subtract, or take average with this variable.

Conceptual Quiz

Which of the following is NOT a numerical variable?

a.) Temperature

b.) How many hours a week you spend on Instagram

c.) Numerically coded political data where: 0 = Independent, 1 = Republican, 2 = Democrat.

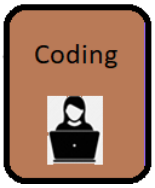
Beginning a Data Science Project

1. Two main ways to <u>begin</u> a data science project

Basic Data Analysis on Data with One and Two Categorical Variables

1. Data: 2017 Pew Research

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



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.

In [2]:
```
# read zip file into python object
zf = zp.ZipFile('../data/Feb17-public.zip')
#
# extract data file and read into a data frame
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')
```

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.

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

Out[3]:

	psraid	sample	int_date	fcall	version	attempts	refusal	ilang	cregion	state
0	100008	Landline	21017	170207	Client changes	4	No	English	Midwest	Illinois
1	100019	Landline	21217	170207	Client changes	4	Yes	English	South	North Carolina
2	100020	Landline	21217	170207	Client changes	4	Yes	English	Northeast	New York
3	100021	Landline	20717	170207	Initial version	1	No	English	Midwest	Minnesota
4	100024	Landline	20717	170207	Initial version	1	No	English	Midwest	Illinois

5 rows × 130 columns

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

In [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' 'q5af
1'
 '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' 'atten
d'
 '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.

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

Out[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( )**

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

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

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

Out[7]:
```
(1503,)
```

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

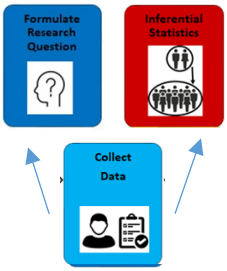
In [8]:
```
df.index
```

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

Similarly, the column labels are accessed as:

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

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



Inference Preliminaries

- How does the **way in which the data was collected** influence the types of **inferences** we can make and the **types of research questions we can ask**?

2. What research questions can we ask using this data?

2.1. First, formulate your own in the breakout room. Try to involve just one or two CATEGORICAL variables in your question. Write it here.

2.2. What kind of research questions can we ask with this dataset?

Circle all of the following research questions that you think we can feasibly ask and answer with this dataset.

a.) Is there an *association* between people *in this dataset* that use cellphones and the region of the country that they live in?

b.) Is there an *association* between *all adults living in the US* that use cellphones and the region of the country that they live in?

c.) Does being from the South *cause* the people *in this dataset* to be more likely to use a cellphone?

d.) Does being from the South *cause all adults living in the US* to be more likely to use a cellphone?

BASICS: Descriptive Analytics for ONE Categorical Variable

- **Summary Statistics:** Counts, Percentages
- **Visualizations:** Barplots

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

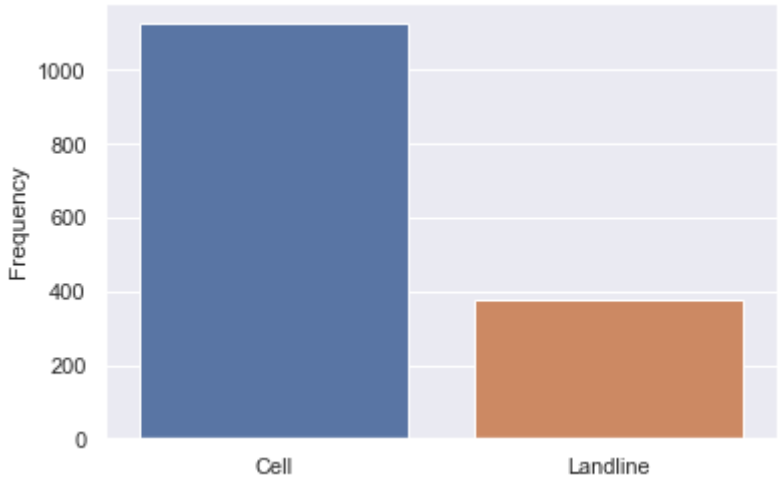
- **matplotlib.pyplot** - Basic python graphics functions
- **seaborn** - Enhanced graphics functions with additional styles and capabilities

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

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

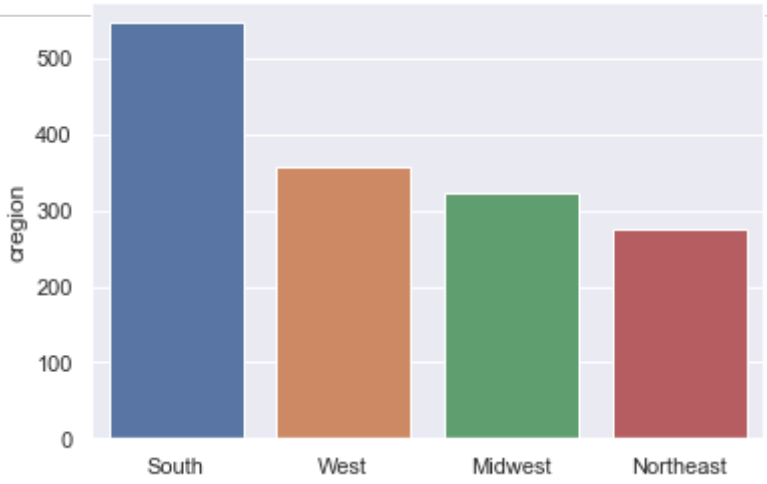
```
(2,)

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

```
In [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.

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



BASICS: Descriptive Analytics for TWO Categorical Variables

- **Summary Statistics: Counts, Percentages**
- **Visualizations: Barplots**

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

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.

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

Out[14]:

sample	Cell	Landline
cregion		
Midwest	244	80
Northeast	195	80
South	415	132
West	272	85

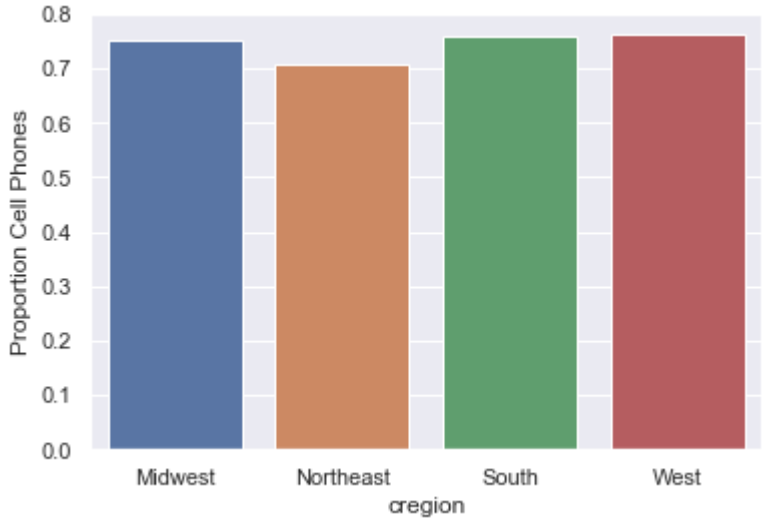
Those are the raw counts. Let's convert to row proportions to better compare across regions. Note that "index" here refers to rows. We devide each row by the row total to normalize it. If we wanted to normalize by columns we'd pass "columns" instead of "index" for the normalization.

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

Out[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

In [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.

```
In [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.

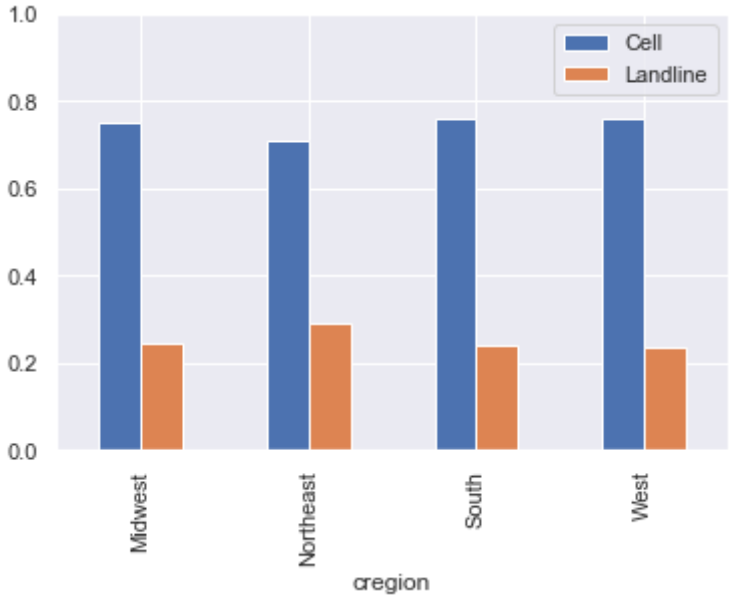
```
In [18]: temp['Cell']
```

```
Out[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.

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



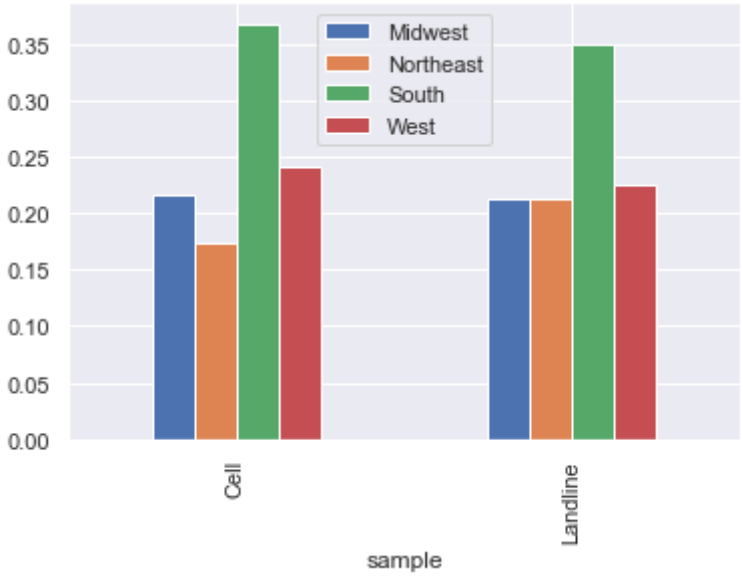
Remark on order of variables: If we had reversed the order of variables in the crosstab, the resulting data frame is transposed. Rows become columns and vice versa. We would then get a different presentation, showing the regional distribution within cell phone and landline users.

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

Out[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

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



Answering the Research Question:

Is there an **association** between using a cell phone and region of the country for the **people surveyed in the dataset**?

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.

In [ ]:

In [ ]:

In [ ]:

In [ ]: