Homework 1

September 19, 2017

1 Homework 1: Exploring & Visualizing Data

Make you have seaborn and missingno installed. Run `pip3 install seaborn` and `pip3 install missingno` in your container/shell if you don't.

1.1 Setup

In this homework, we will more rigorously explore data visualization and data manipulation with a couple datasets. Please fill in the cells with `## YOUR CODE HERE` following the appropriate directions.

```
In [3]: # removes the need to call plt.show() every time
        %matplotlib inline
```

Seaborn is a powerful data visualization library built on top of matplotlib. We will be using seaborn for this homework (since it is a better tool and you should know it well). Plus seaborn comes default with *much* better aesthetics (invoked with the `set()` function call).

```
In [5]: import missingno as msno
        import seaborn as sns
        sns.set()

        import ssl

        ssl._create_default_https_context = ssl._create_unverified_context
```

Import `numpy` and `pandas` (remember to abbreviate them accordingly!)

```
In [158]: import numpy as np
          import pandas as pd
```

1.2 Getting to know a new dataset

First we load the `titanic` dataset directly from seaborn. The `load_dataset` function will return a pandas dataframe.

```
In [7]: titanic = sns.load_dataset('titanic') ##pd.read_csv('titanic.csv')
```

Use a couple pandas functions to get a quick overview and some statistics on the dataset (remember the commands we used from lecture). Take a quick glance at the overview you create.

```
In [8]: titanic.head()
```

```
Out[8]:    survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
        0         0       3    male  22.0      1      0   7.2500        S  Third
        1         1       1  female  38.0      1      0  71.2833        C  First
        2         1       3  female  26.0      0      0   7.9250        S  Third
        3         1       1  female  35.0      1      0  53.1000        S  First
        4         0       3    male  35.0      0      0   8.0500        S  Third

             who  adult_male deck  embark_town alive  alone
        0    man        True  NaN  Southampton    no  False
        1  woman       False    C    Cherbourg   yes  False
        2  woman       False  NaN  Southampton   yes   True
        3  woman       False    C  Southampton   yes  False
        4    man        True  NaN  Southampton    no   True
```

```
In [9]: titanic.describe()
```

```
Out[9]:          survived      pclass         age       sibsp       parch        fare
        count  891.000000  891.000000  714.000000  891.000000  891.000000  891.000000
        mean     0.383838    2.308642   29.699118    0.523008    0.381594   32.204208
        std      0.486592    0.836071   14.526497    1.102743    0.806057   49.693429
        min      0.000000    1.000000    0.420000    0.000000    0.000000    0.000000
        25%      0.000000    2.000000   20.125000    0.000000    0.000000    7.910400
        50%      0.000000    3.000000   28.000000    0.000000    0.000000   14.454200
        75%      1.000000    3.000000   38.000000    1.000000    0.000000   31.000000
        max      1.000000    3.000000   80.000000    8.000000    6.000000  512.329200
```

With your created overview, you should be able to answer these questions:

- What was the age of the oldest person on board? 80
- What was the survival rate of people on board? 38%
- What was the average fare of people on board? 32.2

Pro tip: What about if we wanted to know not just the overall survival rate, but the survival rate broken down by sex and embark_town?

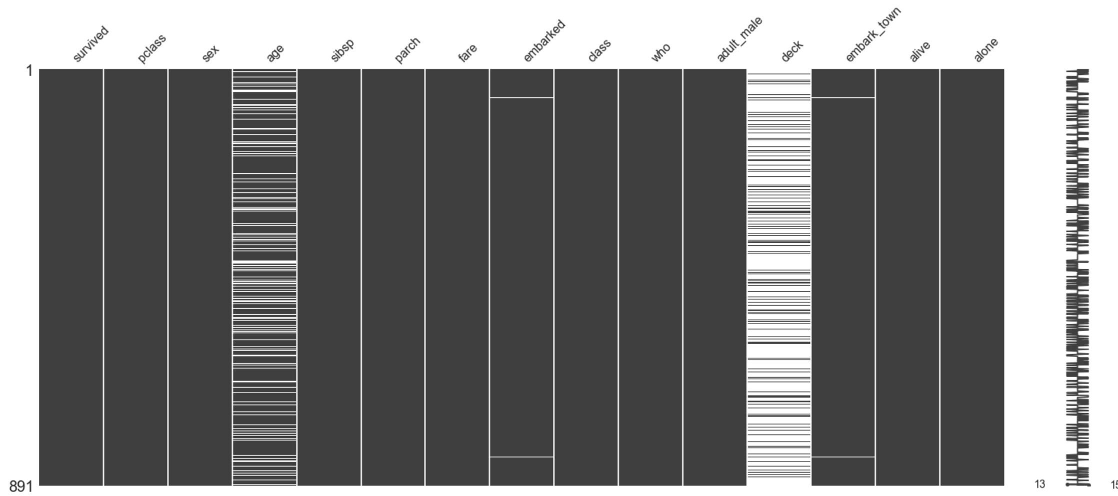
```
In [10]: titanic.groupby(['sex','embark_town'])['survived'].mean()
```

```
Out[10]: sex     embark_town
         female  Cherbourg      0.876712
                 Queenstown     0.750000
                 Southampton    0.689655
         male    Cherbourg      0.305263
                 Queenstown     0.073171
                 Southampton    0.174603
         Name: survived, dtype: float64
```

Now we have an overview of our dataset. The next thing we should do is clean it - check for missing values and deal with them appropriately.

`missingno` allows us to really easily see where missing values are in our dataset. It's a simple command:

```
In [11]: msno.matrix(titanic)
```



The white lines show us the missing data. One quick observation is that `deck` has a lot of missing data. Let's just go ahead and drop that column from the dataset since it's not relevant.

```
In [12]: titanic.drop('deck', axis=1, inplace=True)
```

Now let's rerun the matrix and see. All that white is gone! Nice.

We still have a bunch of missing values for the age field. We can't just drop the age column since it is a pretty important datapoint. One way to deal with this is simply to just remove the records with `dropna()`, but this would end up removing out a significant amount of our data.

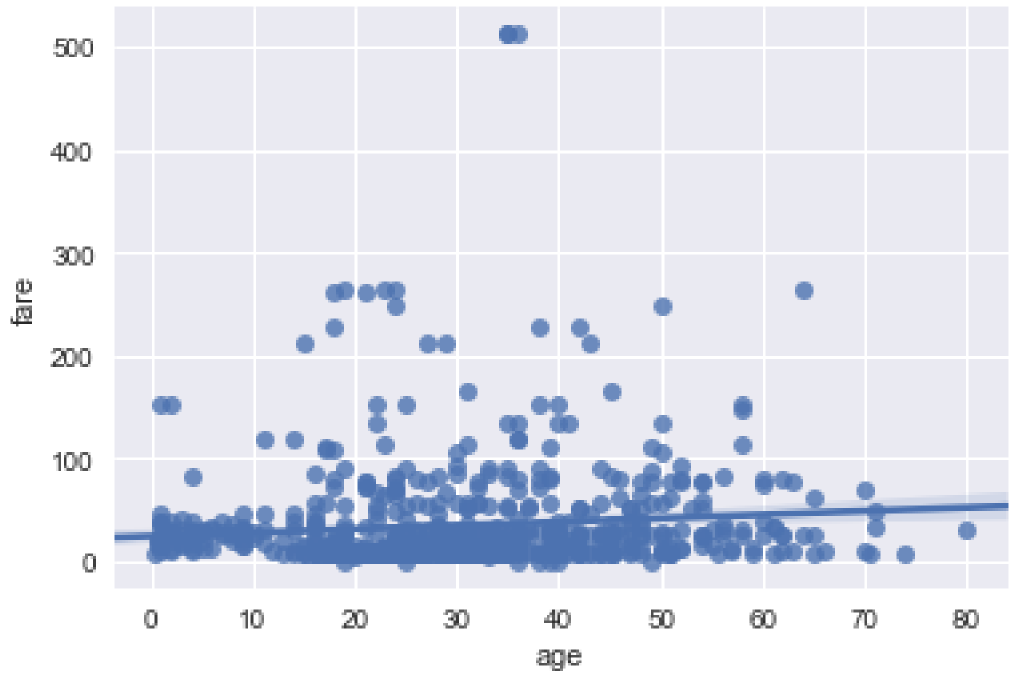
What do we do now? We can now explore a technique called **missing value imputation**. What this means is basically we find a reasonable way to *replace* the unknown data with workable values.

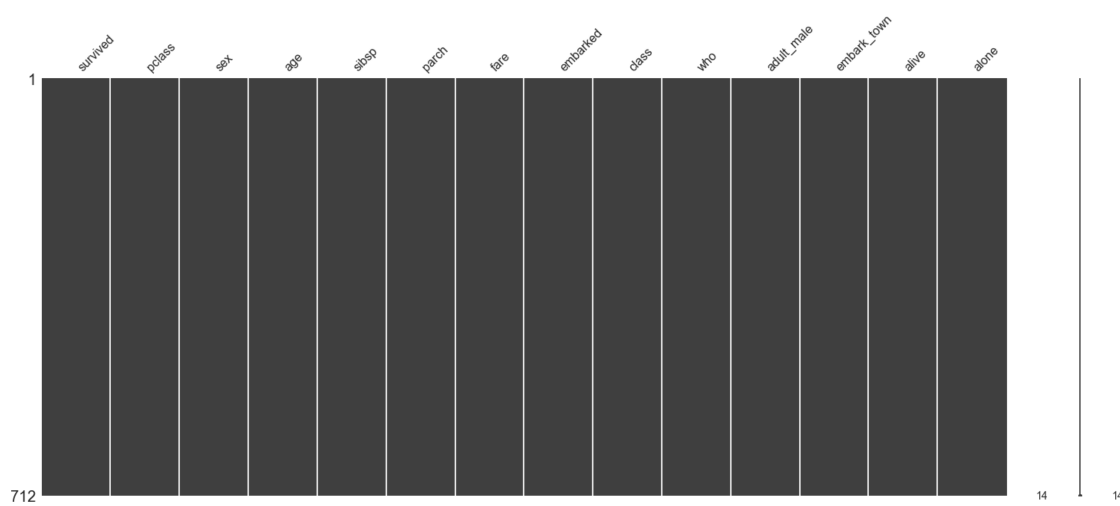
There's a lot of theory regarding how to do this properly, (for the curious look here). We can simply put in the average age value for the missing ages. But this really isn't so great as it would skew our stats towards the mean without taking into account various trends within the data.

If we assume that the data is missing *at random* (which actually is rarely the case), we can fit a model to predict the missing value based on the other factors in the dataset. One popular way to do this is a linear regression (coming forth in lecture #3!) `regplot` is a seaborn function to easily plot a linear regression.

Considering all these factors, assumptions and trade-offs, you must now make you own decision on how to deal with the missing data. You may choose any of the methods discussed above, or choose to not do anything at all (in which case you would only drop missing values when plotting). After writing your code below, verify the result by rerunning the matrix.

```
In [13]: sns.regplot(x='age',y='fare',data=titanic)
         clean_titanic=titanic.dropna()
         msno.matrix(clean_titanic)
         clean_titanic.describe()
```





Out[13]:

	survived	pclass	age	sibsp	parch	fare
count	712.000000	712.000000	712.000000	712.000000	712.000000	712.000000

```
mean     0.404494    2.240169   29.642093    0.514045    0.432584    34.567251
std      0.491139    0.836854   14.492933    0.930692    0.854181    52.938648
min      0.000000    1.000000    0.420000    0.000000    0.000000     0.000000
25%      0.000000    1.000000   20.000000    0.000000    0.000000     8.050000
50%      0.000000    2.000000   28.000000    0.000000    0.000000    15.645850
75%      1.000000    3.000000   38.000000    1.000000    1.000000    33.000000
max      1.000000    3.000000   80.000000    5.000000    6.000000   512.329200
```

1.3 Intro to Seaborn

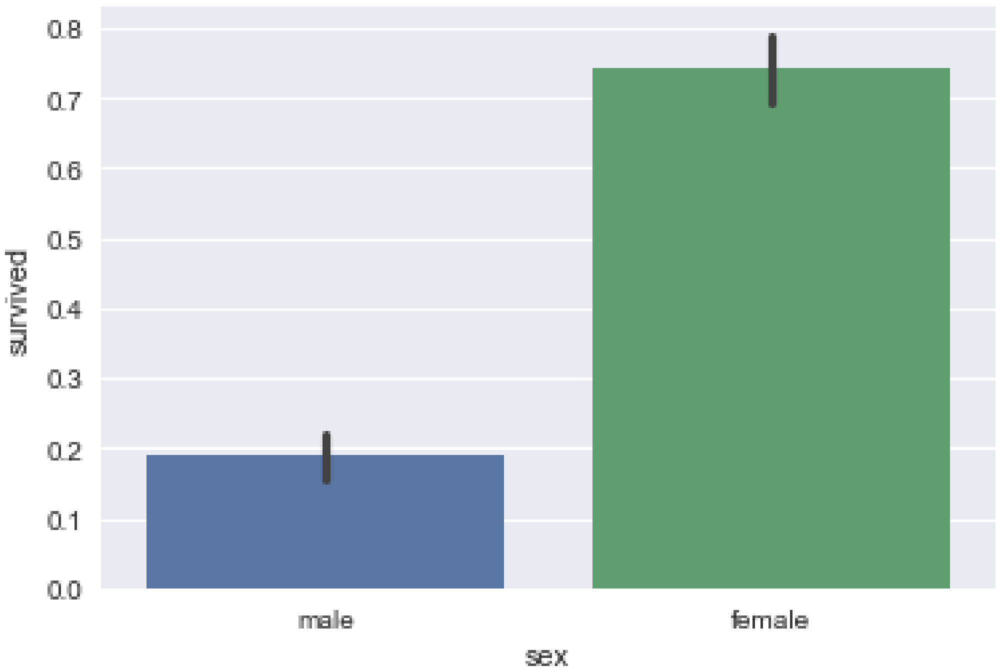
There are 2 types of data in any dataset: categorial and numerical data. We will first explore categorical data.

One really easy way to show categorical data is through bar plots. Let's explore how to make some in seaborn. We want to investigate the difference in rates at which males vs females survived the accident. Using the documentation here and example here, create a `barplot` to depict this. It should be a really simple one-liner.

```
In [14]: #x=titanic.sex
         #y=[titanic.loc[titanic['sex']=='male'].survived.sum(),titanic.loc[titanic['sex']=='f
         #sns.barplot(x,y)

         sns.barplot('sex','survived',data=titanic)#,hue="sex")
```

```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x10a1b3240>
```

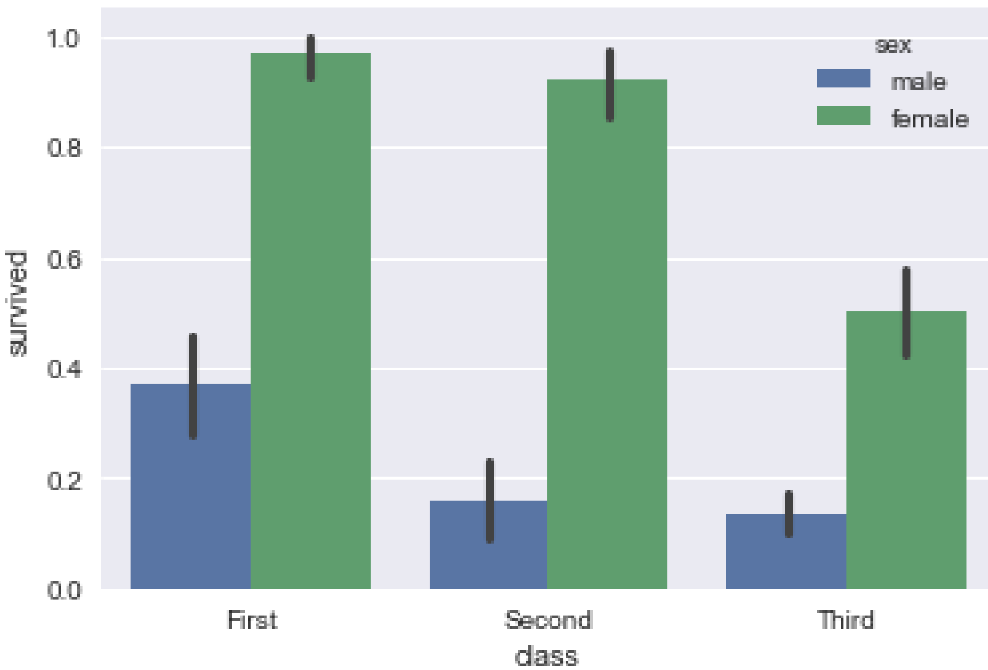


Notice how it was so easy to create the plot! You simply passed in the entire dataset, and just specified the `x` and `y` fields that you wanted exposed for the barplot. Behind the scenes seaborn ignored `NaN` values for you and automatically calculated the survival rate to plot. Also, that black tick is a 95% confidence interval that seaborn plots.

So we see that females were much more likely to make it out alive. What other factors do you think could have an impact on surival rate? Plot a couple more barplots below. Make sure to use *categorical* values like `sex` used above, not something numerical like age or fare.

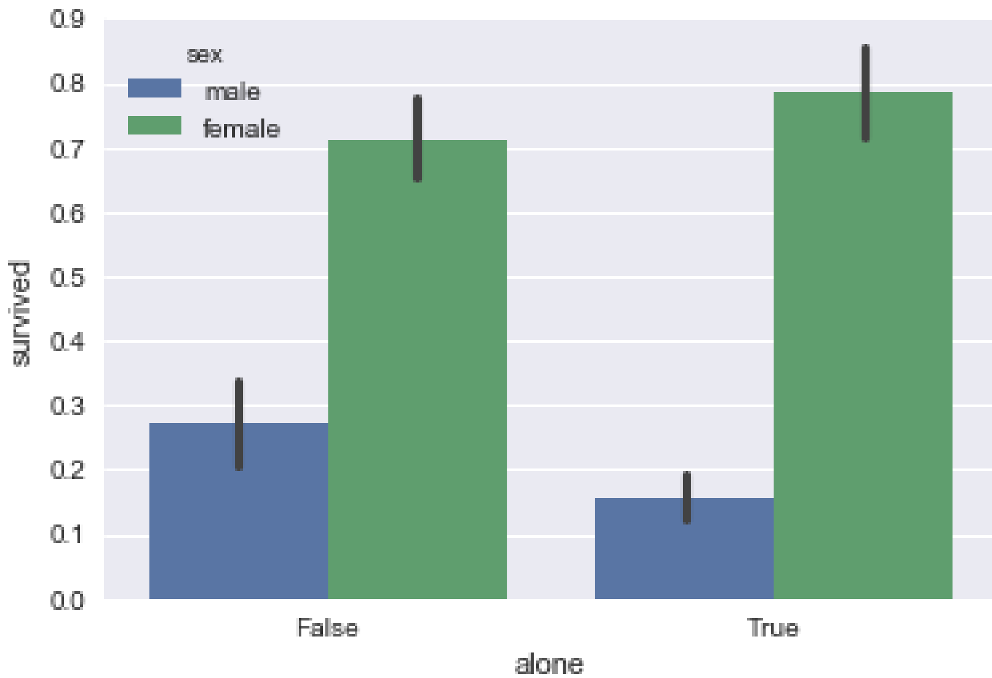
```
In [15]: sns.barplot('class','survived',data=titanic,hue="sex")
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x10fccc4e0>
```




```
In [16]: sns.barplot('alone','survived',data=titanic,hue="sex")
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1100cc518>
```



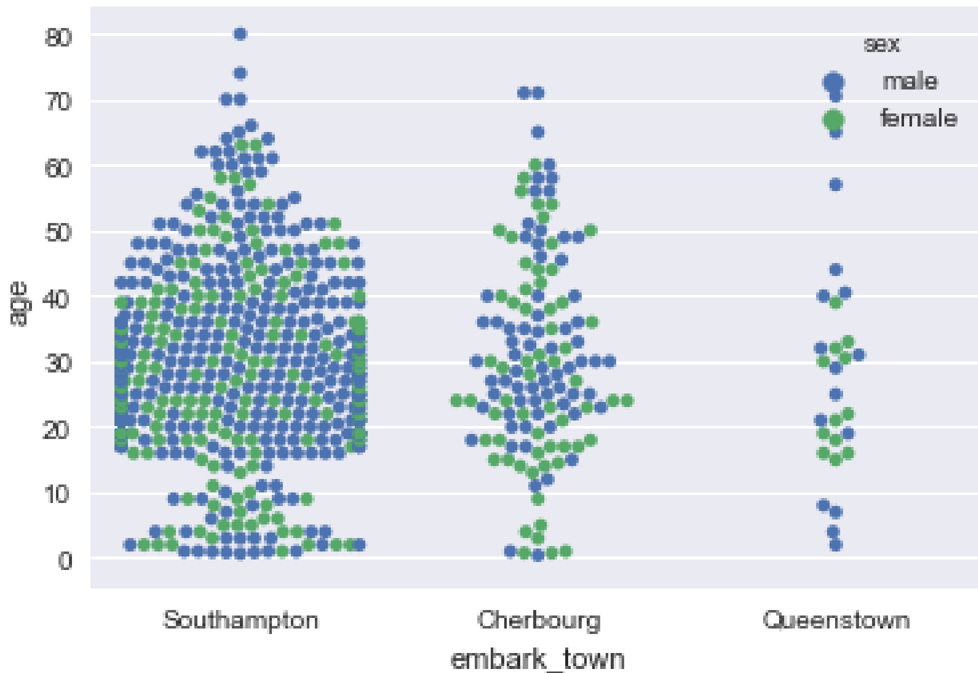
What if we wanted to add a further sex breakdown for the categories chosen above? Go back and add a `hue` parameter for `sex` for the couple plots you just created, and seaborn will split each bar into a male/female comparison.

Now we want to compare the embarking town vs the age of the individuals. We don't simply want to use a barplot, since that will just give the average age; rather, we would like more insight into the relative and numeric *distribution* of ages.

A good tool to help us here is `swarmplot`. Use this function to view `embark_town` vs `age`, again using `sex` as the `hue`.

```
In [17]: sns.swarmplot('embark_town','age',data=titanic, hue='sex')
```

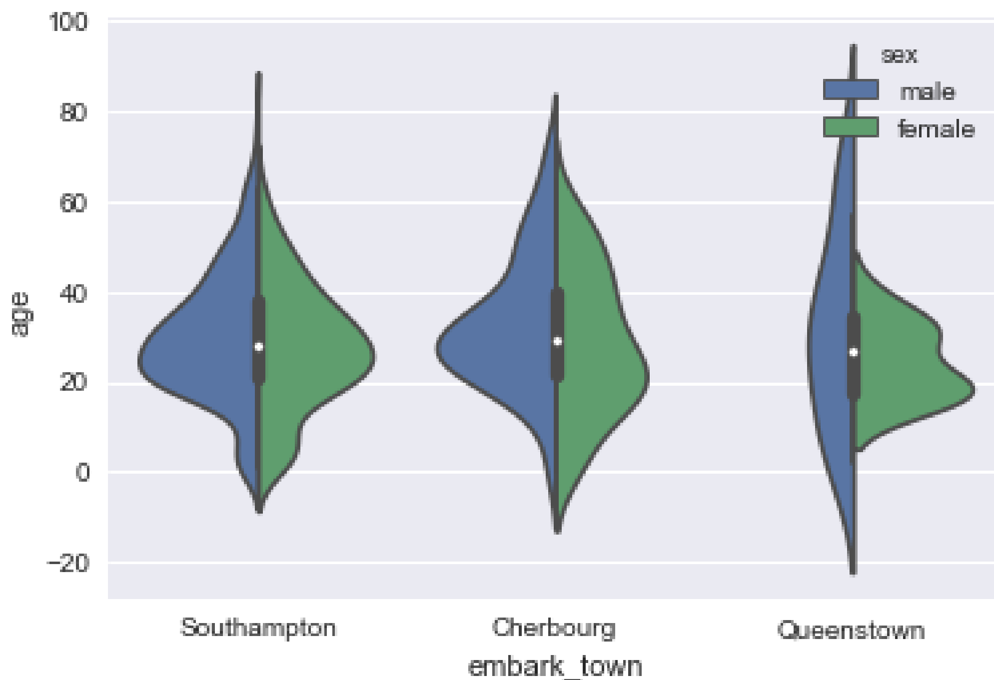
```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x11022cac8>
```



Cool! This gives us much more information. What if we didn't care about the number of individuals in each category at all, but rather just wanted to see the *distribution* in each category? `violinplot` plots a density distribution. Plot that.

```
In [18]: sns.violinplot('embark_town','age',data=titanic, hue='sex',split='True')
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x110418160>
```



Go back and clean up the violinplot by adding `split='True'` parameter.

Now take a few seconds to look at the graphs you've created of this data. What are some observations? Jot a couple down here.

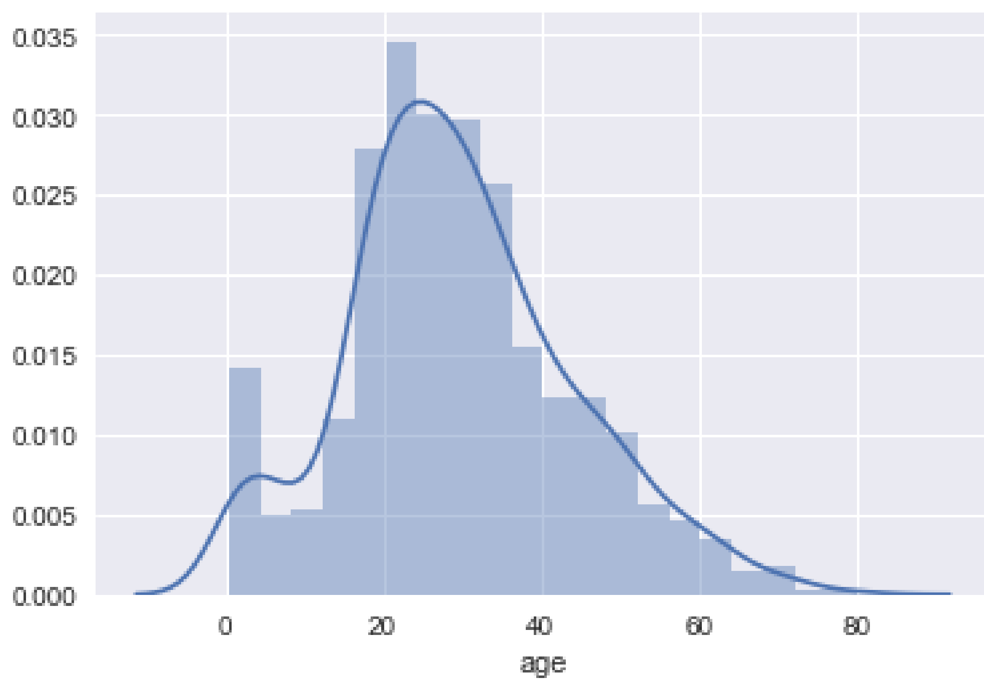
- Queenstown has a much wider range of ages for males than females.
- Most of the inhabitants in Southampton are the same ages.
- The average age of women in Cherbourg is slightly lower than the men's average.

As I mentioned, data is categorical or numeric. We already started getting into numerical data with the swarmplot and violinplot. We will now explore a couple more examples.

Let's look at the distribution of ages. Use `displot` to make a histogram of just the ages.

```
In [19]: sns.distplot(clean_titanic.age,hist='True')
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x110406f60>
```

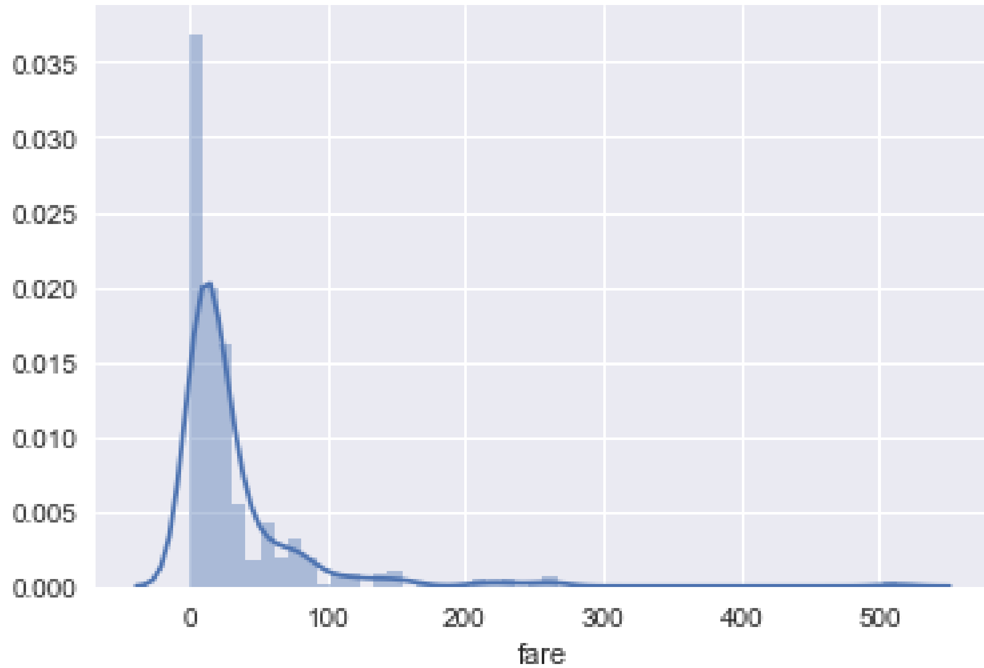


A histogram can nicely represent numerical data by breaking up numerical ranges into chunks so that it is easier to visualize. As you might notice, seaborn also automatically plots a gaussian kernel density estimate.

Do the same thing for fares - do you notice something odd about that histogram? What does that skew mean?

```
In [20]: sns.distplot(titanic.fare,hist='True')
```

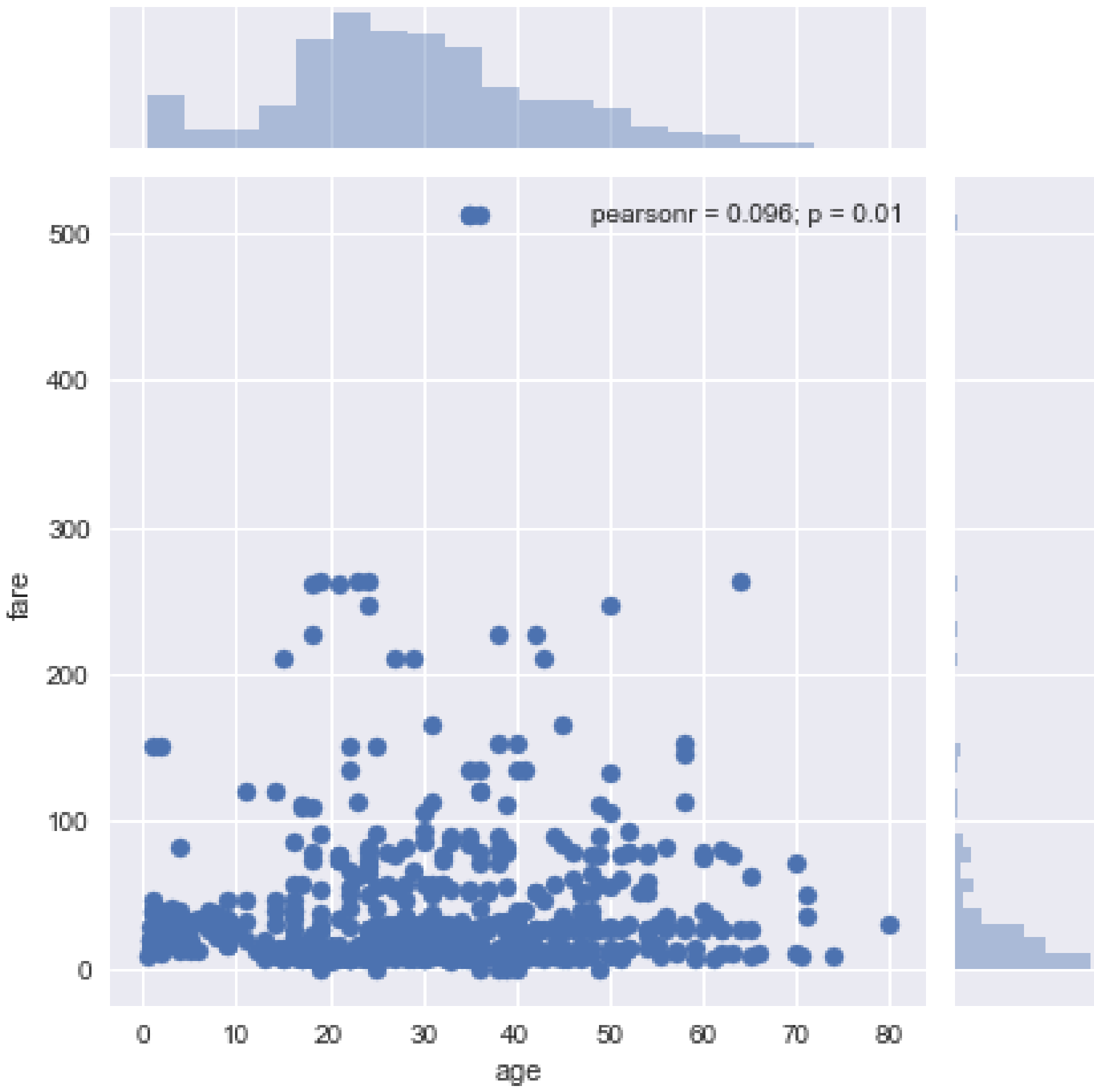
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1107aaac8>



Now, using the `jointplot` function, make a scatterplot of the `age` and `fare` variables to see if there is any relationship between the two.

```
In [21]: sns.jointplot('age','fare',data=titanic)
```

Out[21]: <seaborn.axisgrid.JointGrid at 0x10a199828>



Scatterplots allow one to easily see trends/coorelations in data. As you can see here, there seems to be very little correlation. Also observe that seaborn automatically plots histograms.

1.4 Diving into a familiar dataset

Now you hopefully have a pretty good understanding of both seaborn and matplotlib. You will now apply your learned skills to a familiar dataset, the 2016 election contributions. Navigate here and download ALL.zip.

There will be no hand-holding in this section. You know how to import a dataset, pull out and clean the values you need, and then plot it. You will follow this whole pipeline yourself.

Please plot 2 graphs: * the first graph should show the *cumulative* contributions for the candidate of your choide * the second graph should be a histogram of the contributions (not cumulative), with a bin for each month

You may use whatever outside libraries you wish. The `tsplot` and `distplot` from seaborn might be useful. The `hist` from matplotlib and `cumsum` from numpy may also be useful.

```
In [22]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         from collections import defaultdict
         import datetime as dt
         import matplotlib.dates as mdates
         import folium
         donations = pd.read_csv('2016-donations.csv', index_col=False)
```

```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages/IPython/core/inte
  interactivity=interactivity, compiler=compiler, result=result)
```

```
In [23]: contributions = donations[['cand_nm', 'contb_receipt_dt', 'contb_receipt_amt', 'contbr
         contributions.describe()
```

Out[23]:

	contb_receipt_amt
count	7.440252e+06
mean	1.261310e+02
std	7.623128e+03
min	-9.330800e+04
25%	1.500000e+01
50%	2.800000e+01
75%	9.435000e+01
max	1.277771e+07

```
In [24]: clean_contributions = contributions.dropna()
         rubio_conts = clean_contributions[clean_contributions.cand_nm == 'Rubio, Marco']
```

```
In [25]: sns.tsplot(rubio_conts.contb_receipt_amt)
```

```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages/seaborn/timeseri
  warnings.warn(msg, UserWarning)
```

```
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x10c87fa90>
```

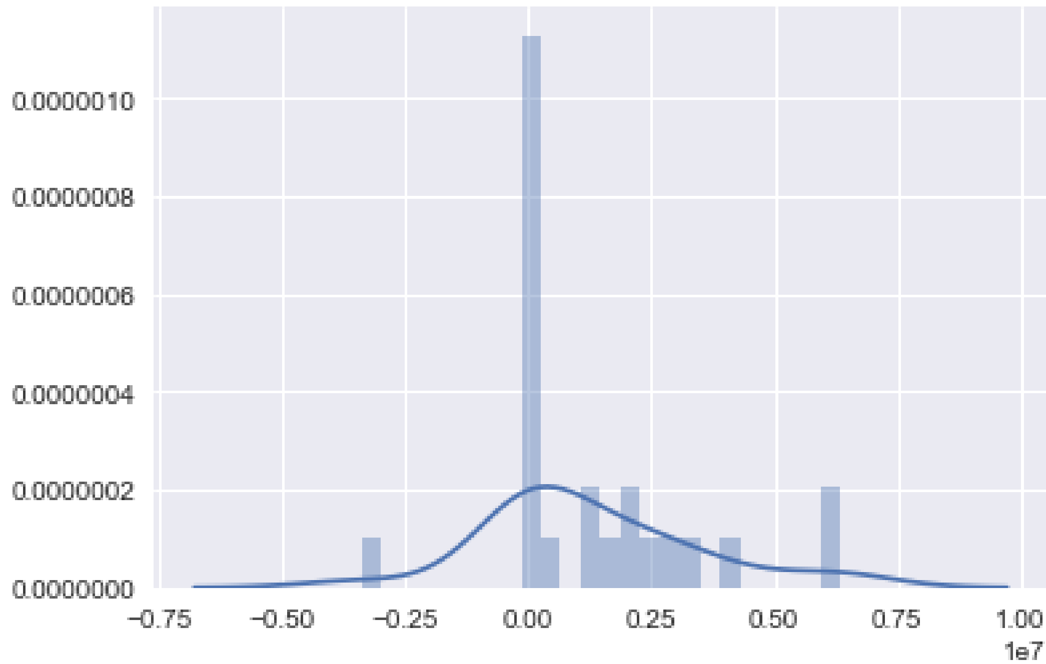

```
In [153]: """def helper(cont):
              #month={JAN:0,FEB:0,MAR:0,APR:0,MAY:0,JUN:0,JUL:0,AUG:0,SEP:0,OCT:0,NOV:0,DEC:0}
              month=['JAN','FEB','MAR','APR','MAY','JUN','JUL','AUG','SEP','OCT','NOV','DEC']
              result={'JAN15':0,'FEB15':0,'MAR15':0,'APR15':0,'MAY15':0,'JUN15':0,'JUL15':0,'A
              for i in range(len(cont.index)):
                  for mo in month:
                      if (mo in cont.contb_receipt_dt[i]) and ('15' in cont.contb_receipt_dt[i
                          result[mo+'15']+=cont.contb_receipt_amt[i]
                      elif (mo in cont.contb_receipt_dt[i]) and ('16' in cont.contb_receipt_dt
                          result[mo+'16']+=cont.contb_receipt_amt[i]
              return result
          """
          def helper2(cont):
              month=['JAN','FEB','MAR','APR','MAY','JUN','JUL','AUG','SEP','OCT','NOV','DEC']
              result={'JAN15':0,'FEB15':0,'MAR15':0,'APR15':0,'MAY15':0,'JUN15':0,'JUL15':0,'AU

              for index, row in cont.iterrows():
                  for mo in month:
                      if (mo in row.contb_receipt_dt) and ('15' in row.contb_receipt_dt):
                          result[mo+'15']+=row.contb_receipt_amt
                      elif (mo in row.contb_receipt_dt) and ('16' in row.contb_receipt_dt):
                          result[mo+'16']+=row.contb_receipt_amt
              return result
          result=helper2(rubio_conts)

In [157]: def resultscrape(result):
              tracker=['JAN15','FEB15','MAR15','APR15','MAY15','JUN15','JUL15','AUG15','SEP15'
```

```
    lst=[]
    for i in tracker:
        lst.append(result[i])
    return lst
sns.distplot(resultscrape(result),  hist='True',bins=24)
```

Out[157]: <matplotlib.axes._subplots.AxesSubplot at 0x16650e9e8>



In [154]: result

```
Out[154]: {'APR15': 2186797.7300000014,
 'APR16': -139312.45,
 'AUG15': 1332331.31,
 'AUG16': 0,
 'DEC15': 6344432.42,
 'DEC16': -6690.0,
 'FEB15': 48065.01,
 'FEB16': 6143994.010000017,
 'JAN15': 142594.16,
 'JAN16': 4044164.2700000005,
 'JUL15': 379922.93999999994,
 'JUL16': -2794.0,
 'JUN15': 2618121.880000001,
 'JUN16': -36300.0,
 'MAR15': 149086.59000000003,
```

```
'MAR16': 1326908.6699999992,
'MAY15': 1613129.7899999998,
'MAY16': -3404369.29,
'NOV15': 3445458.6700000004,
'NOV16': 0,
'OCT15': 2223771.0399999996,
'OCT16': 0,
'SEP15': 2902186.2,
'SEP16': -5400.0}
```