final-project-eda

March 3, 2017

0.1 Set Up

In [39]:
```
# Read in dat
import ggplot
import matplotlib.pyplot as plt
from matplotlib import cm
import numpy as np
import pandas as pd
import seaborn as sns # for visualiation
from scipy.stats import ttest_ind # t-tests
import statsmodels.formula.api as smf # linear modeling
import statsmodels.api as sm
import matplotlib
from sklearn import metrics
matplotlib.style.use('ggplot')
%matplotlib inline

data = pd.read_csv('~/top5europe.csv')
df = data
#import the module so that we can tables when printing dataframes
from IPython.display import display, HTML
pd.options.mode.chained_assignment = None
```

0.2 Data Preparation

Mapped out the countries in Europe with the five highest life expectancies (Switzerland, Spain, Italy, Iceland, France) to have a corresponding number (1, 2, 3, 4, 5 respectively) based on their rank. Removed the one outlier ridiculously high rate.

In [40]:
```
df1 = df
df1['location_name'] = df1['location_name'].map({'Switzerland': 1, 'Spain'
df1 = df1[df1.val < 50]
df1.head()
```

Out[40]:

	measure_id	measure_name	location_id	location_name	sex_id	sex_name	\
0	1	Deaths	83	4	1	Male	
1	1	Deaths	83	4	1	Male	
2	1	Deaths	83	4	1	Male	

```
3           1       Deaths           83              4       1     Male
4           1       Deaths           83              4       1     Male

   age_id   age_name  cause_id  \
0      26  70+ years       526
1      26  70+ years       586
2      26  70+ years       586
3      26  70+ years       586
4      26  70+ years       586

                                          cause_name  rei_id  \
0                                Digestive diseases     169
1  Diabetes, urogenital, blood, and endocrine dis...     110
2  Diabetes, urogenital, blood, and endocrine dis...     111
3  Diabetes, urogenital, blood, and endocrine dis...     113
4  Diabetes, urogenital, blood, and endocrine dis...     114

                    rei_name  metric_id metric_name  year        val  \
0           All risk factors          3        Rate  2015   1.959772
1              Dietary risks          3        Rate  2015  25.228970
2         Diet low in fruits          3        Rate  2015   3.876016
3   Diet low in whole grains          3        Rate  2015   4.596448
4  Diet low in nuts and seeds          3        Rate  2015   4.988863

       upper      lower
0   2.896562   1.291545
1  35.348261  16.803548
2   7.638902   0.784222
3   8.001574   2.265042
4   7.972121   2.411347
```

0.3 Describing Data Structure

```
In [41]: shape = df1.shape
         print "Size: %s" % (shape,)
         print "Variables: Location (str), Sex (str), Age (str), Cause of Death (st

Size: (731, 18)
Variables: Location (str), Sex (str), Age (str), Cause of Death (str), Risk Factors
```

0.4 Univariate Analysis

```
In [42]: df1.describe()

Out[42]:        measure_id  location_id  location_name      sex_id      age_id  \
         count       731.0   731.000000     731.000000  731.000000  731.000000
         mean          1.0    87.012312       2.997264    1.510260   23.775650
```

```
std           0.0     5.307902       1.419046    0.500237    4.786283
min           1.0    80.000000       1.000000    1.000000    1.000000
25%           1.0    83.000000       2.000000    1.000000   24.000000
50%           1.0    86.000000       3.000000    2.000000   25.000000
75%           1.0    92.000000       4.000000    2.000000   25.000000
max           1.0    94.000000       5.000000    2.000000   26.000000
```

```
          cause_id      rei_id  metric_id    year         val       upper
count   731.000000  731.000000      731.0   731.0  731.000000  731.000000
mean    419.663475  127.180575        3.0  2015.0    5.454289    8.731446
std     138.198156   21.332853        0.0     0.0    9.567248   15.070789
min     294.000000  110.000000        3.0  2015.0    0.000004    0.000036
25%     294.000000  114.000000        3.0  2015.0    0.157573    0.259155
50%     294.000000  118.000000        3.0  2015.0    1.040344    1.749419
75%     586.000000  124.000000        3.0  2015.0    5.942234    9.822360
max     586.000000  169.000000        3.0  2015.0   49.584470   81.144145
```

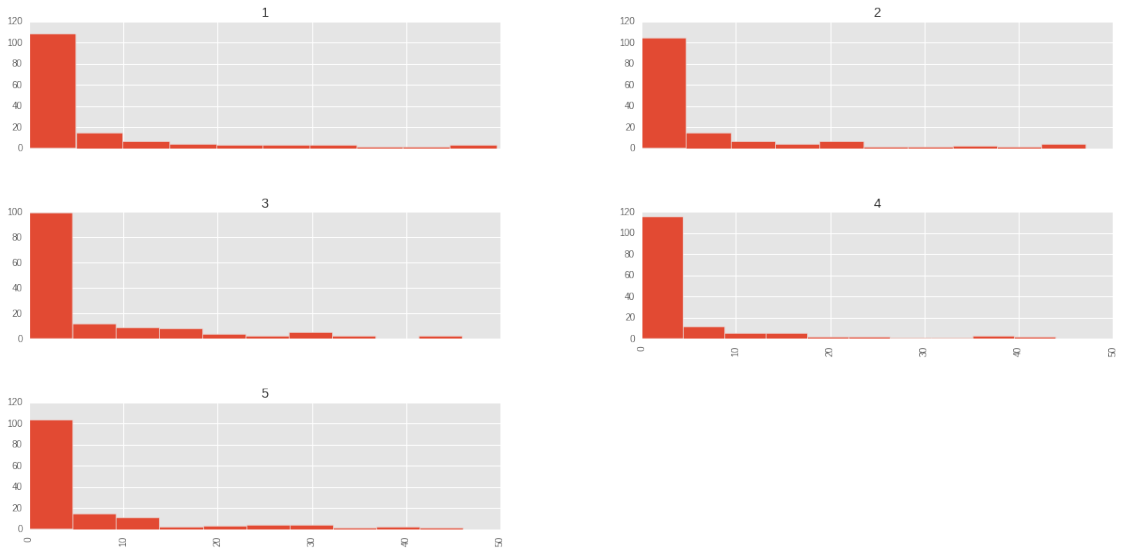
```
            lower
count  731.000000
mean     2.846727
std      5.767767
min      0.000000
25%      0.067334
50%      0.439343
75%      2.388055
max     43.794091
```

0.5 Univariate Analysis by Category

In [43]:
```
#ax = df1['val'].plot(kind='bar', title ="V comp", figsize=(15, 10), leger
#ax.set_xlabel("Hour", fontsize=12)
#ax.set_ylabel("V", fontsize=12)
#plt.show()

df1['val'].hist(by=df1['location_name'], sharex=True, figsize=(20,10))
```

Out[43]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fbb1fde1cd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fbb1fcfd3d0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fbb1fd0fdd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fbb1faa4790>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fbb1fa26910>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fbb1fa08910>]]
```



0.6 Bivariate analysis

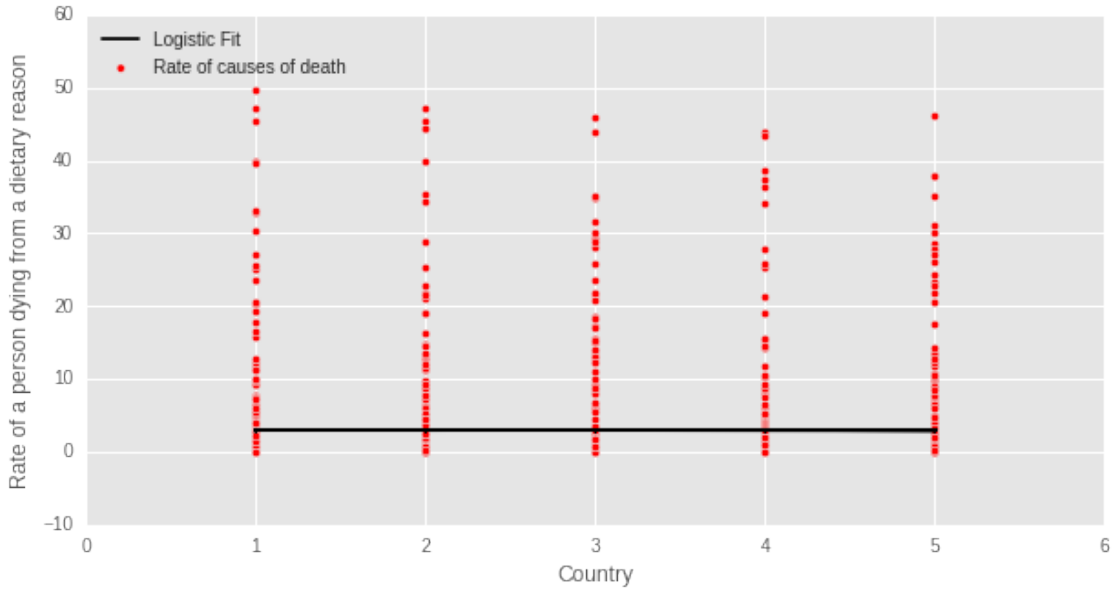
```
In [45]: lm = smf.glm(formula = 'location_name ~ val', data=df1, family=sm.families
         df1['lm'] = lm.predict()

In [46]: lm.summary()

Out[46]: <class 'statsmodels.iolib.summary.Summary'>
         """
                          Generalized Linear Model Regression Results
         ==============================================================================
         Dep. Variable:          location_name   No. Observations:
         Model:                            GLM   Df Residuals:
         Model Family:                 Poisson   Df Model:
         Link Function:                    log   Scale:
         Method:                          IRLS   Log-Likelihood:                -13
         Date:                Fri, 03 Mar 2017   Deviance:                       52
         Time:                        09:04:46   Pearson chi2:
         No. Iterations:                     7
         ==============================================================================
                          coef    std err          z      P>|z|      [95.0% Conf. I
         ------------------------------------------------------------------------------
         Intercept      1.1029      0.025     44.895      0.000         1.055     1
         val           -0.0010      0.002     -0.429      0.668        -0.005     0
         ==============================================================================
         """

In [47]: fig, ax = plt.subplots(figsize=(10, 5))
         ax.scatter(df1.location_name, df1.val, c='red', label="Rate of causes of c
```

```
ax.plot(df1.location_name, df1.lm, c='black', label="Logistic Fit")
ax.legend(numpoints=1, loc='upper left')
ax.set_xlabel('Country')
ax.set_ylabel('Rate of a person dying from a dietary reason')
plt.show()
```



0.7 Summary of Insights

We're trying to look if certain dietary restrictions or changes significantly affect a life expectancy. I took the highest 5 life expectancies by country in Europe and took a look at their rates of deaths caused by different dietary means to see if it correlated with their corresponding life expectancy ranks. In the univariate analysis, we can see that Iceland has higher rates of dietary related deaths than the other countries, but is still ranked higher than France.

In my bivariate analysis where I ran a poisson regression, there doesn't seem to be any correlation between the dietary causes of deaths and the life expectancy. However, it would be interesting to compare the highest life expectancy countries with the lowest life expectancy countries. Or just countries that have more variation in living conditions compared to the five chosen in my report.

In [ ]: