STA 141B Midterm

Information

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

First Name: Sungwon

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Instructions

Answer the questions below, adding cells in your solution notebook between the problem numbers. Don't change the cells in which the exercise numbers have been written.

Once you are finished, print your solution notebook to pdf (make sure that it is not unnecessarily long due to long output) and submit this pdf to gradescope. Also submit a zipped folder containing your solution notebook, dataset, codebook, and pdf to the Canvas assignment 'midterm.' (IMPORTANT: notice you will be submitting work twice, once on Canvas, once on Gradescope!)

Remember, this must be your work, and your work alone. You can post questions on piazza, but do NOT talk about your work or otherwise collaborate with others, inside or outside of the class.

- DO add cells in between the exercise statements and add answers within them and
- DO NOT modify the existing cells
- you MAY add multiple cells between exercise cells when it's convenient

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

Exercise 1.

Sungwon Lee

Exercise 2.

In [188]:
```
import pandas as pd
import numpy as np


# 2.a
df = pd.read_csv("tastdb-2010.csv", encoding='iso-8859-1').replace(r'^\s*$', np.NaN, r
```

In [189]:
```
# 2.b
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32267 entries, 0 to 32266
```

```
Data columns (total 98 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   voyageid      32267 non-null  int64 
 1   evgreen       23893 non-null  object
 2   shipname      30910 non-null  object
 3   national      23773 non-null  object
 4   natinimp      31192 non-null  object
 5   placcons      8797 non-null   object
 6   yrcons        6111 non-null   object
 7   placreg       7193 non-null   object
 8   yrreg         4505 non-null   object
 9   rig           20221 non-null  object
 10  tonnage       15985 non-null  object
 11  tonmod        14956 non-null  object
 12  guns          5934 non-null   object
 13  ownera        20087 non-null  object
 14  ownerb        7472 non-null   object
 15  ownerc        4035 non-null   object
 16  ownerd        2657 non-null   object
 17  ownere        1850 non-null   object
 18  ownerf        1296 non-null   object
 19  ownerg        799 non-null    object
 20  ownerh        450 non-null    object
 21  owneri        191 non-null    object
 22  ownerj        90 non-null     object
 23  ownerk        31 non-null     object
 24  ownerl        15 non-null     object
 25  ownerm        14 non-null     object
 26  ownern        7 non-null      object
 27  ownero        6 non-null      object
 28  ownerp        8 non-null      object
 29  fate          32156 non-null  object
 30  fate2         27852 non-null  object
 31  fate3         26613 non-null  object
 32  fate4         25060 non-null  object
 33  resistance    534 non-null    object
 34  ptdepimp      28582 non-null  object
 35  plac1tra      19719 non-null  object
 36  plac2tra      2676 non-null   object
 37  plac3tra      501 non-null    object
 38  mjbyptimp     24862 non-null  object
 39  npafttra      1672 non-null   object
 40  sla1port      22909 non-null  object
 41  adpsale1      1181 non-null   object
 42  adpsale2      86 non-null     object
 43  mjslptimp     28296 non-null  object
 44  portret       10594 non-null  object
 45  yearam        32267 non-null  int64 
 46  Date_dep      21329 non-null  object
 47  Date_buy      6463 non-null   object
 48  Date_leftAfr  6979 non-null   object
 49  Date_land1    16201 non-null  object
 50  Date_depam    5607 non-null   object
 51  Date_end      10378 non-null  object
 52  voy1imp       12056 non-null  object
 53  voy2imp       4376 non-null   object
 54  captaina      29259 non-null  object
 55  captainb      3339 non-null   object
 56  captainc      193 non-null    object
 57  crew1         11608 non-null  object
 58  crew3         2204 non-null   object
 59  crewdied      4431 non-null   object
 60  slintend      7071 non-null   object
 61  ncar13        1801 non-null   object
 62  ncar15        389 non-null    object
 63  ncar17        70 non-null     object
 64  tslavesd      7574 non-null   object
 65  slaximp       31293 non-null  object
```

```
 66  slaarriv      16657 non-null  object
 67  slas32        2292 non-null   object
 68  slas36        509 non-null    object
 69  slas39        37 non-null     object
 70  slamimp       30990 non-null  object
 71  menrat7       3077 non-null   object
 72  womrat7       3075 non-null   object
 73  boyrat7       3035 non-null   object
 74  girlrat7      3033 non-null   object
 75  malrat7       3507 non-null   object
 76  chilrat7      3621 non-null   object
 77  jamcaspr      13 non-null     object
 78  vymrtimp      5768 non-null   object
 79  vymrtrat      5768 non-null   object
 80  sourcea       32253 non-null  object
 81  sourceb       20329 non-null  object
 82  sourcec       13666 non-null  object
 83  sourced       9358 non-null   object
 84  sourcee       6686 non-null   object
 85  sourcef       4716 non-null   object
 86  sourceg       3518 non-null   object
 87  sourceh       2697 non-null   object
 88  sourcei       2006 non-null   object
 89  sourcej       1349 non-null   object
 90  sourcek       810 non-null    object
 91  sourcel       473 non-null    object
 92  sourcem       261 non-null    object
 93  sourcen       128 non-null    object
 94  sourceo       78 non-null     object
 95  sourcep       34 non-null     object
 96  sourceq       19 non-null     object
 97  sourcer       5 non-null      object
dtypes: int64(2), object(96)
memory usage: 24.1+ MB
```

 # 2.c

Definition of columns

voyageid : Voyage identification(number format: F6)

evgreen : Voyage in 1999 CD-Rom

shipname : Name of vessel

[national, natinimp] : Country number in which ship registered

[placcons, yrcons, yrreg] : Information about vessel's construction

placreg : Vessel's registration

rig : Rig of vessel(type of the ship)

[tonnage, tonmode] : ton and definition of ton used in tonnage of vessel

guns: Guns mounted

[ownera, ownerb, ownerc, ownerd, ownere, ownerf, ownerg, ownerh, owneri, ownerj, ownerk, ownerl, ownerm, ownern, ownero, ownerp] : owners of the slave ships

[fate, fate2, fate3, fate4] : Outcome of voyage

Resistance : African resistance

ptdepimp : imputed port where voyage began

[plac1tra, plac2tra, plac3tra] : place where slave purchase

mjbyptimp : place where slave purchased

npafttra : port of call before Atlantic crossing

[sla1port, adpsale1, adpsale2] : place of slave landing

mjslptimp : imputed principal port of slave disembarkation

portret : place where voyage ended

yearam : year of arrival at port of disembarkation

[Date_buy, Date_leftAfr, Date_land1, Date_depam, Date_end] : Date of slave and voyage events

[voy1imp, voy2imp] : voyage length of disembarkation(days)

[captaina, captainb, captainc] : captin's name

[crew1, crew3, crewdied] : information of crews

slintend : slaves intended from first port of purchase

[ncar13, ncar15, ncar17] : slaves carried

tslavesd : total slaves on board

[slaximp, slaarriv, slas32, slas36, slas39, slamimp] : info of slaves embarked and disembarked

[menrat7, womrat7, boyrat7, girlrat7, malrat7, chilrat7] : percentage of people at departure or arrival

jamcaspr : average price of slaves in Jamaica

[vymrtimp, vymrtrat] : slaves death

[sourcea, sourceb, sourcec, sourced, sourcee, sourcef, sourceg, sourceh, sourcei, sourcej, sourcek, sourcel, sourcem, sourcen, sourceo, sourcep, sourceq, sourcer] : Source information

Exercise 3.

 # 3.a

What variable would you use to estimate the total number of captives taken from Africa?

Ans. "tslavesd"

In [190]:
```
Tot_TSmissing = df['tslavesd'].isnull().sum()
print(f"There are total {Tot_TSmissing: ,} values are missing.")
```

```
There are total  24,693 values are missing.
```

In [191]:
```
# 3.b

tot_slaves = pd.to_numeric(df['tslavesd']).sum()
nonMissing = df['tslavesd'].describe()[0]
```

```
tot_slaves/(nonMissing/len(df))
print(f"Preliminary estimate of the total number of captives taken from Africa: {tot_s
```

```
Preliminary estimate of the total number of captives taken from Africa:  10,585,559.37
4849632
```

 # 3.c

What other variables do you expect to be associated with Var A and why? Select 2 top possibilities.

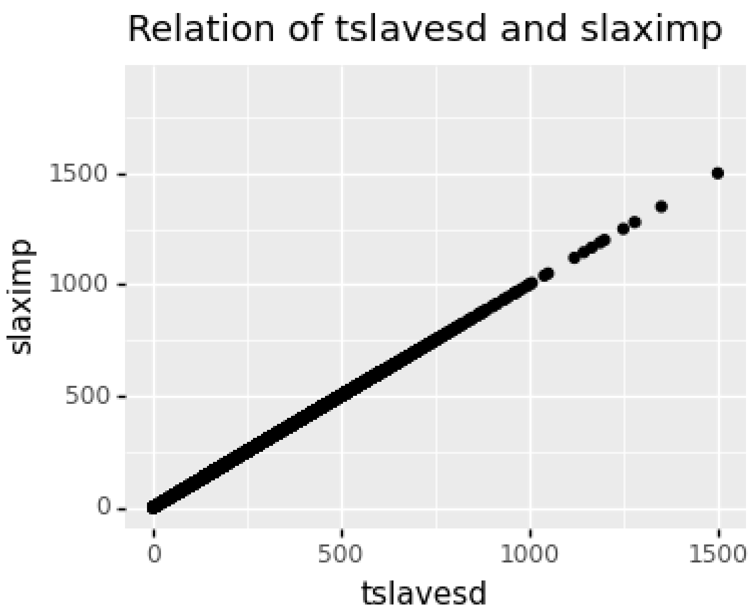
In my opinion, variables of "slaximp" and "slaarriv" are the two variables that are most likely associated with Var A. "slaximp" is representing the total imputed slaves embarked on the voyage. Since, the slaves were probably embarked to the ship after they were purchased, "tslavesd" variable and "slaximp" variable would have similar data values. For the same reason, "slaariv" variable would also be highly related to "tslavesd", because "slaarriv" represents the total slaves arrived at first port of disembarkation.

In [192]:
```
import plotnine as p9
from plotnine import *
```

In [193]:
```
DFslave = pd.DataFrame({'tslavesd' : pd.to_numeric(df['tslavesd']), 'slaximp' : pd.to_
```

In [194]:
```
gg = p9.ggplot(DFslave)
gg += p9.aes(x="tslavesd", y="slaximp")
gg += p9.geom_point()
gg += p9.ggtitle("Relation of tslavesd and slaximp")
gg += p9.theme(figure_size=(4, 3))

gg
```

```
C:\Users\pumad\anaconda3\lib\site-packages\plotnine\layer.py:401: PlotnineWarning: geo
m_point : Removed 24693 rows containing missing values.
```

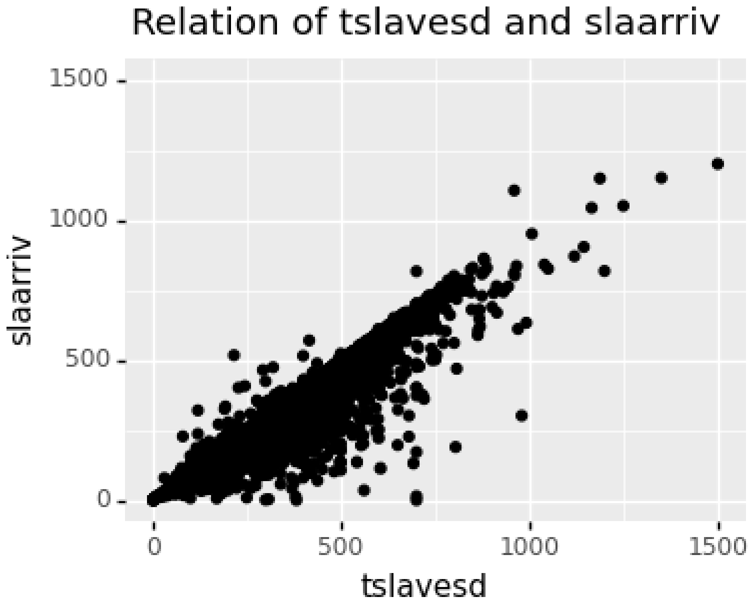


Out[194]: <ggplot: (183771686852)>

In [195]:
```
gg = p9.ggplot(DFslave)
gg += p9.aes(x="tslavesd", y="slaarriv")
gg += p9.geom_point()
gg += p9.ggtitle("Relation of tslavesd and slaarriv")
gg += p9.theme(figure_size=(4, 3))
```

```
gg
```

C:\Users\pumad\anaconda3\lib\site-packages\plotnine\layer.py:401: PlotnineWarning: geom_point : Removed 27028 rows containing missing values.



Out[195]: <ggplot: (183772713409)>

In [196]:
```
# preliminary estimate by using "slaximp"
tot_slaves = pd.to_numeric(df['slaximp']).sum()
nonMissing = df['slaximp'].describe()[0]

tot_slaves/(nonMissing/len(df))
```

Out[196]: 9568845.978130955

According to the graphs above, we can see that both "slaximp" and "slaarriv" variables have positive realtionship with Var A(tslavesd). Especially the first graph shows that "slaximp" and Var A(tslavesd) have almost same values. Therefore, when we preliminary estimate the total number of captives from Africa using the "slaximp", we could get the value of approximately 9,568,845. The difference of the answer on 3.b and 9,568,845 is approximately 1016714. Since the difference is huge, it is hard to trust the answer to 3.b because "slaximp" had less missing values, so it would give us more precise result.

Exercise 4.

In [197]:
```
# 4.a

# Subselect the values of national that have more than 300 voyages with that value.

pd.DataFrame(df['national'].value_counts() > 300)[pd.DataFrame(df['national'].value_cc
```

Out[197]: Index(['7', '4', '10', '9', '8', '1', '5'], dtype='object')

In [198]:
```
# 4.b

# Create a DataFrame that filters out the voyages where national does not have one of

new_df = pd.DataFrame(df[df['national'].isin(df['national'].value_counts()[df['nationa
```

In [199]:
```
new_df.head()
```

Out[199]:

	voyageid	evgreen	shipname	national	natinimp	placcons	yrcons	placreg	yrreg	rig	...	s
0	1	1	Pastora de Lima	4	6	NaN	NaN	NaN	NaN	40	...	
15	16	1	Sociedade	4	6	NaN	NaN	NaN	NaN	40	...	
94	95	1	Patrocínio	4	6	NaN	NaN	NaN	NaN	2	...	
113	114	1	NaN	10	10	NaN	NaN	NaN	NaN	4	...	
114	115	1	NaN	10	10	NaN	NaN	NaN	NaN	4	...	

5 rows × 98 columns

In [200]:

```
# 4.c

# nationality = {"Spain" : "1", "Portugal" : "4", "Brazil" : "5",
#                "Great Britiain" : "7", "Netherlands" : "8", "U.S.A" : "9",
#                "France" : "10"}


def assn(data):
    if data['national'] == "1":
        val = "Spain"
    elif data['national'] == "4":
        val = "Portugal"
    elif data['national'] == "7":
        val = "Great Britain"
    elif data['national'] == "5":
        val = "Brazil"
    elif data['national'] == "8":
        val = "Netherlands"
    elif data['national'] == "9":
        val = "U.S.A"
    elif data['national'] == "10":
        val = "France"

    return val


new_df['nationality'] = new_df.apply(assn, axis=1)
```

In [201]:

```
new_df[['national', 'nationality']]
```

Out[201]:

	national	nationality
0	4	Portugal
15	4	Portugal
94	4	Portugal
113	10	France
114	10	France
...	...	...
32260	4	Portugal
32261	10	France

	national	nationality
32262	4	Portugal
32263	10	France
32265	4	Portugal

23445 rows × 2 columns

In [202]:
```
new_df
```

Out[202]:

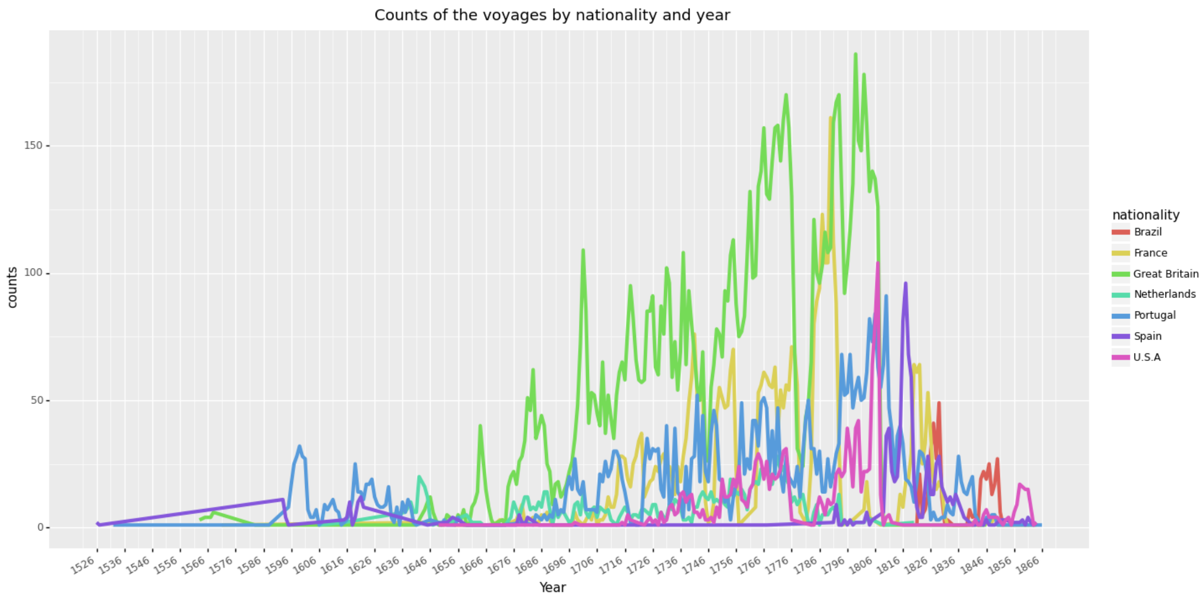
	voyageid	evgreen	shipname	national	natinimp	placcons	yrcons	placreg	yrreg	rig	.
0	1	1	Pastora de Lima	4	6	NaN	NaN	NaN	NaN	40	.
15	16	1	Sociedade	4	6	NaN	NaN	NaN	NaN	40	.
94	95	1	Patrocínio	4	6	NaN	NaN	NaN	NaN	2	.
113	114	1	NaN	10	10	NaN	NaN	NaN	NaN	4	.
114	115	1	NaN	10	10	NaN	NaN	NaN	NaN	4	.
...	...	...	...	...	...	...	...	...	...	...	.
32260	900231	NaN	NS do Rosario	4	NaN	NaN	NaN	NaN	NaN	20	.
32261	900232	NaN	Tourville	10	NaN	NaN	NaN	NaN	NaN	20	.
32262	900233	NaN	General Rêgo	4	NaN	NaN	NaN	NaN	NaN	1	.
32263	900234	NaN	Duas Clementinas	10	NaN	NaN	NaN	NaN	NaN	1	.
32265	900236	NaN	Rio Tâmega	4	NaN	NaN	NaN	NaN	NaN	7	.

23445 rows × 99 columns

In [203]:
```
# 4.d


# (ggplot(new_df) +
#  aes(x='yearam', y = new_df.nationality.value_counts())
# )


# df.groupby(['years', 'causes'])['something_else'].count()

cnts = new_df.groupby(['yearam', 'nationality'])['voyageid'].count()
cnts = cnts.reset_index()
```

In [204]:
```
gg = p9.ggplot(cnts)
gg += p9.aes(x='yearam',
             y='voyageid',
             color='nationality') # add color mapping
gg += p9.geom_line(alpha=1, size =1.7)
gg += ylab('counts')
gg += xlab("Year")
gg += labs(title = "Counts of the voyages by nationality and year")
```

```
gg += theme(figure_size=(16, 8),
            axis_text_x  = element_text(angle = 30, hjust = 1))
gg += scale_x_continuous(breaks=range(1526,1867,10))

gg
```



Out[204]: <ggplot: (183799865893)>

 # 4.e

In this plot, the aesthetic mapping is the x-axis, y-axis, and colors that I used to represent each nationality. The x-axis is yearam, which refers to the year that the ship had arrived at the port of disembarkation. The y-axis is representing the number of voyages counted for each year. The geometric element used in this plot is the shape of the graph. Here, I used a line graph to illustrate the data followed by time series so that it could show readers how did the number of voyages of each nationality had changed over time. Lastly, I used other components of the grammar of graphics such as theme. Since each year is four digits and I scaled from the year 1526 to 1866 by every 10th year. Thus, to prevent overlapping x-labels, I rotated the x-labels by 30 degrees so that I could increase the readability. Also, I made the line width to be thicker than the default, because the default size was to thin to easily get the interpretation.

 # 4.f

We could observe the drastic change of the counts from Great Britain and France. The two nations had similar patterns. The number of voyages count was rapidly dropped and then rose between the years 1776 and 1786. The major event that could possibly affect the Trading Slave was The Franco-American Alliance in 1778. In 1778, the United States and France formed a military alliance to counter Great Britain. Also, before the 1770s, most of the Europeans provided only markets for slavery. However, starting in 1778, many Europeans began to actively intervene in the slave trade, such as sailing directly to Africa. Hence, I think these are the main reasons that caused the abrupt changes of the plot between 1776 and 1786.

Exercise 5.

In [205]:

```
# 5.a

# new_df[new_df['shipname']=='r₩'][['yearam', 'placcons', 'placreg','yrreg','captaina

arr = np.where(new_df.shipname.str.contains(r'(Brook)') == True)
```

```
lst = []
for i in arr[0][0:]:
    lst.append(i)



Brook_df = new_df.iloc[lst]
```

```
C:\Users\pumad\anaconda3\lib\site-packages\pandas\core\strings.py:2001: UserWarning: T
his pattern has match groups. To actually get the groups, use str.extract.
```

In [206]:
```
Brook_df[['shipname', 'yearam', 'placcons','yrcons','placreg', 'yrreg', 'tonnage', 'tc
         'fate', 'fate2', 'fate3', 'fate4', 'Date_dep']]
```

Out[206]:

	shipname	yearam	placcons	yrcons	placreg	yrreg	tonnage	tonmod	captaina	captainb
10364	Brooke	1752	10432	1737	10432	1747	150	272.3	Meadows	Kewley, Thomas
11525	Brooke	1748	10432	1737	10432	1747	150	272.3	White, John	NaN
26856	Brooke	1800	10433	1784	10432	1800	352	352	Molyneux, Thomas	NaN
26857	Brooke	1802	10433	1784	10432	1800	352	352	Hayes, John	NaN
26858	Brooke	1803	10433	1784	10432	1800	352	352	Tucker, Joseph	NaN
26859	Brooke	1807	10433	1784	10432	1804	352	352	Cormack, George S	NaN
26860	Brooks	1782	10432	1781	10432	1781	297	297	Noble, Clement	NaN
26861	Brooks	1784	10432	1781	10432	1783	297	297	Noble, Clement	NaN
26862	Brooks	1785	10432	1781	10432	1783	297	297	Noble, Clement	NaN
26863	Brooks (a) Brookes	1787	10432	1781	10432	1786	297	297	Molyneux, Thomas	NaN
26864	Brooks	1792	10432	1781	10432	1791	319	319	Hauit, George	NaN
26865	Brooks	1793	10432	1781	NaN	NaN	319	319	Hewan, John	NaN
26866	Brooks	1797	10432	1781	NaN	NaN	319	319	Richards, John	NaN
26867	Brooks	1798	10432	1781	NaN	NaN	319	319	Richards, John	Williams, John
26868	Brooks	1799	10432	1781	NaN	NaN	319	319	Joynson, Moses	NaN
26869	Brooks	1801	10432	1781	NaN	NaN	353	353	Joynson, Moses	NaN
26870	Brooks	1804	10432	1781	NaN	NaN	353	353	Murdock, William	NaN

	shipname	yearam	placcons	yrcons	placreg	yrreg	tonnage	tonmod	captaina	captainb
31593	Brooks	1777	10432	1772	10432	1775	200	305.3	Noble, Clement	NaN
31594	Brooks	1775	10432	1772	10432	1775	210	317.3	Noble, Clement	NaN
31746	Brooke	1737	10399	NaN	10432	NaN	150	272.3	Cowley, James	NaN
31769	Brooke	1739	10399	NaN	10432	NaN	150	272.3	Cowley, James	NaN
31813	Brooke	1740	10399	NaN	10432	NaN	120	218.3	Doran, Felix	NaN
31840	Brooke	1742	10399	NaN	10432	NaN	150	272.3	Doran, Felix	NaN
31873	Brooke	1744	10399	NaN	10432	NaN	150	272.3	Doran, Felix	NaN

In [207]:

```
Filtered_Br = Brook_df[(Brook_df['yrcons'] == '1781') & (Brook_df['tonnage'].isin(['29
Filtered_Br
```

Out[207]:

	voyageid	evgreen	shipname	national	natinimp	placcons	yrcons	placreg	yrreg	rig	...
26860	80663	1	Brooks	7	7	10432	1781	10432	1781	4	...
26861	80664	1	Brooks	7	7	10432	1781	10432	1783	4	...
26862	80665	1	Brooks	7	7	10432	1781	10432	1783	4	...
26863	80666	1	Brooks (a) Brookes	7	7	10432	1781	10432	1786	4	...
26864	80667	1	Brooks	7	7	10432	1781	10432	1791	4	...
26865	80668	1	Brooks	7	7	10432	1781	NaN	NaN	4	...
26866	80669	1	Brooks	7	7	10432	1781	NaN	NaN	4	...
26867	80670	1	Brooks	7	7	10432	1781	NaN	NaN	4	...
26868	80671	1	Brooks	7	7	10432	1781	NaN	NaN	4	...
26869	80672	1	Brooks	7	7	10432	1781	NaN	NaN	4	...
26870	80673	1	Brooks	7	7	10432	1781	NaN	NaN	4	...

11 rows × 99 columns

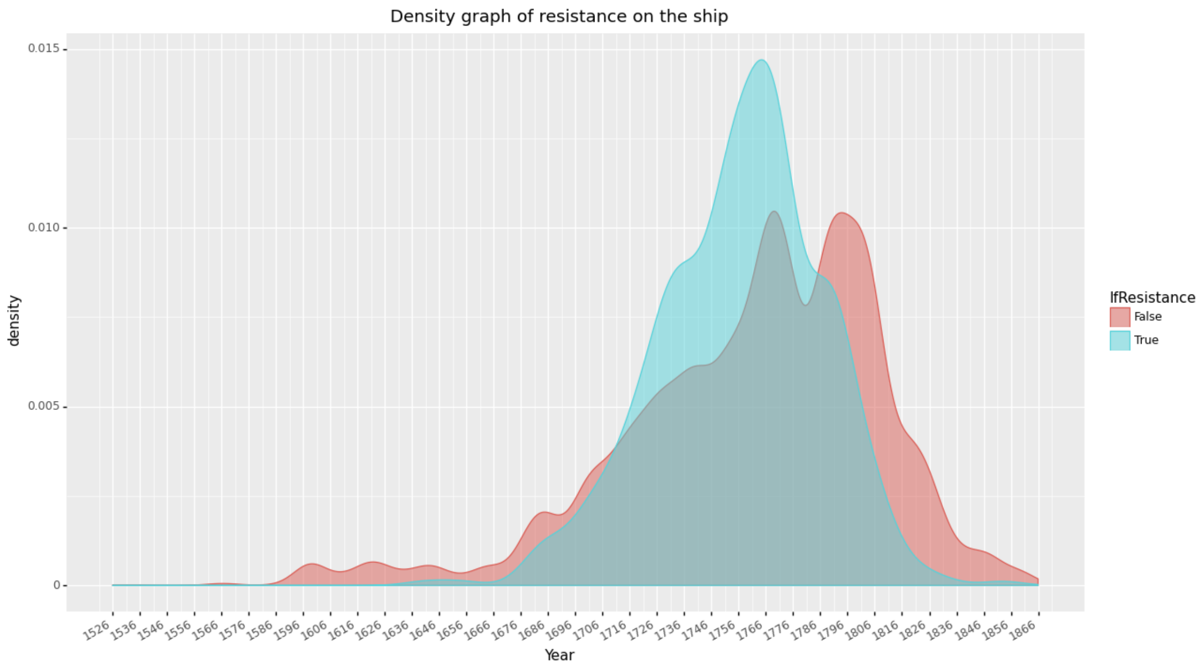
In [208]:
```
print(f"By filtering according to the certain conditions mentioned in Wikipedia, we cc
```

By filtering according to the certain conditions mentioned in Wikipedia, we could get the result of 11 voyages total are in the data.

In [209]:
```
# 5.b

def assn2(data):
    if data['resistance'] == "1" or data['resistance'] == '2' or data['resistance'] ==
        val = True
    else:
        val = False

    return val
```

In [210]:
```
new_df['IfResistance'] = new_df.apply(assn2, axis=1)
```

In [211]:
```
(
    ggplot(new_df, aes(x='yearam', color='IfResistance', fill='IfResistance'))
    + geom_density(alpha=0.5)
    + labs(title = "Density graph of resistance on the ship")
    + xlab("Year")
    + theme(figure_size = (14,8),
           axis_text_x  = element_text(angle = 30, hjust = 1))
    + scale_x_continuous(breaks=range(1526,1867,10))
)
```



Out[211]: <ggplot: (183799780840)>

In this plot, the blue graph is showing that there was resistance or at least trying to revolt on the ship or the shore. The red graph shows False or uncertain values. Since it represents the density of each variable, not the real counts, this does not mean that there are more cases of rebellion on the ship than there have been none. According to the plot, we can see both True and False graph increase over time especially in the 1700s because the 18th century was the peak of voyages for the slave trade. Also, from this density graph, we can observe that approximately from the 1750s to 1770s had the largest density difference between True and False. which means that many rebels happened during that period.

In [212]:
```
# 5.c
```

```
year = list(range(1839,1849,1))

new_df[new_df['yearam'].isin(year) & new_df['IfResistance'] == True]


arr = np.where(new_df.shipname.str.contains(r'(Amistad)') == True)

lst = []
for i in arr[0][0:]:
    lst.append(i)



Amistad_df = new_df.iloc[lst]
# Amistad_df[new_df['yearam'].isin(year)]

Amistad_df[['voyageid','shipname','rig','yearam','ownera','fate','fate2','fate3','fate
```

```
C:\Users\pumad\anaconda3\lib\site-packages\pandas\core\strings.py:2001: UserWarning: T
his pattern has match groups. To actually get the groups, use str.extract.
```

Out[212]:

	voyageid	shipname	rig	yearam	ownera	fate	fate2	fate3	fate4	resistance	nationality
769	774	Amistad Habanera	2	1829	NaN	1	1	14	1	NaN	Spain
935	940	Amistad Habanera	2	1829	NaN	1	1	14	1	NaN	Spain
959	964	Amistad Habanera	51	1830	NaN	1	1	14	1	NaN	Spain
1159	1196	Amistad Habanera	51	1830	NaN	49	1	14	1	NaN	Spain
5551	14622	Amistad	45	1815	NaN	49	1	14	1	NaN	Spain
5584	14656	Amistad	45	1816	NaN	49	1	14	1	NaN	Spain
5667	14742	Amistad	45	1817	NaN	49	1	14	1	NaN	Spain
5767	14844	Nueva Amistad	45	1818	NaN	1	1	14	1	NaN	Spain

In [213]:

```
Amistad_df[Amistad_df['rig']=='2'][['voyageid','shipname','rig','yearam','ownera','fat
```

Out[213]:

	voyageid	shipname	rig	yearam	ownera	fate	fate2	fate3	fate4	resistance	nationality
769	774	Amistad Habanera	2	1829	NaN	1	1	14	1	NaN	Spain
935	940	Amistad Habanera	2	1829	NaN	1	1	14	1	NaN	Spain

According to the aspects depicted in the "https://en.wikipedia.org/wiki/La_Amistad", we could find only two ships that were matching the aspects in 10 year period. However, we could not assure that this is the "La Amistad" ship because the resistance variable is missing and the fate of this ship was not ended with the slave revolt and also it did not captured to US navy.

Exercise 6.

In [214]:

```
# 6.a
```

```
A_df = new_df[new_df['ptdepimp'].notnull() & new_df['sla1port'].notnull()].reset_index
```

In [215]:
```
A_df = A_df.drop(['index'], axis=1)
```

In [216]:
```
A_df['LastDep'] = ["Europe" if x.startswith("1") else "North America" if x.startswith(
```

In [217]:
```
A_df['FirstArr'] = ["Europe" if x.startswith("1") else "North America" if x.startswith
```

In [218]:
```
A_df[['LastDep', 'FirstArr']]
```

Out[218]:

	LastDep	FirstArr
0	Brazil	Brazil
1	Brazil	Brazil
2	Brazil	Brazil
3	Europe	Caribbean
4	Europe	Caribbean
...	...	...
16722	Europe	Spanish Americas
16723	Europe	Caribbean
16724	Europe	Caribbean
16725	Brazil	Brazil
16726	Europe	Brazil

16727 rows × 2 columns

The column "LastDep" is the variable that shows the last departure of the ship.

The column "FirstArr" is the variable that shows the first arrival of the ship.

Code :

10000~19999 => Europe

20000~29999 => North America(Mainland North America)

30000~39999 => Caribbean

40000~49999 => Spanish Americas(Spanish Mainland Americas)

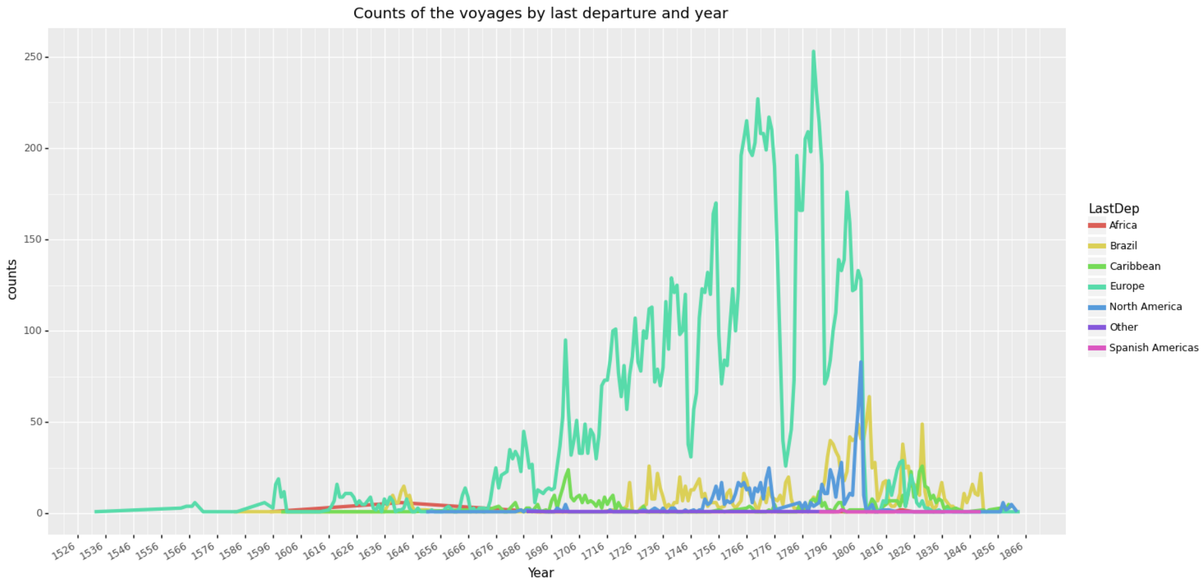
50000~59999 => Brazil

60000~69999 => Africa

80000~89999 => Others

In [219]:
```
# 6.b



counts = A_df.groupby(['yearam', 'LastDep'])['voyageid'].count()
counts = counts.reset_index()
```

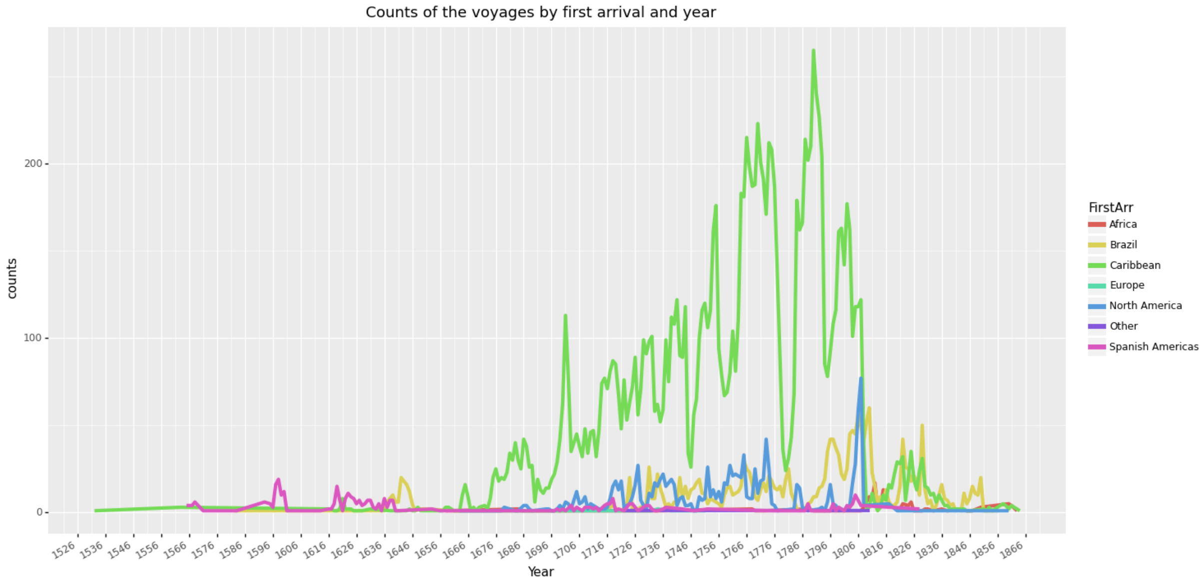
```
gg = p9.ggplot(counts)
gg += p9.aes(x='yearam',
             y='voyageid',
             color='LastDep') # add color mapping
gg += p9.geom_line(alpha=1, size =1.7)
gg += ylab('counts')
gg += xlab("Year")
gg += labs(title = "Counts of the voyages by last departure and year")
gg += theme(figure_size=(16, 8),
           axis_text_x  = element_text(angle = 30, hjust = 1))
gg += scale_x_continuous(breaks=range(1526,1867,10))


gg
```



Out[219]: <ggplot: (183797606428)>

According to this plot, we could see that Europe was the location where most of the voyage was departed.

In [220]:
```
# 6.c

counts = A_df.groupby(['yearam', 'FirstArr'])['voyageid'].count()
counts = counts.reset_index()



gg = p9.ggplot(counts)
gg += p9.aes(x='yearam',
             y='voyageid',
             color='FirstArr') # add color mapping
gg += p9.geom_line(alpha=1, size =1.7)
gg += ylab('counts')
gg += xlab("Year")
gg += labs(title = "Counts of the voyages by first arrival and year")
gg += theme(figure_size=(16, 8),
           axis_text_x  = element_text(angle = 30, hjust = 1))
gg += scale_x_continuous(breaks=range(1526,1867,10))


gg
```



Out[220]: <ggplot: (183777287024)>

It shows that Caribbean was the location where most of voyages arrived as the first place. As a result of above two plots, we could observe that most of the voyages started from Europe and passed by Caribbean, which meant that Caribbean had the largest slave market.

In [221]:
```
# 6.d

men_df = new_df[new_df['menrat7'].notnull()].reset_index()
```

In [222]:
```
men_df.groupby(['yearam', 'menrat7']).count()
```

Out[222]:

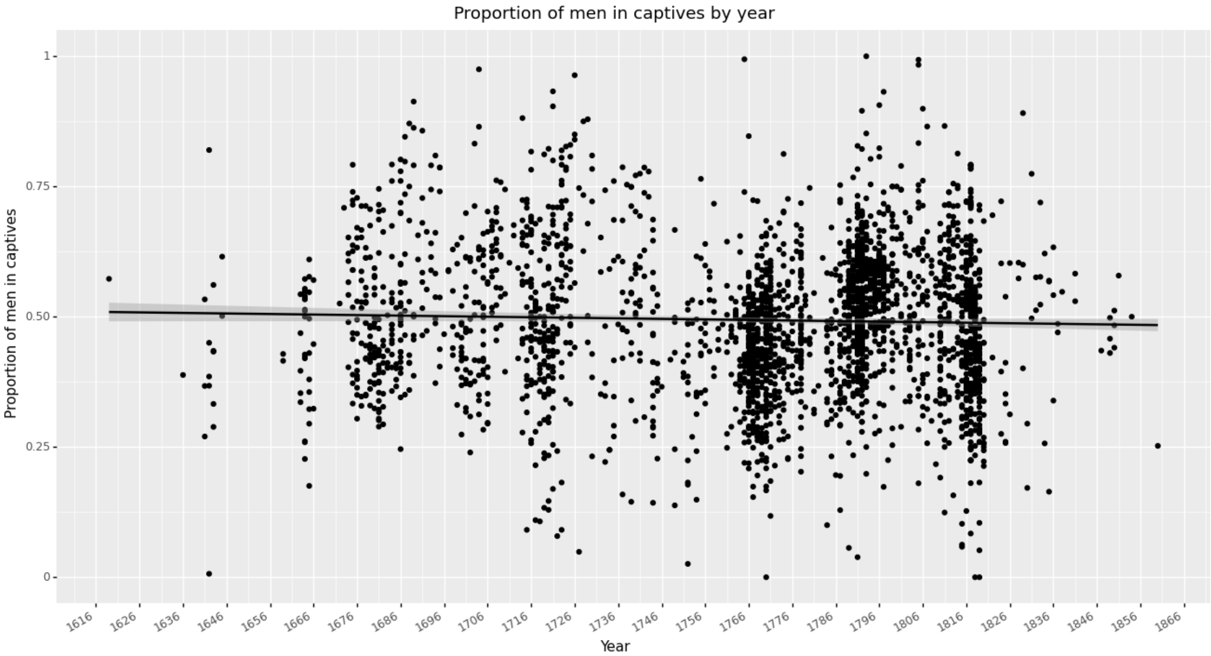
yearam	menrat7	index	voyageid	evgreen	shipname	national	natinimp	placcons	yrc
1619	.572769953051643	1	1	1	1	1	1	0	
1636	.388235294117647	1	1	1	1	1	1	0	
1641	.270142180094787	1	1	0	1	1	1	0	
	.367149758454106	1	1	0	1	1	1	0	
	.533333333333333	1	1	0	1	1	1	0	
...	...	...	...	...	...	...	...	...	
1850	.483443708609272	1	1	1	1	1	1	0	
	.511811023622047	1	1	1	0	1	1	0	
1851	.578947368421053	1	1	1	1	1	1	0	
1854	.5	1	1	1	1	1	1	0	
1860	.252161383285303	1	1	1	1	1	1	1	

2837 rows × 99 columns

In [223]:
```
men_df['menrat7'] = pd.to_numeric(men_df['menrat7'])
men_df[['menrat7']].dtypes
```

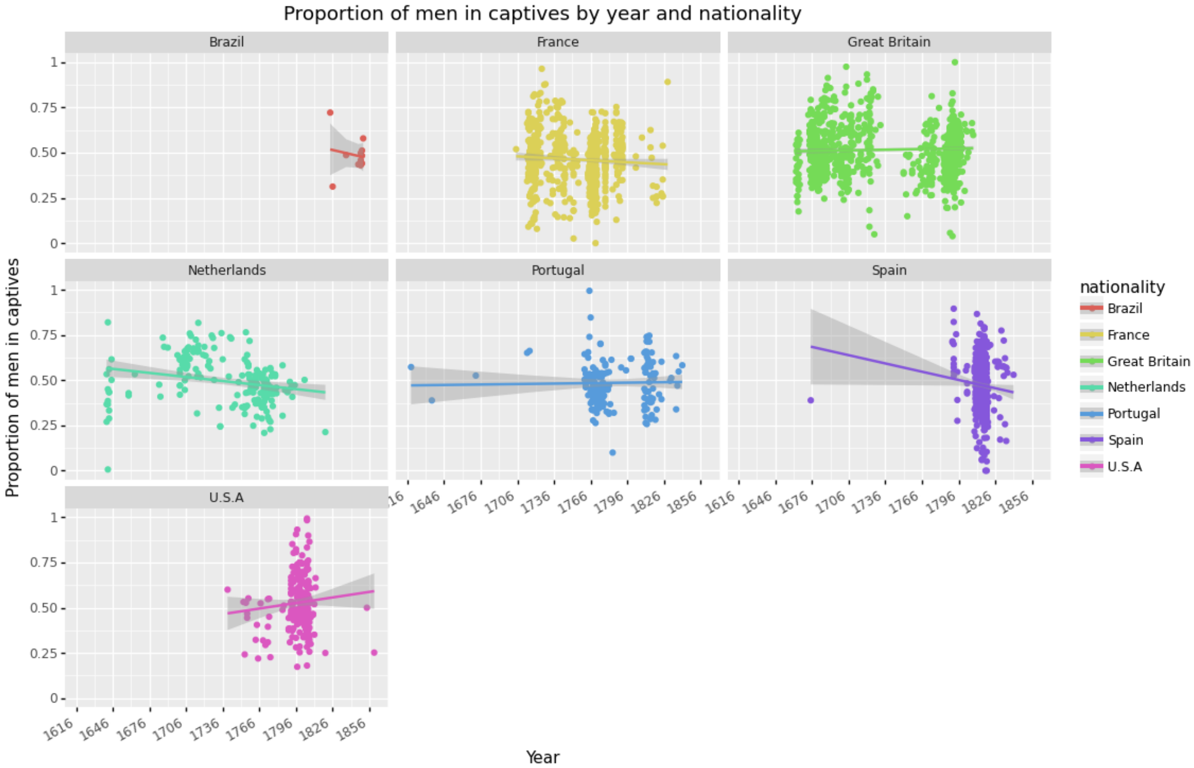
Out[223]:
```
menrat7     float64
dtype: object
```

In [224]:
```
# Graph of the proportion of captives that are men as a function of year + smooth

gg = p9.ggplot(men_df)
gg += p9.aes(x = 'yearam', y = 'menrat7')
gg += geom_point()
gg += geom_smooth()
gg += ylab("Proportion of men in captives")
gg += xlab("Year")
gg += labs(title="Proportion of men in captives by year")
gg += scale_x_continuous(breaks=range(1526,1867,10))
gg += theme(figure_size=(16, 8),
           axis_text_x  = element_text(angle = 30, hjust = 1))

gg
```



Out[224]: <ggplot: (183795180066)>

In [225]:
```
# Graph of the proportion of captives that are men as a function of year + smooth + o

gg = p9.ggplot(men_df)
gg += p9.aes(x = 'yearam', y = 'menrat7', color='nationality')
gg += p9.facet_wrap('~nationality')
# gg += p9.scale_color_hue(color_space='husl')
gg += geom_point()
gg += geom_smooth(se=True)
gg += ylab("Proportion of men in captives")
gg += xlab("Year")
gg += labs(title="Proportion of men in captives by year and nationality")
gg += scale_x_continuous(breaks=range(1526,1867,30))
gg += theme(figure_size=(12, 8),
           axis_text_x  = element_text(angle = 30, hjust = 1))

gg
```



Out[225]: <ggplot: (183777380051)>

 # 6. e

Here, I used the data "men_df" which excluded missing values for the variable "menrat7" for both plots. In the first graph, the aesthetic mappings are y-axis(the proportion of men that were captured as slaves), x-axis(year). The first geometric is scatter plots that shows all the ratio of captives that were men in middle passage. The second geometric is the smoother to show the linear regression fit line of the scatter plots. The theme was also added on the first plot to show the proper title and labels of x-axis and y-axis. In the second graph, the aesthetic mappings are y-axis, x-axis, and color which represents the nationality. Next, the geometries used are the scatter plots and smoother for the same purpose as those of the first graph. Also, I applied facet to separate the graph by each nationality to make easier to interpret by each country. Lastly, I added the theme to change the labels and the title and adjust the size of the graph.