Overview

1) Importing relevant Libraries/data ● Understanding the shape of the data 2) Data Cleaning ● A quick overview of the shape of the data using describe method. ● checking for null values ● lighter look at the data info ● observing distribution of data in order to fill the null values 3) Data Exploration ● checking for outliers ● Correlation between the metrics ● Plotting heatmaps to check for correlations 4) Feature Engineering ● Exploring relevant feature to bring important insights 5) Analysis based on gender of the users 6) Analysis based on the least active users on Facebook 7) Analysis based on the user accessibility (Mobile Devices vs. Web Devices)

NOTE

I am not doing the model pre-processing steps like:Feature scalling , data spliting, Feature/label Encoding because we are not building the model(as per the requirement).

Assignment:

Exploratory Data Analysis(EDA) on Facebook Utilization Data

Problem Statement:

The objective of the proposed framework is to study and analyse the differences in the way users are using Facebook based on their gender, age-group, etc. and Identify a pattern out of it.

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import warnings
```

In [2]:

```
# Hides warning
warnings.filterwarnings('ignore')
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore",category=UserWarning)
```

In [3]:

```
df = pd.read_csv('facebook user data - facebook user data.csv')
```

In [4]:

```
df.head()
```

Out[4]:

	userid	age	dob_day	dob_year	dob_month	gender	tenure	friend_count	friendships_initiated	likes	likes_received	mol
0	2094382	14	19	1999	11	male	266.0	0	0	0	0	
1	1192601	14	2	1999	11	female	6.0	0	0	0	0	
2	2083884	14	16	1999	11	male	13.0	0	0	0	0	
3	1203168	14	25	1999	12	female	93.0	0	0	0	0	
4	1733186	14	4	1999	12	male	82.0	0	0	0	0	

In [5]:

```
df.shape
```

Out[5]:

```
(99003, 15)
```

In [6]:

```
# taking few numeric columns to see their basic statistics
df_data = df[['age','tenure','friend_count','likes','likes_received']]
```

Data Cleaning & Analysis

In [7]:

```
df_data.describe()
```

Out[7]:

	age	tenure	friend_count	likes	likes_received
count	99003.000000	99001.000000	99003.000000	99003.000000	99003.000000
mean	37.280224	537.887375	196.350787	156.078785	142.689363
std	22.589748	457.649874	387.304229	572.280681	1387.919613
min	13.000000	0.000000	0.000000	0.000000	0.000000
25%	20.000000	226.000000	31.000000	1.000000	1.000000
50%	28.000000	412.000000	82.000000	11.000000	8.000000
75%	50.000000	675.000000	206.000000	81.000000	59.000000
max	113.000000	3139.000000	4923.000000	25111.000000	261197.000000

 # Here's a quick breakdown of the above describe table: ● count: there are around 99000 rows in the dataset, which is filtered to these columns. ● mean: the average value of these features.(e.g average age is 37, avg friend_count is 196 etc.) ● std: measures the dispersion(spread) of a dataset relative to its mean. ● min: the minnimum values in the dataset for these perticular columns. ● 25%: the 25th percentile. 25% of values corresponding to these columns were lower than these stated values(eg. 25% of user's age is less than 20 years). ● 50%: the 50th percentile, or the median.50% of values corresponding to these columns were lower than these stated values. ● 75%: the 75th percentile. 75% of values corresponding to these columns were lower than these stated values. ● max: the maximum :-age, tenure,friend_count,total likes given, total likes_received are:113 ,3139, 4923, 25111, 261197 respectively. .

In [8]:

```
# Checking for null values and we can see gender has-175 null values and tenure has 2.
df.isnull().sum()
```

Out[8]:

```
userid                     0
age                        0
dob_day                    0
dob_year                   0
dob_month                  0
gender                   175
tenure                     2
friend_count               0
friendships_initiated      0
likes                      0
likes_received             0
mobile_likes               0
mobile_likes_received      0
www_likes                  0
www_likes_received         0
dtype: int64
```

In [9]:

In [9]:

```
# looking at first 5 rows of the dataset
df.head()
```

Out[9]:

	userid	age	dob_day	dob_year	dob_month	gender	tenure	friend_count	friendships_initiated	likes	likes_received	mol
0	2094382	14	19	1999	11	male	266.0	0	0	0	0	
1	1192601	14	2	1999	11	female	6.0	0	0	0	0	
2	2083884	14	16	1999	11	male	13.0	0	0	0	0	
3	1203168	14	25	1999	12	female	93.0	0	0	0	0	
4	1733186	14	4	1999	12	male	82.0	0	0	0	0	

In [10]:

```
# quick info of the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99003 entries, 0 to 99002
Data columns (total 15 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   userid                 99003 non-null  int64  
 1   age                    99003 non-null  int64  
 2   dob_day                99003 non-null  int64  
 3   dob_year               99003 non-null  int64  
 4   dob_month              99003 non-null  int64  
 5   gender                 98828 non-null  object 
 6   tenure                 99001 non-null  float64
 7   friend_count           99003 non-null  int64  
 8   friendships_initiated  99003 non-null  int64  
 9   likes                  99003 non-null  int64  
 10  likes_received         99003 non-null  int64  
 11  mobile_likes           99003 non-null  int64  
 12  mobile_likes_received  99003 non-null  int64  
 13  www_likes              99003 non-null  int64  
 14  www_likes_received     99003 non-null  int64  
dtypes: float64(1), int64(13), object(1)
memory usage: 11.3+ MB
```

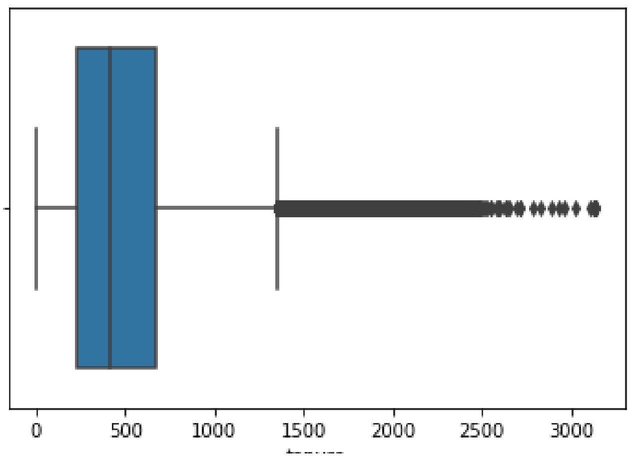
1) Load the data and impute missing values

In [11]:

```
# Checking Data Distribution for 'Tenure' by ploting boxplot
sns.boxplot(df.tenure)
```

Out[11]:

```
<AxesSubplot:xlabel='tenure'>
```



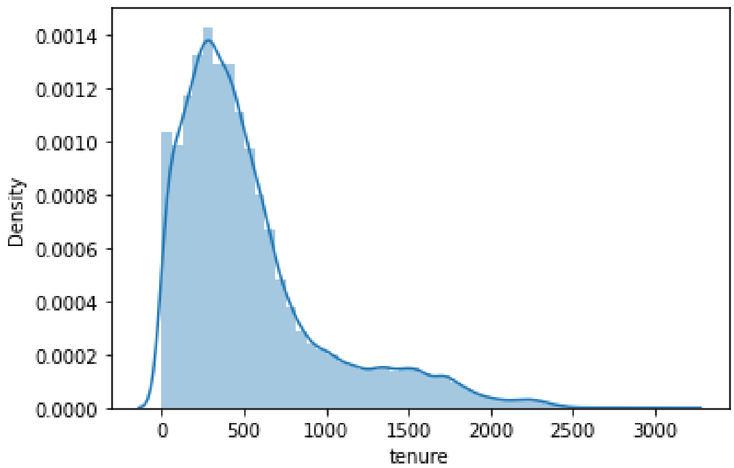
tenure

In [12]:

```
# Checking Data Distribution for 'Tenure' by ploting distribution plot
sns.distplot(df.tenure)
```

Out[12]:

```
<AxesSubplot:xlabel='tenure', ylabel='Density'>
```



As from the above disttribution plot we can easily conclude that it is Right-skewed b/c : For a normal distribution, 68% of the observations are within +/- one standard deviation of the mean, 95% are within +/- two standard deviations, and 99.7% are within +- three standard deviations.skewness of data: Data are skewed right when most of the data are on the left side of the graph and the long skinny tail extends to the right. Data are skewed left when most of the data are on the right side of the graph and the long skinny tail extends to the left.

In [13]:

```
#tenure imputation with median as it is right-skwed
df['tenure'].fillna(df['tenure'].median() , inplace=True)
```

In [14]:

```
#imputing with mode b/c it is a catagorical value
df['gender'].fillna(df['gender'].mode()[0] , inplace=True)
```

In [15]:

```
# Now after imputing the values we have zero null values.
df.isnull().sum()
```

Out[15]:

```
userid                   0
age                      0
dob_day                  0
dob_year                 0
dob_month                0
gender                   0
tenure                   0
friend_count             0
friendships_initiated    0
likes                    0
likes_received           0
mobile_likes             0
mobile_likes_received    0
www_likes                0
www_likes_received       0
dtype: int64
```

In [16]:

```
df.shape
```

Out[16]:

(99003, 15)

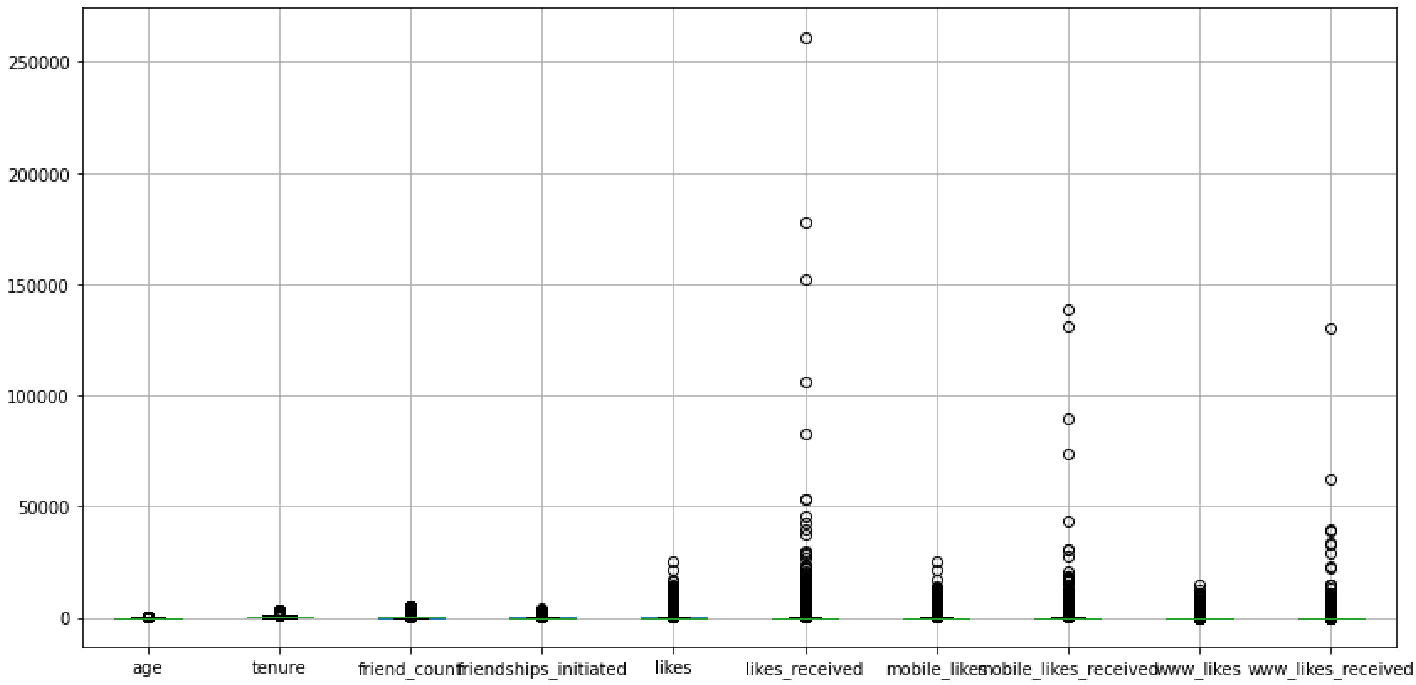
Checking for outliers

In [17]:

```
# As we can se there are very few values which are greater than 50k and they may distort the model accuracy in future , so we will remove them.
df.boxplot(column=['age','tenure','friend_count','friendships_initiated','likes','likes_received','mobile_likes','mobile_likes_received','www_likes','www_likes_received'], figsize=(14, 7))
```

Out[17]:

<AxesSubplot:>



In [18]:

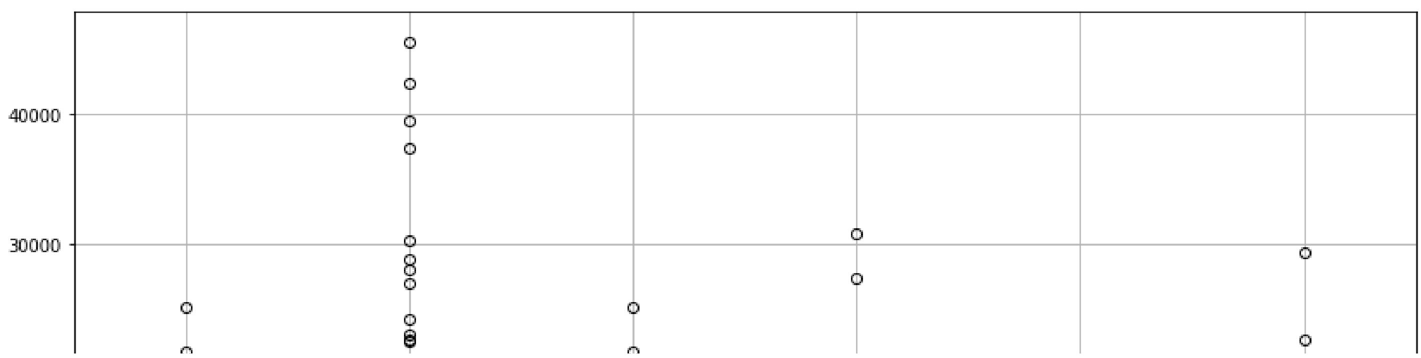
```
# removing values greater than 50000
df = df[df['likes_received'] <= 50000]
df = df[df['mobile_likes'] <= 50000]
df = df[df['mobile_likes_received'] <= 50000]
df = df[df['www_likes'] <= 50000]
df = df[df['www_likes_received'] <= 50000]

# df = df[df[['likes_received','mobile_likes','mobile_likes_received','www_likes','www_likes_received']] <= 50000]
```

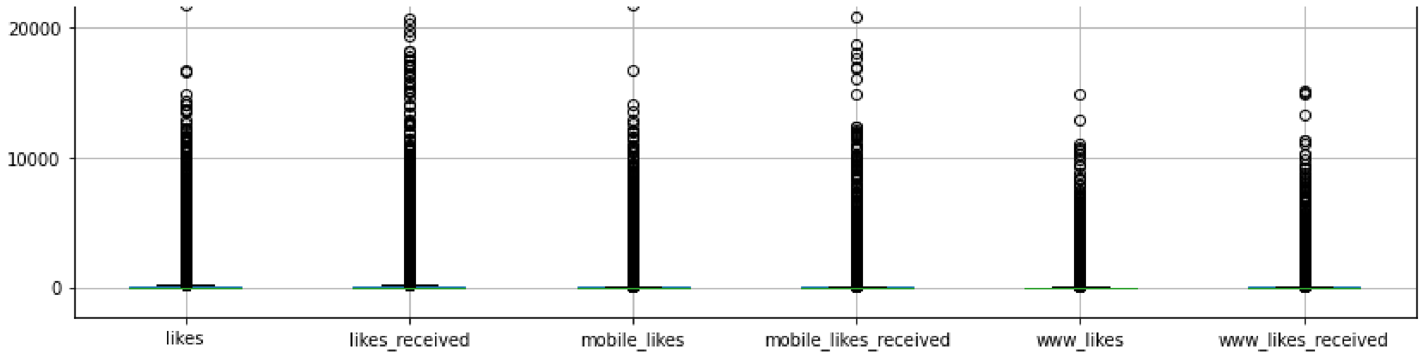
In [19]:

```
df.boxplot(column=['likes','likes_received','mobile_likes','mobile_likes_received','www_likes','www_likes_received'], figsize=(14, 7))
```

Out[19]:

<AxesSubplot:>



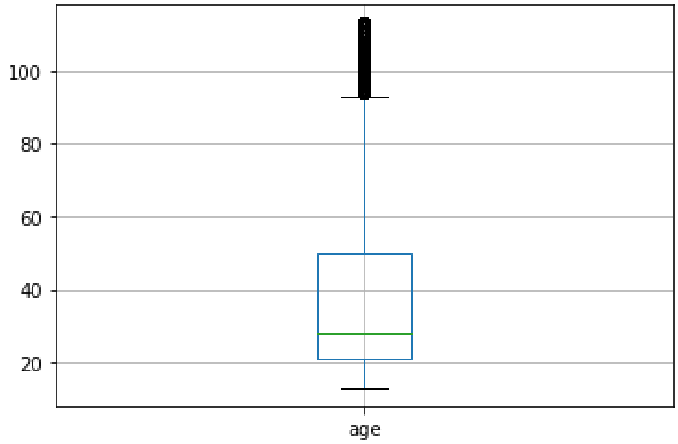


In [20]:

```
# checking outliers for age
df.boxplot(column=['age'])
```

Out[20]:

<AxesSubplot:>



In [21]:

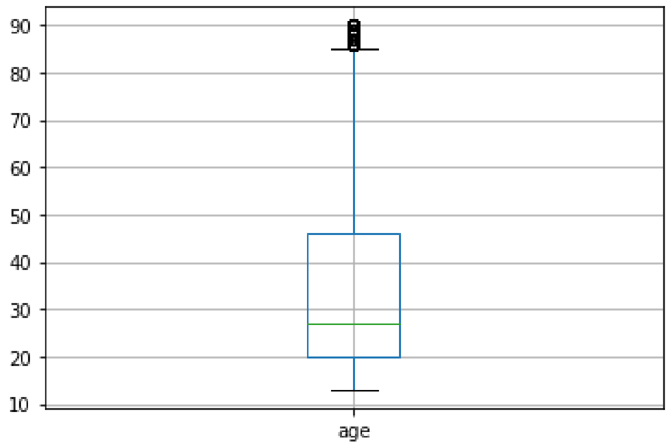
```
# removing users having age greater than 90 b/c they don't affect the model much as they
are few in numbers
df = df[df['age'] <= 90]
```

In [22]:

```
df.boxplot(column=['age']) #93280-shape 93273- 94090
```

Out[22]:

<AxesSubplot:>



In [23]:

```
df.shape
```

Out[23]:

(94090, 15)

(94090, 15)

Data manipulation and Feature Engineering

Dividing the age into several age groups and creating relavent features Defining the dataset with respective age groups: Youth - less than equal to 30 years old Millennials - from 30-50 years old Boomers - from 50-70 years old Post_War - from 70-90 years old

In [24]:

```
df['Youth'] = df.age.apply(lambda x:1 if x<=30 else 0)
df['Millennials'] = df.age.apply(lambda x:1 if 30<x<=50 else 0)
df['Boomers'] = df.age.apply(lambda x:1 if 50<x<=70 else 0)
df['Post_War'] = df.age.apply(lambda x:1 if 70<x<=90 else 0)
```

For numeric data

Made histograms to understand distributions Corrplot Pivot table comparing survival rate across numeric variables

For Categorical Data

Made bar charts to understand balance of classes Made pivot tables to understand relationship with gender catagory and other numerical features.

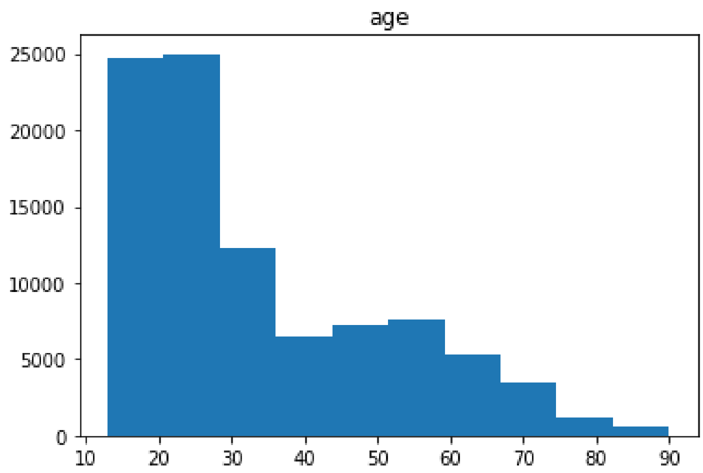
In [25]:

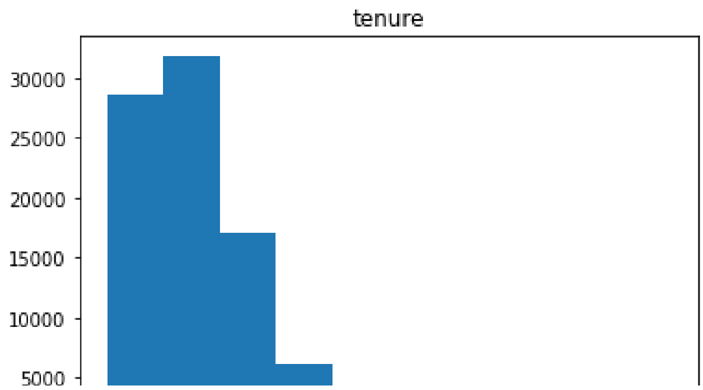
```
# Defining Catagorical features
df_cat = df[['gender','Youth','Millennials','Boomers','Post_War']]
# Defining Numerical features
df_num = df[['age','tenure','friend_count','friendships_initiated','likes','likes_receive
d','mobile_likes','mobile_likes_received','www_likes','www_likes_received']]
```

2) Plot heatmap / correlation matrix on all the columns

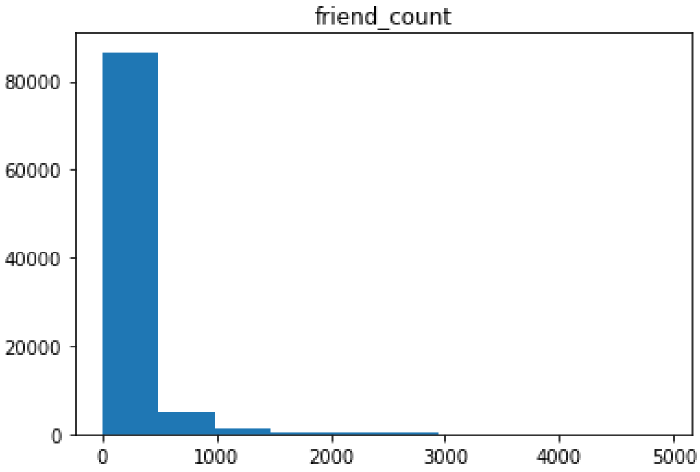
In [26]:

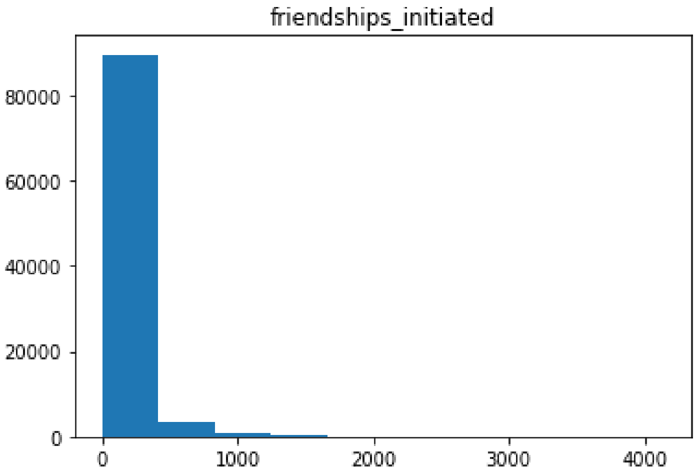
```
#distributions for all numeric variables
for i in df_num.columns:
    plt.hist(df_num[i])
    plt.title(i)
    plt.show()
```

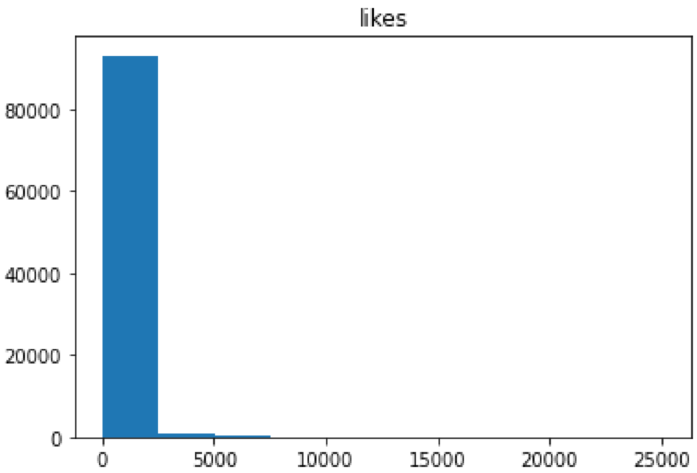


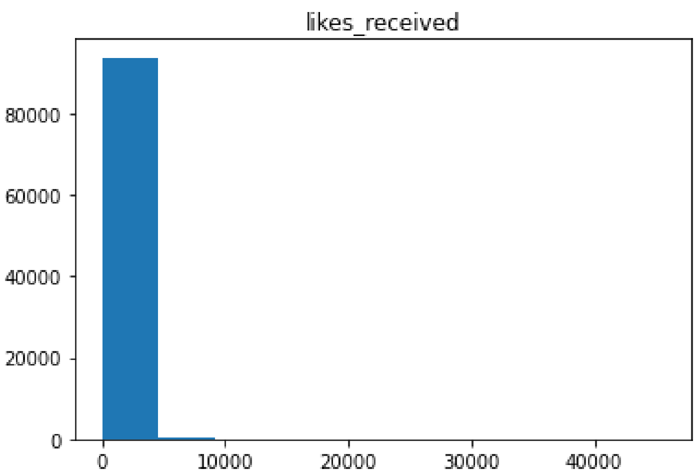



0
0
500
1000
1500
2000
2500

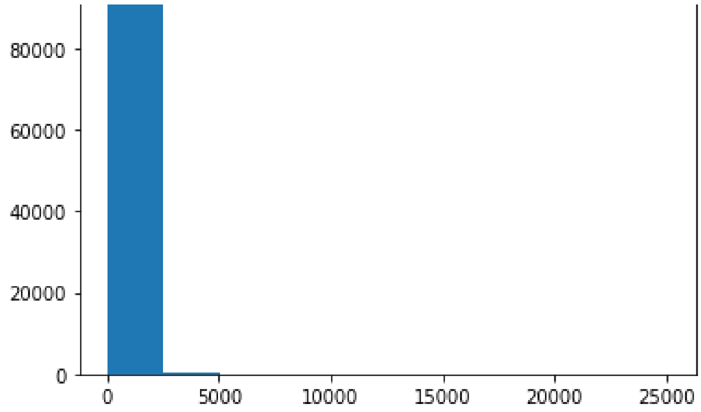

friend_count
80000
60000
40000
20000
0
0
1000
2000
3000
4000
5000

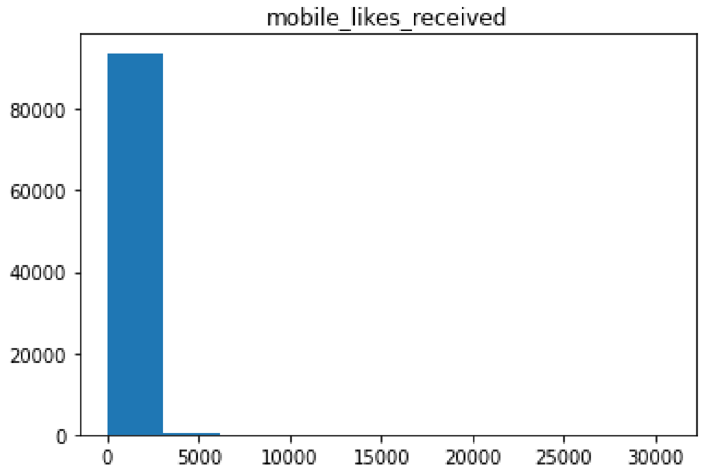

friendships_initiated
80000
60000
40000
20000
0
0
1000
2000
3000
4000

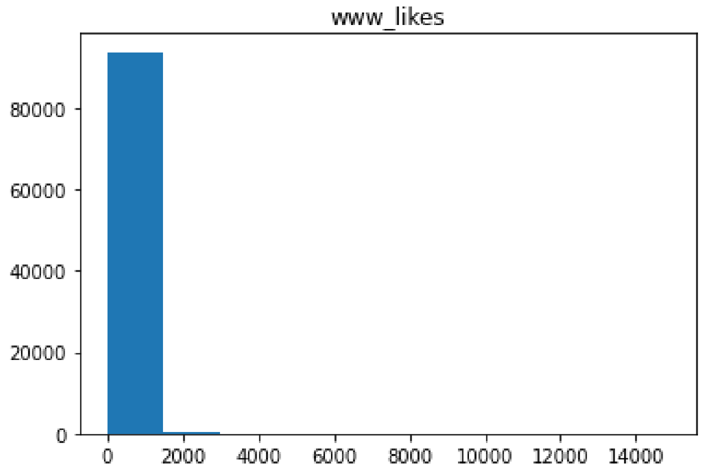

likes
80000
60000
40000
20000
0
0
5000
10000
15000
20000
25000

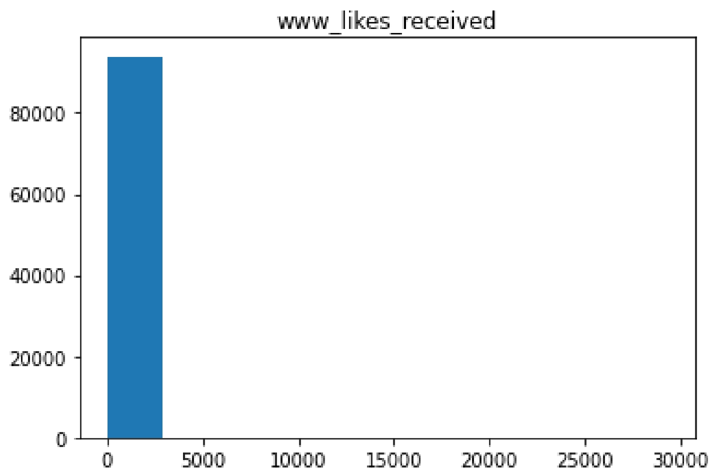

likes_received
80000
60000
40000
20000
0
0
10000
20000
30000
40000


mobile_likes









In [27]:

```
# correlation of all the columns w.r.t. each other
corr_matrix = pd.DataFrame(df_num.corr())
corr_matrix
```

Out[27]:

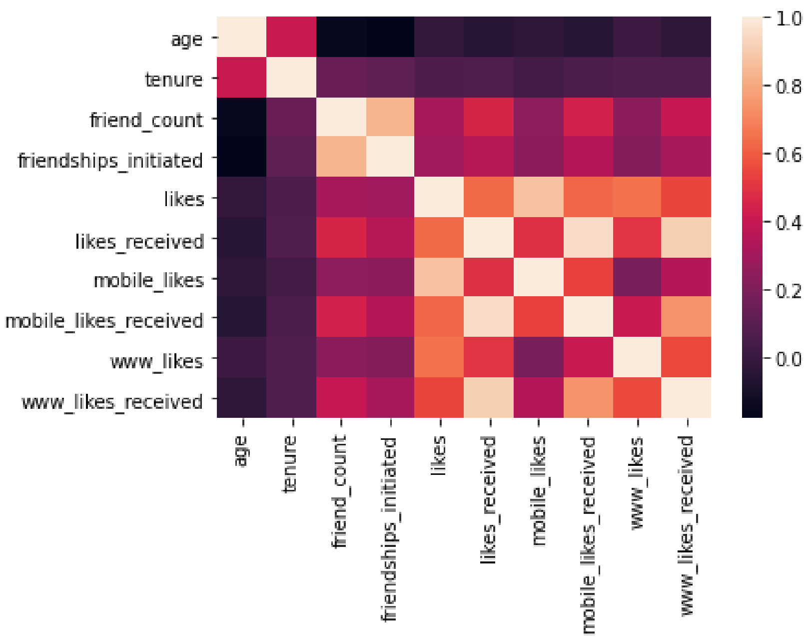
	age	tenure	friend_count	friendships_initiated	likes	likes_received	mobile_likes	mobile_lik
age	1.000000	0.406893	-0.151008	-0.176141	-0.016628	-0.049414	-0.031845	
tenure	0.406893	1.000000	0.141175	0.111912	0.064040	0.067679	0.034294	
friend_count	-0.151008	0.141175	1.000000	0.831734	0.308546	0.450663	0.245434	
friendships_initiated	-0.176141	0.111912	0.831734	1.000000	0.293173	0.355394	0.236549	
likes	-0.016628	0.064040	0.308546	0.293173	1.000000	0.629483	0.870918	
likes_received	-0.049414	0.067679	0.450663	0.355394	0.629483	1.000000	0.487553	
mobile_likes	-0.031845	0.034294	0.245434	0.236549	0.870918	0.487553	1.000000	
mobile_likes_received	-0.056368	0.058620	0.442382	0.349781	0.619494	0.949604	0.537852	
www_likes	0.016163	0.074771	0.235869	0.218930	0.647419	0.501637	0.189313	
www_likes_received	-0.032532	0.069074	0.391293	0.307365	0.544474	0.910502	0.345150	

In [28]:

```
sns.heatmap(df_num.corr())
```

Out[28]:

<AxesSubplot:>

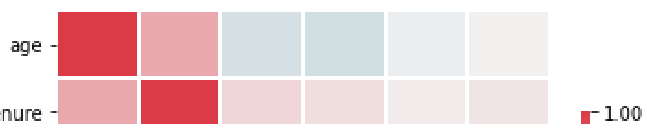


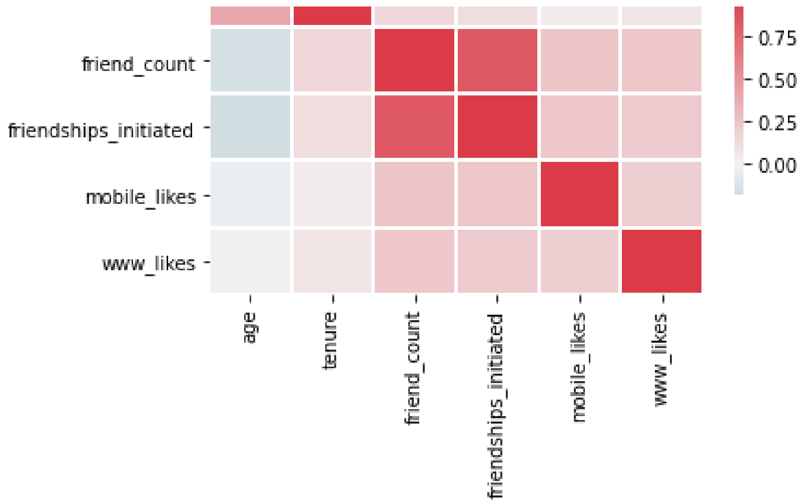
In [29]:

```
# Another heatmap with few features for more clearity
cmap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(df[['age','tenure','friend_count','friendships_initiated','mobile_likes', 'www_likes']].corr(),vmax=1.0, center=0, cmap=cmap,
            square=False, linewidths=.4, cbar_kws={"shrink": 0.5})
```

Out[29]:

<AxesSubplot:>





In [30]:

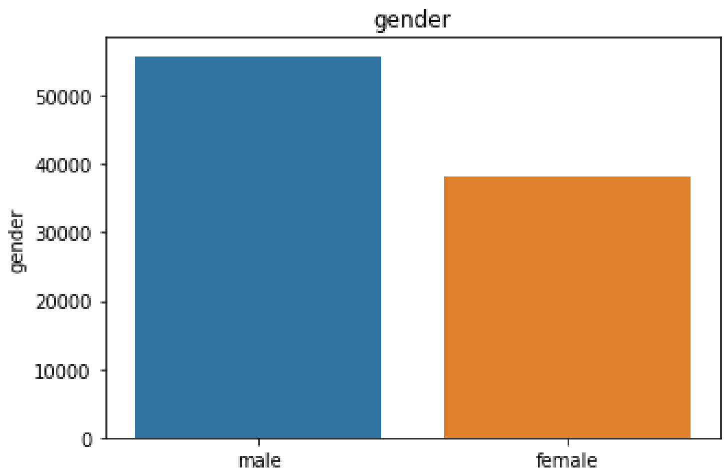
```
pd.pivot_table(df, index = 'gender', values = ['age','tenure','friend_count','likes','li
kes_received'])
```

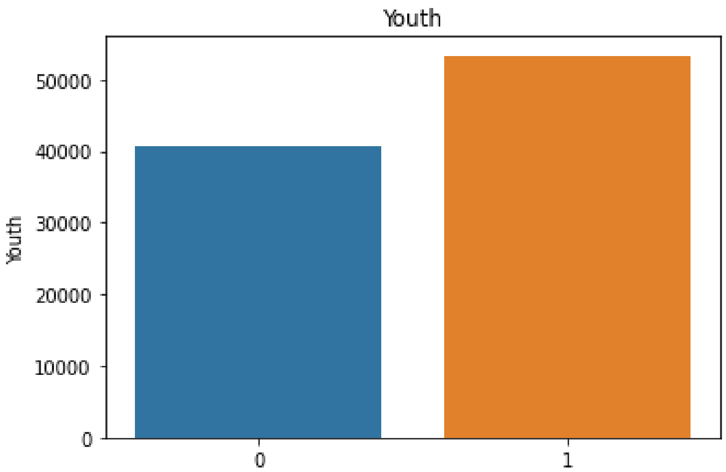
Out[30]:

	age	friend_count	likes	likes_received	tenure
gender					
female	36.229788	233.217052	263.762409	238.027585	559.997599
male	32.170928	153.469680	81.970612	62.253801	473.570250

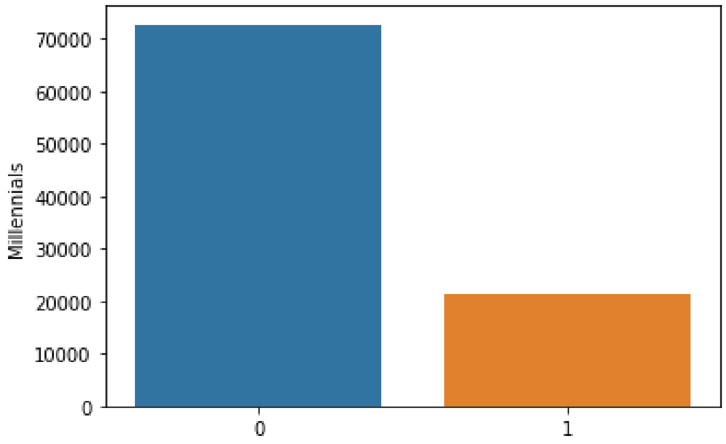
In [31]:

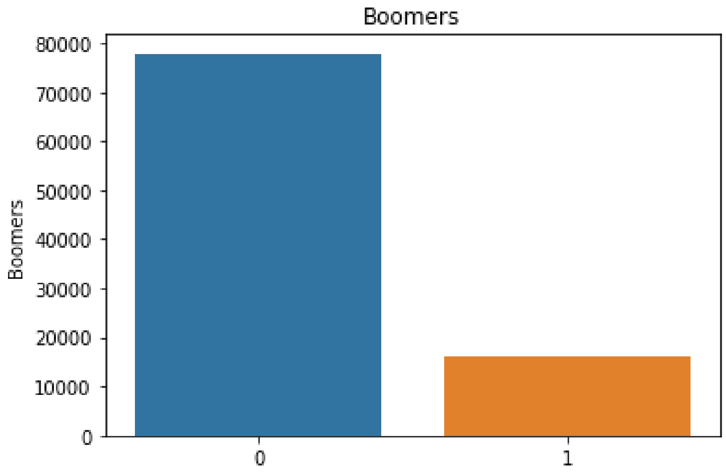
```
for i in df_cat.columns:
    sns.barplot(df_cat[i].value_counts().index,df_cat[i].value_counts()).set_title(i)
    plt.show()
```

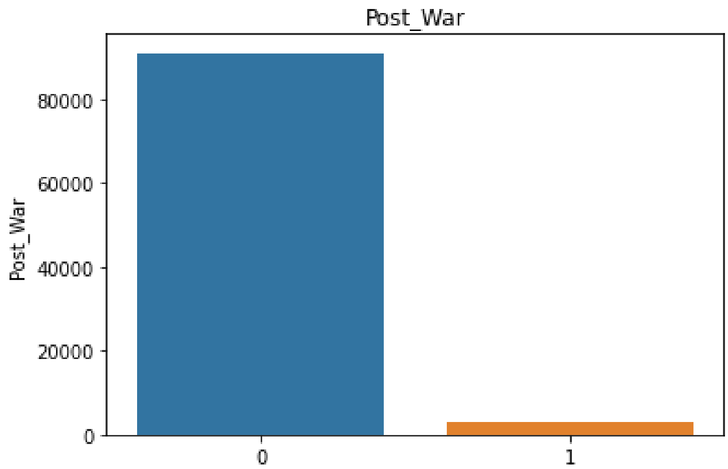




Millennials







In [32]:

```
# Percentage of Boomers(age-[50-70]), Millennials([30-50]), Post_War([more than 70]) ,You
th([upto 30]) among female, male gender catagory
pd.pivot_table(df, index = 'gender', values = ['Youth','Millennials','Boomers','Post_War
'])
```

Out[32]:

	Boomers	Millennials	Post_War	Youth
gender				
female	0.223916	0.224933	0.042121	0.509030
male	0.136162	0.230223	0.026035	0.607581

3) Analysis based on gender of the users

In [33]:

```
df.describe()
```

Out[33]:

	userid	age	dob_day	dob_year	dob_month	tenure	friend_count	friendships_initiate
count	9.409000e+04	94090.000000	94090.000000	94090.000000	94090.000000	94090.000000	94090.000000	94090.000
mean	1.597187e+06	33.823892	14.529068	1979.176108	6.287097	508.767648	185.946668	103.167
std	3.441226e+05	17.153293	8.992253	17.153293	3.521267	427.932070	371.645301	184.341
min	1.000008e+06	13.000000	1.000000	1923.000000	1.000000	0.000000	0.000000	0.000
25%	1.298914e+06	20.000000	7.000000	1967.000000	3.000000	221.000000	29.000000	16.000
50%	1.596143e+06	27.000000	14.000000	1986.000000	6.000000	399.000000	78.000000	44.000
75%	1.896004e+06	46.000000	22.000000	1993.000000	9.000000	640.000000	195.000000	111.000
max	2.193542e+06	90.000000	31.000000	2000.000000	12.000000	2595.000000	4917.000000	4144.000

- **What is composition of male and female users?**

In [34]:

```
df.columns
```

Out[34]:

```
Index(['userid', 'age', 'dob_day', 'dob_year', 'dob_month', 'gender', 'tenure',
       'friend_count', 'friendships_initiated', 'likes', 'likes_received',
       'mobile_likes', 'mobile_likes_received', 'www_likes',
       'www_likes_received', 'Youth', 'Millennials', 'Boomers', 'Post_War'],
      dtype='object')
```

In [35]:

```
# Number of males and females
df.gender.value_counts()
```

Out[35]:

```
male      55772
female    38318
Name: gender, dtype: int64
```

In [36]:

```
# quick look at the statistics values
df.agg(
        {
         "age": ["min", "max", "median","mean"],
         "tenure": ["min", "max", "median", "mean"],
         "friend_count": ["min", "max", "median", "mean"],
         "likes": ["min", "max", "median", "mean"],
         "likes_received": ["min", "max", "median", "mean"],
         "mobile_likes": ["min", "max", "median", "mean"],
        "www_likes": ["min", "max", "median", "mean"]
      }
 )
```

Out[36]:

	age	tenure	friend_count	likes	likes_received	mobile_likes	www_likes
min	13.000000	0.000000	0.000000	0.000000	0.00000	0.00000	0.000000
max	90.000000	2595.000000	4917.000000	25111.000000	45633.00000	25111.00000	14865.000000
median	27.000000	399.000000	78.000000	10.000000	8.00000	4.00000	0.000000
mean	33.823892	508.767648	185.946668	156.005027	133.83739	106.47665	49.528313

In [37]:

```
# calculating average values of users on basis of their gender for reference
df.groupby(['gender']).mean()
```

Out[37]:

gender	userid	age	dob_day	dob_year	dob_month	tenure	friend_count	friendships_initiated	lik
female	1.597815e+06	36.229788	15.047054	1976.770212	6.438384	559.997599	233.217052	111.719323	263.7624
male	1.596755e+06	32.170928	14.173187	1980.829072	6.183156	473.570250	153.469680	97.291723	81.9706

Which category of gender has more friends?

In [38]:

```
# We can see from the table that Female-Youth catagory has the highest friend_count and M
ale-Millennials has least
pd.pivot_table(df, index=['gender','Youth','Millennials','Boomers','Post_War'] ,values =
['friend_count'])
```

Out[38]:

gender	Youth	Millennials	Boomers	Post_War	friend_count
female	0	0	0	1	148.134449
			1	0	120.656993
		1	0	0	125.605059
	1	0	0	0	337.323507
male	0	0	0	1	187.473829
			1	0	117.945878
		1	0	0	92.313162
	1	0	0	0	183.146934

Which category of gender initiated more friendships?

In [39]:

```
# We can see from the table that Female-Youth catagory has the highest friendships_initia
ted
pd.pivot_table(df, index=['gender','Youth','Millennials','Boomers','Post_War'] ,values =
'friendships_initiated')
```

Out[39]:

gender	Youth	Millennials	Boomers	Post_War	friendships_initiated
female	0	0	0	1	65.798017
			1	0	63.031002
		1	0	0	70.051166
	1	0	0	0	155.349193
male	0	0	0	1	91.732782
			1	0	64.744930
		1	0	0	55.102414

	1	0	0	0	120.810069

friendships_initiated

What is the distribution of tenure across different categories of gender?

In [40]:

```
# As we can see both female/male-Post war group has been on facebook around same tenure(n
o of days)
pd.pivot_table(df, index=['gender','Youth','Millennials','Boomers','Post_War'] ,values =
'tenure')
```

Out[40]:

					tenure
gender	**Youth**	**Millennials**	**Boomers**	**Post_War**	
female	**0**	**0**	**0**	**1**	977.755886
			1	**0**	823.037296
		1	**0**	**0**	543.437754
	1	**0**	**0**	**0**	417.038708
male	**0**	**0**	**0**	**1**	998.880165
			1	**0**	766.218199
		1	**0**	**0**	473.839875
	1	**0**	**0**	**0**	385.375111

4) Analysis based on the least active users on Facebook

How many users have no friends?

In [41]:

```
(df['friend_count'] == 0).sum()
```

Out[41]:

1952

How many users did not like any posts?

In [42]:

```
(df['likes'] == 0).sum()
```

Out[42]:

21831

How many users did not receive any likes

In [43]:

```
(df['likes_received'] == 0).sum()
```

Out[43]:

23923

5) Analysis based on the user accessibility (Mobile Devices vs. Web Devices)

What is the average number of posts liked by users (based on gender) through web vs. mobile devices?

In [44]:

```
# We can see significantly there are much more mobile users than web users, hence posts l
iked by mobile user are more.
pd.pivot_table(df, index=['gender','Youth','Millennials','Boomers','Post_War'] ,values =
['likes','mobile_likes','www_likes'])
```

Out[44]:

gender	Youth	Millennials	Boomers	Post_War	likes	mobile_likes	www_likes
female	0	0	0	1	161.353160	85.483271	75.869888
			1	0	229.993240	124.070280	105.922960
		1	0	0	237.690567	175.563058	62.127277
	1	0	0	0	298.611997	206.509972	92.101923
male	0	0	0	1	84.835399	38.168733	46.666667
			1	0	94.271794	56.190809	38.080985
		1	0	0	63.476324	50.161215	13.315031
	1	0	0	0	86.098920	63.404828	22.694062

What is the average number of likes received by users (based on gender) through web vs. mobile devices?

In [45]:

```
# Similary we can see likes received via mobile apps are significantly more.
pd.pivot_table(df, index=['gender','Youth','Millennials','Boomers','Post_War'] ,values =
['likes','mobile_likes_received','www_likes_received'])
```

Out[45]:

gender	Youth	Millennials	Boomers	Post_War	likes	mobile_likes_received	www_likes_received
female	0	0	0	1	161.353160	42.689591	36.060719
			1	0	229.993240	67.609790	68.699883
		1	0	0	237.690567	102.573500	73.888966
	1	0	0	0	298.611997	193.296950	129.859523
male	0	0	0	1	84.835399	37.994490	45.059229
			1	0	94.271794	32.277719	26.910719
		1	0	0	63.476324	29.734579	18.404128
	1	0	0	0	86.098920	41.735614	25.662338

In [ ]: