STA 141B: Midterm (or Super-Homework if you prefer)

Worth 300 Points

Fall 2018

Information

After the colons (in the same line) please write just your first name, last name, and the 9 digit student ID number below.

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Instructions

Please print your answer notebook to pdf (make sure that it is not unnecessarily long due to long output) and submit as the homework solution with your zip file.

For readability you,

- MUST add cells in between the exercise statements and add answers within them and
- MUST NOT modify the existing cells, particularly not the problem statement
- you may add multiple cells between exercise cells

To make markdown, please switch the cell type to markdown (from code) - you can hit 'm' when you are in command mode - and use the markdown language. For a brief tutorial see: [https://daringfireball.net/projects/markdown/syntax (https://daringfireball.net/projects/markdown/syntax)](https://daringfireball.net/projects/markdown/syntax)

Trans-Atlantic Slave Trade

In this homework, we will uncover some of the numbers behind the Trans-atlantic slave trade (TAST), also known as the middle passage, that brought African slaves to the Americas. The middle passage is reported to have forcibly migrated over 10 million Africans to the Americas over a roughly 3 century time span. Many aspects of the TAST is little known by most people, such as the countries that constituted this network of slave ships, the regions from which the slaves were taken, and the number of slaves captured from Africa.

This last number is especially important since the number of slaves taken from Africa can impact other estimates that result from this. For example, when estimating the population of Africa in a given decade, demographers will use population growth models and more recent census data. For example, there are roughly X number of people in Africa and such populations tend to grow at rate M. Then if we want to calculate the population one century ahead then we just apply a simple formula that assumes that the population grows at this rate. But if the population is being drained by the slave trade, then this number will tend to be underestimated because the growth rate is overestimated. To account for this models need to take into account this drain on the population.

Throughout this homework you will need to follow the principles of graphical excellence and the grammar of graphics. **Use only Plotnine for your graphics**, do not use Pyplot, Seaborn, or Plotly since they do not follow closely the grammar of graphics. Be sure to include titles and necessary contextual captions.

Warning: The Trans-Atlantic Slave Trade remains one of the most horrific abuses of human rights in history. This homework deals with the numbers behind this forced migration, please be aware that this is a sensitive topic for possibly yourself and others. A suitable amount of respect and seriousness is required when dealing with this data.

Exercise 1. The data.

1. Read in the Trans-Atlantic Slave Trade database with Pandas. Hint: if you use the unix tool `file` you can find that this CSV is encoded with iso-8859-1 character set. Make sure that all missing values are encoded as NaN.
2. There is lots of missingness in this data, and some of these variables are imputed. We will be imputing some of these variables ourselves, so delete any variable that ends with 'imp'.
3. Open up the pdf file: TAST_codebook.pdf which is the data dictionary for this and other related datasets. Many of the variables in the codebook are not in this dataset because it is describing an updated dataset.
4. Create a list where you describe the meaning of the columns of your imported dataframe. You can group similar columns together when describing their rough meaning, such as ownera,...,ownerp are owners of the slave ships.

Throughout we will disregard all time variables other than year since they are unreliable.

In [1]:
```
import pandas as pd
import os
import numpy as np
import matplotlib.pyplot as plt
import plotnine as p9
from sklearn import linear_model, metrics
import statsmodels.api as sm

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data = pd.read_csv('tastdb-2010.csv',encoding='iso-8859-1',skipinitialspace=True)
```

In [3]:
```
data.shape
```

Out[3]:
```
(34941, 98)
```

In [4]:
```
imp_col = data.columns[data.columns.str.endswith('imp')] #columns that end with im
ndata = data.drop(imp_col,axis=1)#drop columns according imp_col
ndata.shape
```

Out[4]: (34941, 89)

In [5]:
```
#extract year from yearam
year = []
for date in ndata.yearam:
    yr = str(date).split('/')[-1]
    year.append(float(yr))
ndata['year'] = year
```

{**voyageid**:Voyage identification;**evgreen**:If voyage in 1999(yes=1) CD-ROM;**shipname**:Name of the ship; **national**:Country in which the ship registered;**placcons**:Place where the ship constructed;**yrcons**:Year of the ship's construction;**placreg**:Place where the ship registered;**yrreg**:Year of ship's registration;**rig**:Rig of the ship;**tonnage**:Tonnage of the ship;**tonmod**:Tonnage standardized on British measured tons,1773-1835;**guns**:Guns the ship has;**owner[a-p]**:owners of the ship;**fate[1-4]**:the outcomes of a particular voyage;**resistance**:level of resistance the Africans performed;**plac[1-3]tra**:the places where to purchase slave;**npafttra**:Port of call before Atlantic crossing;**sla1por,adpsale[1-2]**:Places of slave landing;**protret**:Place at which voyage ended;**yearam**:Year of arrival at port of disembarkation;**Date_[dep,buy,leftAfri,land1,depam,end]**:Date the ship performed differnt activities;**captainn[a-c]**:Names of the captains;**crew[1,3]**:# of crew at a particular time;**crewdie**:# of crew died during complete voyage;**slintend**:Slaves intended from first port of purchase;**ncar[13,15,17]**:# of slaves carried from differnt port of purchase;**tslavesd**:Total slaves on board at departure from last slaving port;**slaarriv**:Total slaves arrived at first port of disembarkation;**slas[32,36,39]**:# of slaves disembarked at [first,second,third] place; **[men,wom,boy,girl,mal,child]rat7**:Percentage of a particular category of slaves at departure or arrival;**jamcaspr**:Average price of slaves standardized on sterling cash price of prime slaves sold in Jamaica;**vymrtrat**:Slave mortality rate (slave deaths / slaves embarked);**source[a-r]**:sources of information}

Exercise 2. First pass at estimating the total number of captives.

1. We will ultimately try to estimate the number of people captured into slavery and forced through the middle passage. What variable would you use to estimate the total number of captives taken from Africa? Let me call this variable Var A in this problem statement. How much of the data for Var A is missing?
2. Create an initial estimate of the total number of captives taken from Africa by assuming that Var A is Missing Completely at Random.
3. What other variables do you expect to be associated with Var A and why? Give at least three possibilities. Which will probably be the most strongly associated with this variable? (I will be looking for a specific variable to be listed so be sure to think about the most strongly associated one.)

1. I would use variable **tslavesd** to estimate the totalnumber of captives taken from Africa. There are 26734 mising value.

In [6]:
```
var_na = ndata.tslavesd.isnull().sum()
var_na
```

Out[6]:
```
26734
```

2. Using variables ncar13, ncar15, ncar17 to estimate the total number of slaves are captured

In [7]:
```
sl_pur = ndata[['ncar13','ncar15','ncar17']] #fill nan as zero
```

In [8]:
```
est_tot = sl_pur['ncar13']+sl_pur['ncar15']+sl_pur['ncar17'] #add up 3 variables t
```

In [9]:
```
est_tot.sort_values(ascending=False)
```

Out[9]:
```
17048    685.0
16018    618.0
6437     605.0
17706    507.0
19435    447.0
19508    443.0
33645    427.0
34642    422.0
15696    410.0
15912    405.0
7139     403.0
17452    380.0
7164     376.0
7451     358.0
19431    349.0
7138     345.0
17535    341.0
7020     333.0
7340     331.0
```

3

- Variables **slaarriv, vymrtrat, slas[32,36,39]** are also associated with variable A, because by adding up variables slas[32,36,39], we can also estimate the number of slaves were captured. And slaarriv/vymtrat can also estimate the number of slaves were captured.
- Variable **slaarriv** is the most strongly associated with variable A, because the mean of death rate is approximately 12%, by knowing total slaves arrived at first port of disembarkation we can make a guess of variable A.

In [10]:
```
ndata.vymrtrat.mean()
```

Out[10]:
```
0.11938669072909454
```

Exercise 3. The flag that the ships flew.

1. We want to understand the trends of the nationality of the slave ships (the flag that they flew under is in the national variable). Subselect the values of `national` that have more than 100 voyages with that value.
2. Create a DataFrame that filters out the voyages where `national` does not have one of these values. You should be retaining voyages with only these most common values.
3. Create a variable, `flag` , that is a string of easily readable names for these values by looking them up in the pdf codebook.
4. Using Plotnine, plot the counts of the voyages by flag as a function of voyage year. Think about how best to display the count of a voyage by year and then how should you be including the flag variable.
5. In this plot, what are the geometric elements and aesthetic mappings? What other components of the grammar of graphics are you using?
6. Do you observe any abrupt changes in the patterns of these counts for a given flag? Investigate the cause for this change (using Google, etc.).

1.

In [11]:
```
import collections
```

In [12]:
```
nation_count = dict(collections.Counter(ndata[~ndata.national.isnull()].national).
nation_count
```

Out[12]:
```
{7.0: 11009,
 4.0: 5303,
 10.0: 4069,
 9.0: 1575,
 1.0: 1249,
 8.0: 1237,
 5.0: 788,
 11.0: 248,
 12.0: 60,
 13.0: 10,
 2.0: 8,
 19.0: 6,
 18.0: 3,
 16.0: 2,
 17.0: 1,
 14.0: 1,
 24.0: 1}
```

In [13]:
```
more100 = []
less100 = []
for inx, val in nation_count.items():
    if val > 100:
        more100.append(inx)#assign the nations which have more than 100
    else:
        less100.append(inx)#assign the nations which have less than 100
```

In [14]:
```
more100
```

Out[14]: [7.0, 4.0, 10.0, 9.0, 1.0, 8.0, 5.0, 11.0]

In [15]:
```
less100
```

Out[15]: [12.0, 13.0, 2.0, 19.0, 18.0, 16.0, 17.0, 14.0, 24.0]

2.

In [16]:
```
less_vo = ndata.query('national>=12.0|national==2.0') #nations has less than 100 v
less_vo.national.unique()
```

Out[16]: array([13., 2., 16., 17., 12., 19., 14., 18., 24.])

3.

In [17]:
```
flag = {1:'Spain', 2:'Uruguay', 4:'Portugal',5:'Brazil',7:'Great Britain',8:'Nethe
12:'Brandenburg',13:'Sweden',14:'Norway',16:'Argentina',17:'Russia',18:'Sardinia',
```

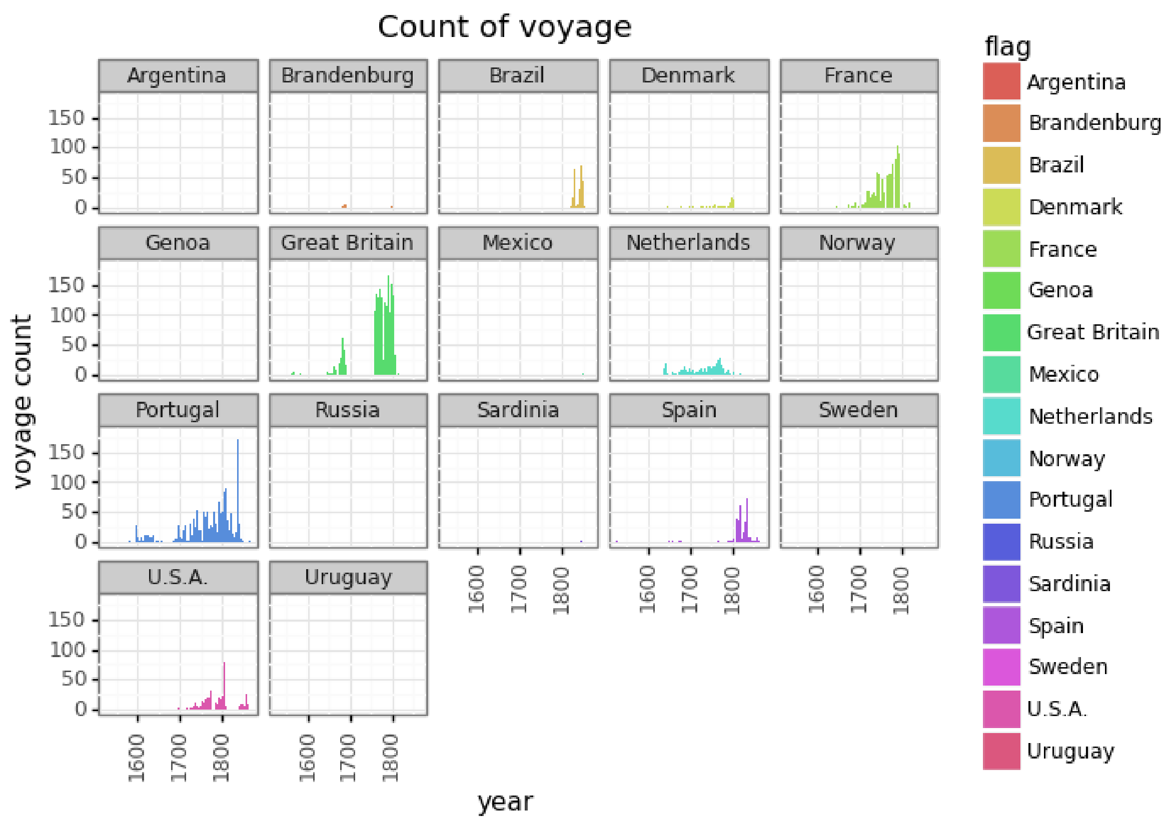
4.

In [18]:
```
count_yr = ndata[['national','voyageid','year']]
count_yr.set_index(['national','year']) #set row index as national and year
count_yr = count_yr.groupby(['year','national']).count().reset_index() #count base
count_yr['flag'] = count_yr.national.map(flag) #mapping nations according dictiona
count_yr[['year','flag','voyageid']]
```

Out[18]:

	year	flag	voyageid
0	1526.0	Spain	2
1	1527.0	Spain	1
2	1532.0	Portugal	1
3	1535.0	Portugal	1
4	1563.0	Great Britain	3
5	1565.0	Great Britain	4
6	1567.0	Great Britain	4
7	1568.0	Great Britain	6
8	1571.0	France	1
9	1582.0	Portugal	1
10	1583.0	Great Britain	1

In [19]:
```
p9.ggplot(count_yr, p9.aes(x='year', y='voyageid',fill='flag')) + p9.geom_col(stat
+ p9.labels.ggtitle('Count of voyage') + p9.labels.ylab('voyage count')\
+ p9.theme_bw()\
+ p9.theme(axis_text_x = p9.themes.element_text(rotation=90))+p9.facet_wrap('~flag
```



Out[19]: <ggplot: (12902685)>

5. I used geom_col as geomtric elements; Used **year** of voyage departure as x axis, count of voyage as y axis, used fill to distinguish differnt nations; I also used theme_bw to change the backgroud and x labe text positioin; used labels to change change title and y label
6. As we can see in the plot, voyage counts of principal slave-trading flags like Great Britain, France and Netherland dropped rapidly in 1800s and there were almost no slave trade after 1830. The reason for this is nations started to ban slave trade after 1800. Therefore, slave trade became an illegal activity in some countries.

Exercise 4. Looking at some of these ships.

1. Search for the slave ship mentioned in the following wikipedia article: [https://en.wikipedia.org/wiki/Brookes_(ship) (https://en.wikipedia.org/wiki/Brookes_(ship))](https://en.wikipedia.org/wiki/Brookes_(ship)) Hint: Look at all records of ships with 'Brook' in the name and try to match the characteristics to those described. How many voyages for this ship are in the data (try to exclude ships with the same name)?
2. Create a variable that is True if there was a resistance (like a slave revolt) on the ship. Plot the density of ships as a function of year with and without revolts and compare these distributions.
3. The movie Amistad was based on a real slave ship and slave uprising. Read about it here: [https://en.wikipedia.org/wiki/La_Amistad (https://en.wikipedia.org/wiki/La_Amistad)](https://en.wikipedia.org/wiki/La_Amistad) Try to find

this ship by searching for it by name and also searching for ships in the same 10 year period as this event with a slave resistance. If you think you found it describe it, otherwise describe the events of another voyage that you did find.

Additional information fo Brookes ship: [http://www.virtualjamestown.org/map4b.html (http://www.virtualjamestown.org/map4b.html)](http://www.virtualjamestown.org/map4b.html). It was built on 1781 in Liverpool, weighted 297 tons

In [20]:
```
brook = ndata[ndata.shipname.str.contains('brook',na=False,case=False)]
brookes = brook.query('national == 7 & placcons == 10432 & yrcons==1781 & tonnage=
print('1. There are {} voyages for this ship in the data'.format(brookes.shape[0])
brookes
```

```
1. There are 4 voyages for this ship in the data
```

Out[20]:

	voyageid	evgreen	shipname	national	placcons	yrcons	placreg	yrreg	rig	tonnage	..
29534	80663	1.0	Brooks	7.0	10432.0	1781.0	10432.0	1781.0	4.0	297.0	..
29535	80664	1.0	Brooks	7.0	10432.0	1781.0	10432.0	1783.0	4.0	297.0	..
29536	80665	1.0	Brooks	7.0	10432.0	1781.0	10432.0	1783.0	4.0	297.0	..
29537	80666	1.0	Brooks (a) Brookes	7.0	10432.0	1781.0	10432.0	1786.0	4.0	297.0	..

4 rows × 90 columns

2.

In [21]:
```
revolt = []
for val in ndata.resistance:
    if np.isnan(val)==True: #map nan with False: no resistance
        revolt.append(False)
    else:
        revolt.append(True) #map numbers with True: has resistance
```

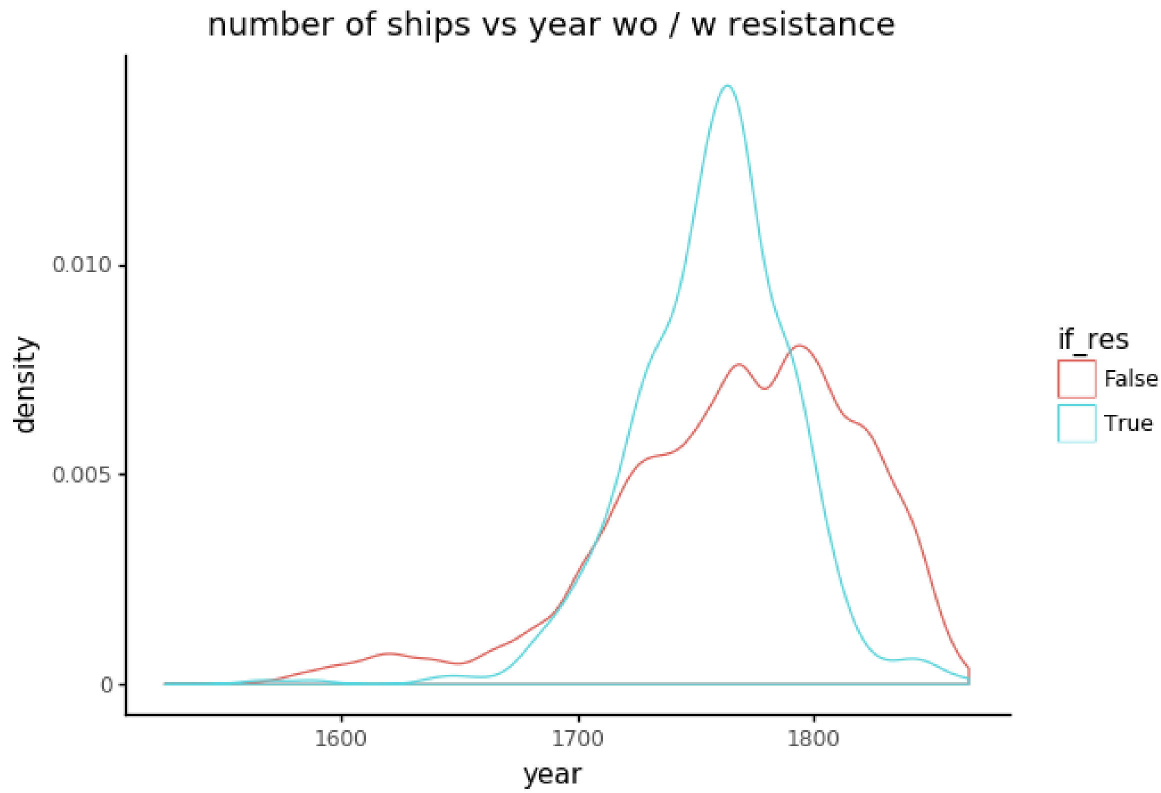
In [22]:

```
ndata['if_res'] = revolt
res = ndata[['if_res','year','shipname']]
res.set_index(['year','if_res','shipname'])
res = res.groupby(['year','if_res','shipname']).size().reset_index(name='count')#c
res
```

Out[22]:

	year	if_res	shipname	count
0	1525.0	False	S Maria de Bogoña	1
1	1527.0	False	Concepción	1
2	1532.0	False	S Antônio	1
3	1532.0	False	S João	1
4	1532.0	False	S Maria da Luz	1
5	1534.0	False	Conceição	1
6	1534.0	False	S Antônio	1
7	1535.0	False	S João	1
8	1535.0	False	S Miguel	1
9	1545.0	False	Galdame	1
10	1545.0	False	Santa Cruz	1

In [23]:
```
#plot density for having resistance and not having resistance
p9.ggplot(res)+p9.aes('year',color='if_res')+p9.geom_density(alpha=.5)\
+p9.ggtitle('number of ships vs year wo / w resistance')+p9.xlab('year')\
+p9.theme_classic()
```



Out[23]: `<ggplot: (12952815)>`

The movie Amistad was based on a real slave ship and slave uprising. Read about it here: [https://en.wikipedia.org/wiki/La_Amistad (https://en.wikipedia.org/wiki/La_Amistad)](https://en.wikipedia.org/wiki/La_Amistad) Try to find this ship by searching for it by name and also searching for ships in the same 10 year period as this event with a slave resistance. If you think you found it describe it, otherwise describe the events of another voyage that you did find.

3. Since all thes ships that contains **'amista'** in their names do not have resistance, the event is not in the data. However, in the same 10 years period (1830-1839), there are 2 ships has revolt and the more recent one happened in 1837. It was a Portuguese ship captained by Fonseca, Camilo Urbano da, with 352 slaves purchased, 46% fo them were man. The fate of the ship was 'Court of Mixed Commission, Sierra Leone, condemned'.

In [24]:
```
amistad = ndata[ndata.shipname.str.contains('amistad',case=False,na=False)] #searc
```

In [25]:
```
amistad.query('if_res==True')
```

Out[25]:

voyageid	evgreen	shipname	national	placcons	yrcons	placreg	yrreg	rig	tonnage	...	sour

0 rows × 91 columns

In [26]:
```
in1830s = ndata.query('1830<=year<=1839')#search ships in the same period:1930s
in1830s=in1830s.query('if_res==True&year==1837')
in1830s.captaina
in1830s[['national','tslavesd','slaarriv','if_res','year','menrat7','fate','captai
```

Out[26]:

	national	tslavesd	slaarriv	if_res	year	menrat7	fate	captaina
2504	4.0	352.0	254.0	True	1837.0	0.461864	120.0	Fonseca, Camilo Urbano da

Exercise 5. Other patterns.

1. The arrival and departure locations are quite detailed. Look in the appendix of the codebook for the location codes. Make a coarser version of both arrival and departure port variables (select just the last departure and first arrival) so that for example,

   ```
   30000 Caribbean 36100 Martinique 36101 Fort-Royale
   ```

   is just encoded as '3' or Caribbean.
2. Plot the trend of voyages as a function of arrival location. What trends do you see?
3. Do the same for departure location.
4. Plot the ratio of captives that are men as a function of year. Include a smoother to describe the over all trend. Also include in the plot another possible confounding variable.
5. Describe the geoms, aesthetic mappings, and other aspects of the plot.

1.

In [27]:
```
def encode(series):
    """arg: series
return: a list of region encoded"""
    ls = []
    for value in series:
        if np.isnan(value)==True:
            ls.append(value)
        else:
            ls.append(int(str(value)[0]))
    return(ls)
```

In [28]:
```
dep_ls = []
"""the last departure location depends on where the ship landed their slaves at th
Therefore, check if the ship made purchased in the second place and the third plac
Order: 'plac3tra'>'plac2tra'>'plac1tra'
"""
for i in range(len(ndata)):
    purs = ndata.loc(0)[i][['plac1tra','plac2tra','plac3ra']]
    if np.isnan(purs[2])==False:
        dep_ls.append(purs[2])
    elif np.isnan(purs[1]) == False:
        dep_ls.append(purs[1])
    else:
        dep_ls.append(purs[0])
```

In [29]:
```
ndata['ladeploc'] = dep_ls
```

In [30]:
```
arr_loc = encode(ndata.sla1port)#first arrival
dep_loc = encode(ndata.ladeploc)#last departure
ndata['arr_loc'] = arr_loc
ndata['dep_loc'] = dep_loc
```

In [31]:
```
region = {1:'Europe',2:'Mainland North America',3:'Caribbean',4:'Spanish Mainland
```

In [32]:
```
#map endcode number to string
ndata['arr_loc'] = ndata.arr_loc.map(region)
ndata['dep_loc'] = ndata.dep_loc.map(region)
```

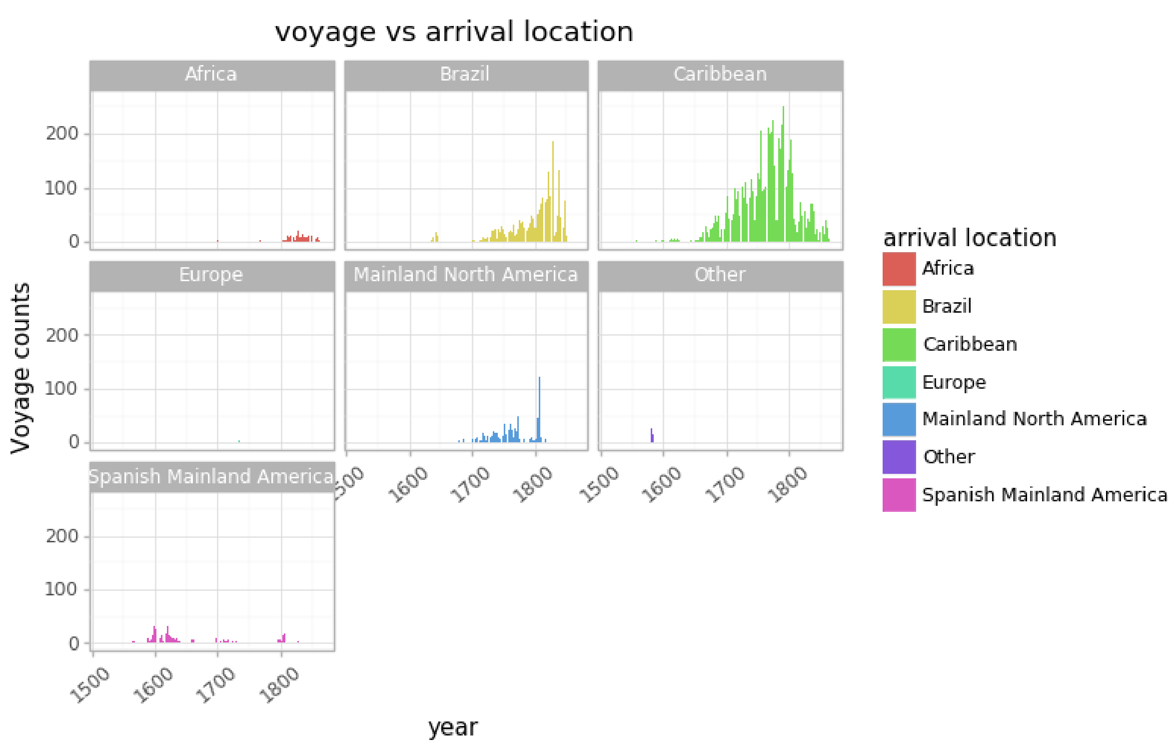
2.

In [33]:
```
arr_df = ndata[['arr_loc','year']]
arr_df=arr_df.set_index(['arr_loc','year'])
arr_df = arr_df.groupby(['arr_loc','year']).size().reset_index(name='count') #coun
arr_df
```

Out[33]:

	arr_loc	year	count
0	Africa	1647.0	1
1	Africa	1658.0	2
2	Africa	1673.0	1
3	Africa	1684.0	2
4	Africa	1685.0	1
5	Africa	1699.0	1
6	Africa	1700.0	2
7	Africa	1734.0	1
8	Africa	1768.0	2
9	Africa	1769.0	1
10	Africa	1771.0	1

In [34]:
```
p9.ggplot(arr_df, p9.aes(x='year', y='count',fill='arr_loc')) + p9.geom_col()\
+p9.ylab('Voyage counts')+p9.xlab('year')+p9.theme_light()\
+p9.theme(axis_text_x = p9.themes.element_text(rotation=40))\
+p9.labs(fill='arrival location')+p9.ggtitle('voyage vs arrival location')+p9.face
```



Out[34]: <ggplot: (12917589)>

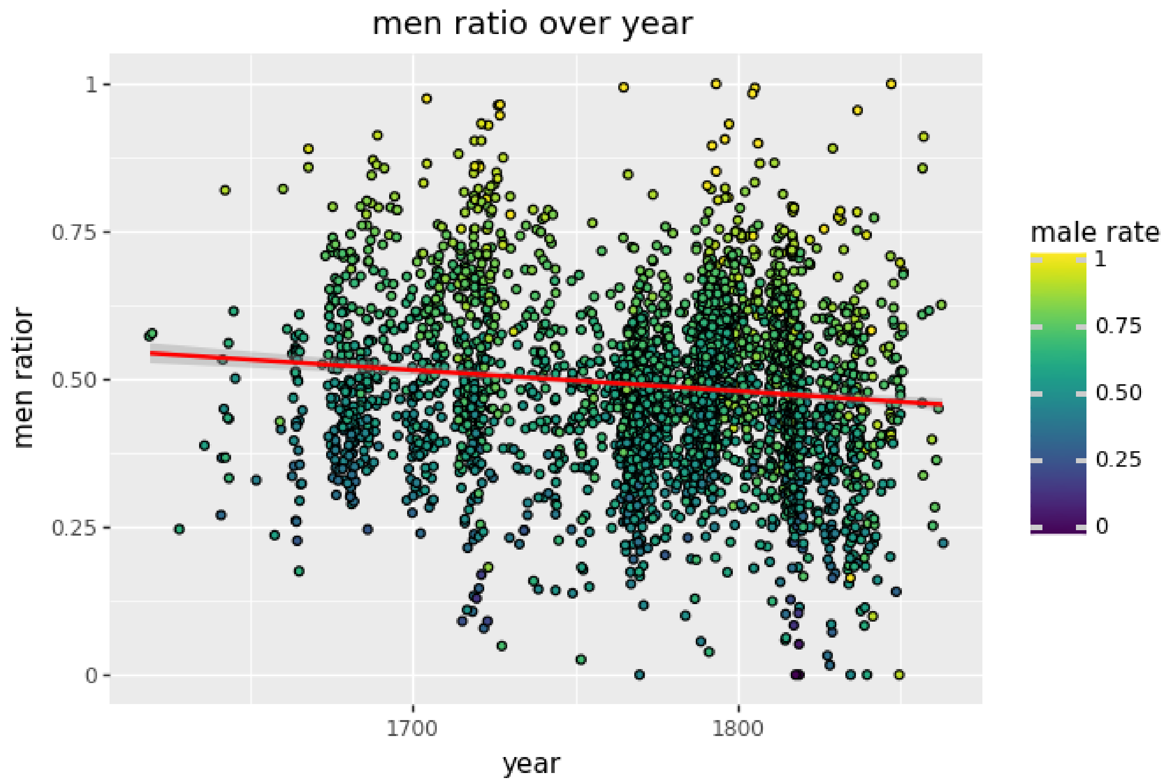
4.

In [35]:
```
men_ratio = ndata[['menrat7','year','malrat7']]
```

In [36]:
```
men_ratio.malrat7
```

Out[36]:
```
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN
5       NaN
6       NaN
7       NaN
8       NaN
9       NaN
10      NaN
11      NaN
12      NaN
13      NaN
14      NaN
15      NaN
16      NaN
17      NaN
18      NaN
```

In [37]:
```
p9.ggplot(men_ratio.dropna(),p9.aes(x='year',y='menrat7',fill='malrat7'))+p9.geom_
+p9.stat_smooth(method='lm',color='red')\
+p9.ylab('men ratior')+p9.ggtitle('men ratio over year')+p9.labs(fill='male rate')
```



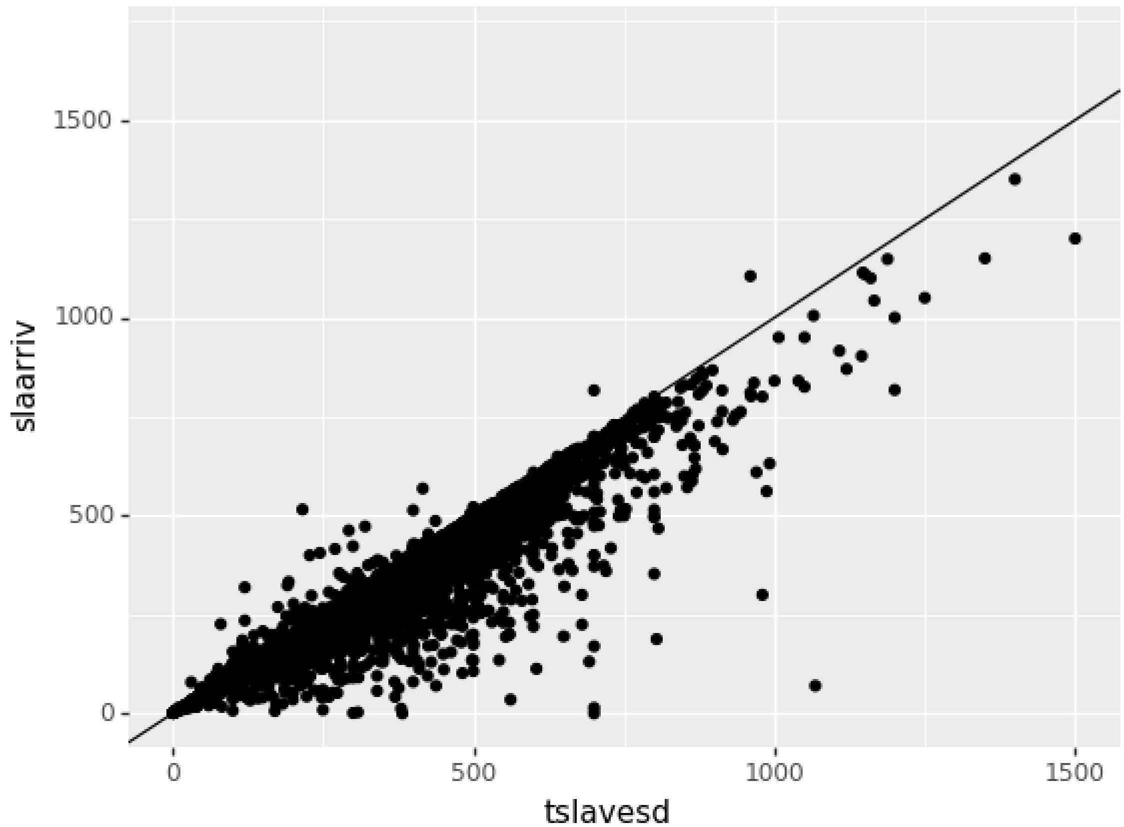
Out[37]: `<ggplot: (15511409)>`

5. Used geom_jitter to plot points, used stat_smooth to fit linear regression line, used y_lab and ggtitle to change text

Exercise 6. Estimating total captives count I.

1. Plot the number of slaves at departure from last slaving and the number that arrived at the first port of disembarkation.
2. Why do these variables concentrate near a line? Most of the data lies on one side of the line, but a small fraction do not, what could have happened for those that did not? Separate the data into these two populations.
3. For those voyages where the number of captives decreased (through death), calculate a death rate (ratio of captives that died).
4. Plot this death rate as a function of year. Make any appropriate scale transformations, and include a trend line or other smoother. What is your interpretation?
5. Guess at two possible predictors and create visualizations that give you a sense of their association with the death rate. Make sure that one of these is categorical, and plot it with the death rate and year so that there are three variables used in the same plot.
6. For these plots, list the geoms, aesthetic mappings, scales, and other notable aspects used.

In [38]:
```
p9.ggplot(ndata) + p9.aes(x='tslavesd',y='slaarriv') + p9.geom_point() \
+ p9.geoms.geom_abline(mapping=p9.aes(slope=1,intercept=0))
#+ p9.stat_smooth(method='lm',color='red')
```



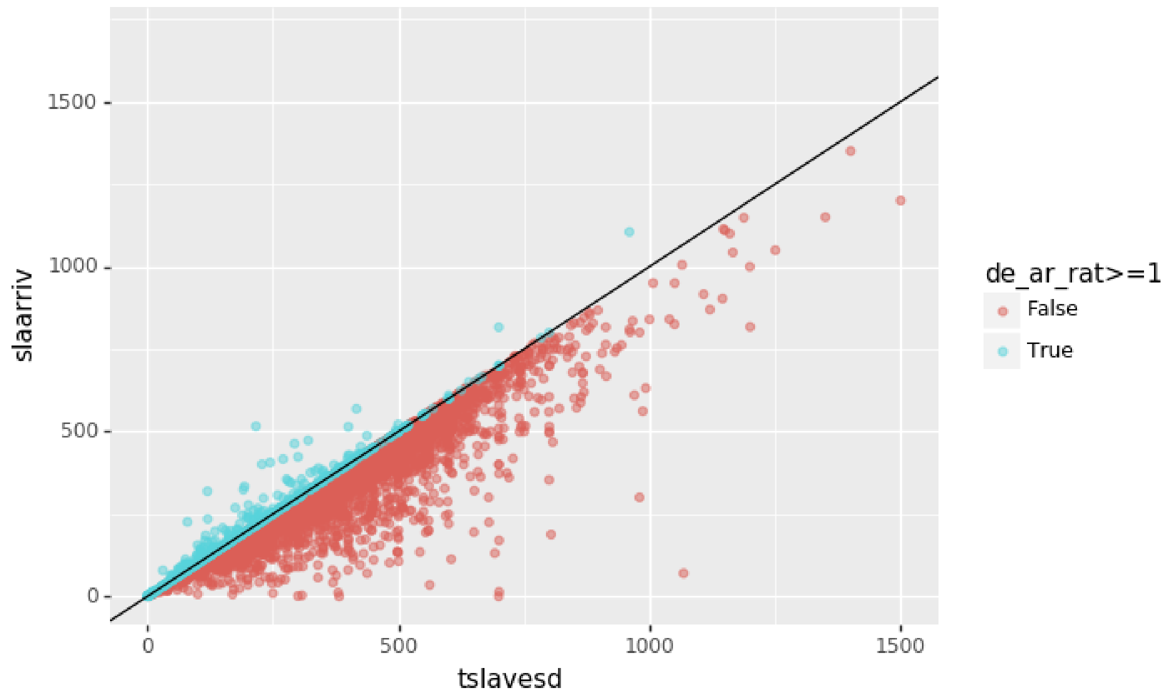
Out[38]: <ggplot: (14684101)>

2

- Because they are high correlated that as the number of slaves at departure from last slaving increases, the number that arrived at the first port of disembarkation increases.
- During the middle passage more slaves are captured so that there are more slaves at the first port of disembarkation than that at departure from last slaving port.

In [39]:
```
de_ar_rat = ndata.slaarriv/ndata.tslavesd
ndata['de_ar_rat'] = de_ar_rat
above = ndata.query('de_ar_rat>=1') #more slaves at arrival than that at departure
below = ndata.query('de_ar_rat<1') #less slaves at arrival than that at departure
```

In [40]:
```
p9.ggplot(ndata) + p9.aes(x='tslavesd',y='slaarriv',color = 'de_ar_rat>=1') + p9.g
+ p9.geoms.geom_abline(mapping=p9.aes(slope=1,intercept=0))
```



Out[40]: <ggplot: (-9223372036841504161)>

3.

In [41]:
```
deathrat = (below.tslavesd-below.slaarriv)/below.tslavesd #dead rate below the slo
below['deathrat'] = deathrat
below.deathrat
```

Out[41]:
```
11      0.153125
16      0.090150
17      0.008639
18      0.119461
19      0.026059
20      0.141680
21      0.040404
22      0.240705
24      0.065315
25      0.031674
26      0.058394
27      0.122278
28      0.108059
29      0.043614
30      0.117207
31      0.022779
32      0.120596
33      0.175644
34      0.051546
```

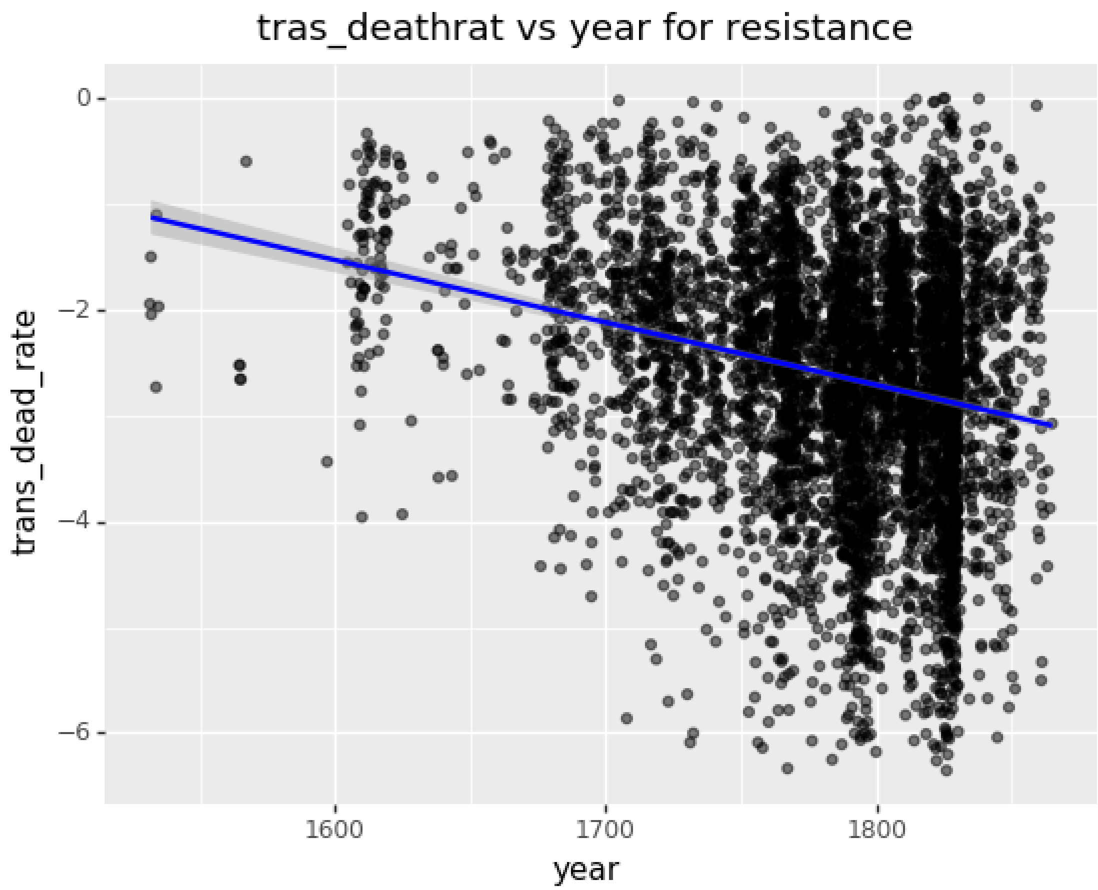
4.

In [42]:
```
dearat=below[['deathrat','year','menrat7','national']]
dearat
```

Out[42]:

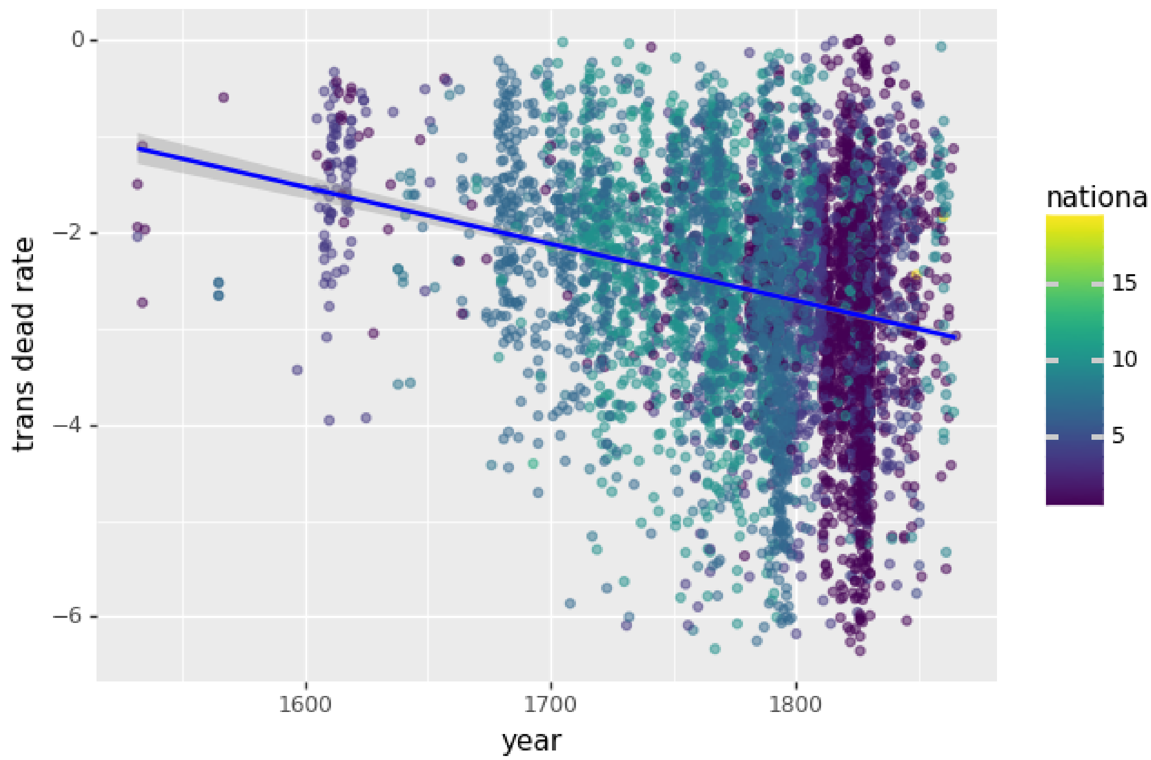
	deathrat	year	menrat7	national
11	0.153125	1817.0	NaN	NaN
16	0.090150	1817.0	NaN	NaN
17	0.008639	1817.0	NaN	NaN
18	0.119461	1817.0	NaN	NaN
19	0.026059	1817.0	NaN	NaN
20	0.141680	1817.0	NaN	NaN
21	0.040404	1817.0	NaN	NaN
22	0.240705	1817.0	NaN	NaN
24	0.065315	1817.0	NaN	NaN
25	0.031674	1817.0	NaN	NaN
26	0.058394	1817.0	NaN	NaN

In [43]:
```
p9.ggplot(dearat) + p9.aes(y='np.log(deathrat)',x='year') + p9.geom_jitter(alpha=0
+ p9.stat_smooth(method='lm',color='blue')\
+p9.ggtitle('tras_deathrat vs year for resistance')+p9.ylab('trans_dead_rate')
```



Out[43]: <ggplot: (14654854)>

In [44]:
```
#5 Use if_res as additional variable
p9.ggplot(dearat) + p9.aes(y='np.log(deathrat)',x='year',color='national') + p9.ge
+ p9.stat_smooth(method='lm',color='blue')+p9.ylab('trans dead rate')
```



Out[44]: <ggplot: (13032733)>

6. Used color to separate data for different nations, used geom_jitter to plot points, fit a linear model used stat_smooth

Exercise 7. Estimating total captives count II.

1. Using the variables selected, fit a prediction of death rate using linear regression and some simple transformations/scales. You do not need to spend time doing automated model selection, just include the most likely predictor or predictors from the previous question.
2. We will impute the number of captives on board at departure, so enumerate the cases for missingness of the variables involved in the prediction.
3. We would like to predict the number of captives on departure from the number that arrived with the following formula,
$$\text{arrived} = \pi(1 - \text{death rate}) \cdot (\text{captives taken}) + (1 - \pi)(\text{average increase})$$
where π is the proportion of voyages with no increase in captives, and the average increase is over those that did see an increase. For those voyages with captives taken missing and arrived not missing, use the estimated death rate to predict the captives taken.
4. Impute the remainder by predicting the captives taken with the year variable, you can use simple linear regression.
5. With the same formula and method impute the number of captives upon arrival whenever it is missing.
6. Give a new estimate of the predicted total number of captives taken on the middle passage, the total number of deaths, and the overall death rate. How does this differ from your first estimate

obtained by assuming MCAR?

1. Altough the R^2 is very low, menrat7 and national are both significant to the model.

In [45]:
```
dr_nona=below[['deathrat','year','malrat7','national']].dropna() #drop missing val
```

In [53]:
```
X = dr_nona[['malrat7','national']]
y= np.log(dr_nona.deathrat) #perform log transformation
X = sm.add_constant(X) #add an intercept for the model
result = sm.OLS(y,X).fit()
print(result.summary())
```

```
                            OLS Regression Results                            
==============================================================================
==
Dep. Variable:               deathrat   R-squared:                       0.0
31
Model:                            OLS   Adj. R-squared:                  0.0
29
Method:                 Least Squares   F-statistic:                     23.
59
Date:                Wed, 07 Nov 2018   Prob (F-statistic):           8.23e-
11
Time:                        12:11:56   Log-Likelihood:                -235
0.6
No. Observations:                1491   AIC:                             470
7.
Df Residuals:                    1488   BIC:                             472
3.
Df Model:                           2
```

3.

In [56]:
```
pi = below.shape[0]/(below.shape[0]+above.shape[0])#calculate the proportion
ai = sum(above.slaarriv-above.tslavesd)/above.shape[0] #calculate average increase
taken = (below.slaarriv - (1+pi)*ai)/(1-below.deathrat)
taken
```

Out[56]:
```
11      618.014906
16      578.536592
17      444.219120
18      497.855433
19      594.883216
20      585.308050
21      574.597431
22      486.479077
24      424.080313
25      422.772353
26      117.226730
27      575.787557
28      525.125729
29      301.532316
30      379.909409
31      419.947373
32      716.828126
33      404.414337
34      368.369492
```

4

In [88]:
```
lm = linear_model.LinearRegression()
model = lm.fit(below[['year']],below[['tslavesd']]) #predict captives that is smal
pre = model.predict(below[['year']])
remainder = pre - below[['slaarriv']] #remainder = predicted captives - arrival
remainder.columns = ['imputed_remainder']
remainder
```

Out[88]:

	imputed_remainder
22	5.154439
26	264.154439
29	86.154439
30	39.154439
33	41.154439
34	25.154439
39	0.154439
42	179.154439
49	91.154439
50	17.154439
51	179.154439

5.

In [89]:
```
model2 = lm.fit(below[['year']],below[['slaarriv']])
arr_pre = model.predict(below[['year']]) #predict arrived captives for ships had i
arr_pre
```

Out[89]:
```
array([[349.52120692],
       [349.52120692],
       [349.52120692],
       ...,
       [248.39125314],
       [351.50414719],
       [374.3079603 ]])
```

6. Used **year** and **if_res** to predict total number of captives taken on the middle passage because they have all recorded data that are relatively accountable. Compared with the first estimation in q2, the old estimation have much more missing values (34887).

In [60]:
```
no_na = ndata[['tslavesd','year','if_res']].dropna()
```

In [61]:
```
model3 = lm.fit(no_na[['year','if_res']],no_na[['tslavesd']]) #predicted captives
tot_pre = model3.predict(ndata[['year','if_res']]) #predict for all the data
tot_pre
```

Out[61]:
```
array([[361.12016302],
       [361.12016302],
       [361.12016302],
       ...,
       [383.60110798],
       [383.60110798],
       [383.60110798]])
```

In [62]:
```
pre_dea = tot_pre - ndata[['slaarriv']] #predicted total death
pre_dea.columns = ['predicted dead']
pre_dea
```

Out[62]:

	predicted dead
0	71.120163
1	138.120163
2	11.120163
3	19.120163
4	-154.879837
5	-153.879837
6	157.120163
7	-12.879837
8	16.120163
9	-116.879837
10	181.120163

In [63]:
```
pre_dr = (tot_pre - ndata[['slaarriv']])/tot_pre #predicted overall death rate
pre_dr.columns = ['predicted deathrate']
pre_dr
```

Out[63]:

	predicted deathrate
0	0.196943
1	0.382477
2	0.030794
3	0.052947
4	-0.428887
5	-0.426118
6	0.435091
7	-0.035666
8	0.044639
9	-0.323659
10	0.501551

In [64]:
```
sum(est_tot.isna()) #count the missing values for first estimation
```

Out[64]: 34887

In [65]:
```
sum(np.isnan(tot_pre)) #count the missing values for new estimation
```

Out[65]:
```
array([0])
```