In [1]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import time
from datetime import datetime
```

In [2]:

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

In [3]:

```
## Loading the train_data
train = pd.read_csv('train.csv')
```

In [4]:

```
train.head(1)
```

Out[4]:

	msno	is_churn
0	waLDQMmcOu2jLDaV1ddDkgCrB/jl6sD66Xzs0Vqax1Y=	1

In [5]:

```
train.shape
```

Out[5]:

```
(992931, 2)
```

In [6]:

```
## Loading the members table
members = pd.read_csv('members_v3.csv')
members.head(1)
```

Out[6]:

	msno	city	bd	gender	registered_via	registration_init_time
0	Rb9UwLQTrxzBVwCB6+bCcSQWZ9JiNLC9dXtM1oEsZA8=	1	0	NaN	11	20110911

In [7]:

```
## Loading the transaction logs file
transaction_logs = pd.read_csv("transactions.csv")
transaction_logs.head(1)
```

Out[7]:

	msno	payment_method_id	payment_plan_days	plan_list_price	actual_amount_paid	is_
0	YyO+tlZtAXYXoZhNr3Vg3+dfVQvrBVGO8j1mfqe4ZHc=	41	30	129	129	

In [8]:

```
## Loading 20M rows Due RAM constraints
user_logs_rows = pd.read_csv('user_logs.csv',nrows=20000000)
```

```
user_logs_rows.head(1)
```

Out[8]:

	msno	date	num_25	num_50	num_75	num_985	num_100	num_unq	total_secs
0	rxIP2f2aN0rYNp+toI0Obt/N/FYQX8hcO1fTmmy2h34=	20150513	0	0	0	0	1	1	280.335

What percent of customer churns ?

In [13]:

```
## Lets find the churn rate
churn_rate  = train.is_churn.value_counts()/len(train)
churn_rate
```

Out[13]:

```
0    0.936077
1    0.063923
Name: is_churn, dtype: float64
```

About 93.6% of customer stayed and 6.3% of churned

In [10]:

```
members.shape
```

Out[10]:

```
(6769473, 6)
```

In [36]:

```
## Calculate the number of null values
members.isnull().sum()
```

Out[36]:

```
msno                          0
city                          0
bd                            0
gender                  4429505
registered_via                0
registration_init_time        0
dtype: int64
```

4429505 data points are NULL for gender class

In [38]:

```
print(f'percentage of null_value:{(members.gender.isnull().sum()/members.shape[0])*100}')
```

```
percentage of null_value:65.43352783887313
```

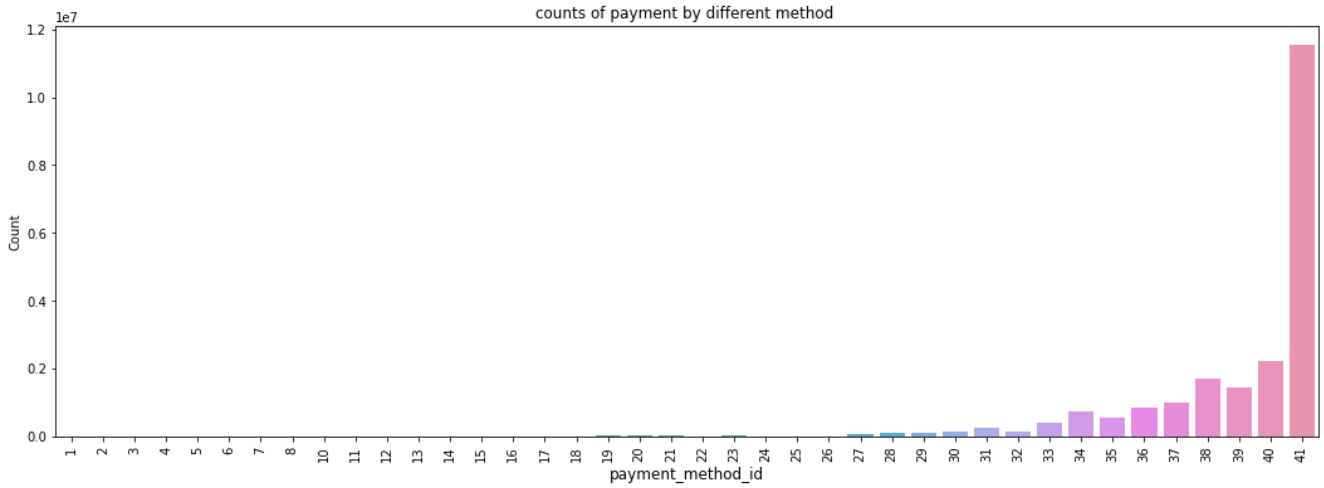
- NULL values are present only gender column
- 65% of the values are NULL in gender column

Q) Which payment method is used by the maximum number of customer ?

In [39]:

```
plt.figure(figsize=(18,6))
```

```
sns.countplot(x="payment_method_id", data=transaction_logs)
plt.ylabel('Count', fontsize=10)
plt.xlabel('payment_method_id', fontsize=12)
plt.xticks(rotation='vertical')
plt.title("counts of payment by different method ", fontsize=12)
plt.show()
```



- Maximum number of payments are done by method "41"

In which payment method maximum number of customer churns ?

In [9]:

```
## Merging the train data and transaction data
train_transaction_logs = pd.merge(train,transaction_logs,on='msno',how='left')
```

In [10]:

```
train_transaction_logs.head(1)
```

Out[10]:

	msno	is_churn	payment_method_id	payment_plan_days	plan_list_price	actual_amoun
0	waLDQMmcOu2jLDaV1ddDkgCrB/jl6sD66Xzs0Vqax1Y=	1	38	7	0	

In [85]:

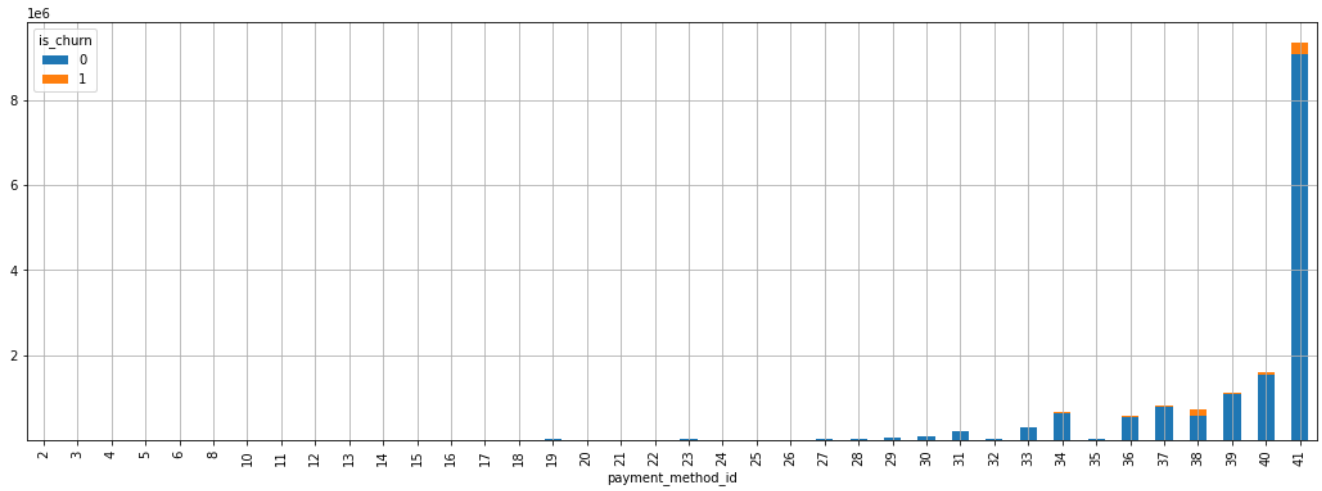
```
plt.figure(figsize=(18,6))
tran_crosstab=pd.crosstab(train_transaction_logs['payment_method_id'],train_transaction_logs['is_churn'])
tran_crosstab.plot(kind='bar', stacked=True, grid=True,figsize=(18,6))
tran_crosstab["Ratio"] =  city_crosstab[1] / city_crosstab[0]
tran_crosstab
```

Out[85]:

is_churn	0	1	Ratio
payment_method_id			
2	7	3	NaN
3	36	15	0.090422
4	1	1	0.097617
5	60	7	0.096048
6	45	17	0.094143
8	141	35	0.107112

is_churn	0	1	Ratio
payment_method_id			
10	1058	0	0.100202
11	1857	0	0.091832
12	619	214	0.107660
13	907	441	0.085462
14	11935	39	0.085122
15	94	75	0.091981
16	7189	477	0.090080
17	1258	847	0.081092
18	12892	461	0.089621
19	28242	504	0.076923
20	4926	2118	0.090177
21	17195	576	0.112140
22	2434	1085	0.091991
23	33060	949	NaN
24	8930	318	NaN
25	2902	741	NaN
26	2523	263	NaN
27	44965	1468	NaN
28	23634	6572	NaN
29	64065	10115	NaN
30	100599	8999	NaN
31	222567	2185	NaN
32	21082	8569	NaN
33	308107	8286	NaN
34	645539	6728	NaN
35	28531	8497	NaN
36	532272	50783	NaN
37	795844	18335	NaN
38	585630	143028	NaN
39	1085455	41149	NaN
40	1535155	67175	NaN
41	9065821	294496	NaN

```
<Figure size 1296x432 with 0 Axes>
```

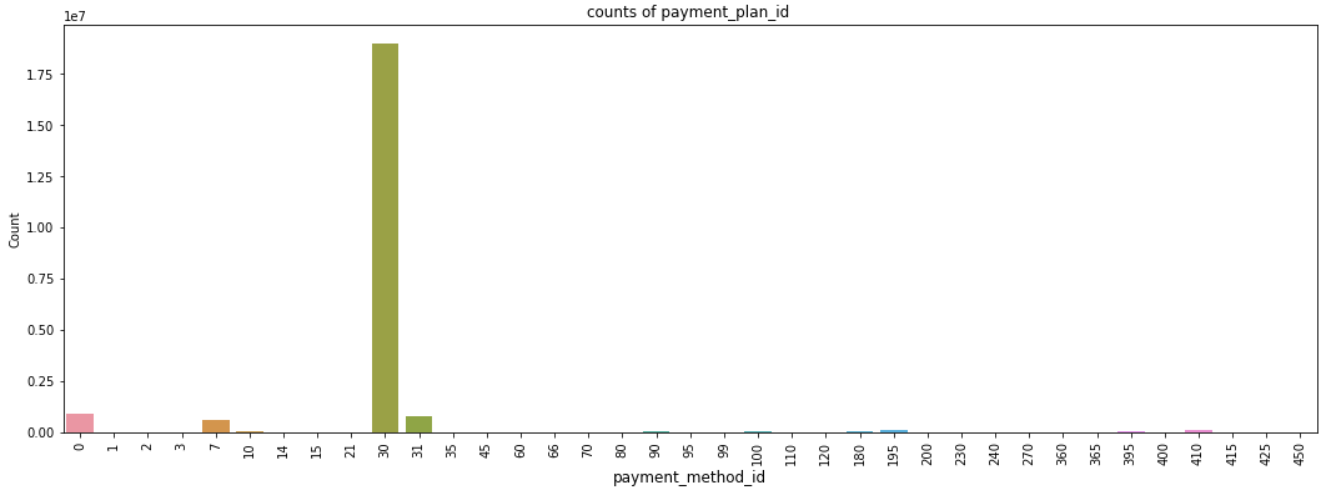


Q) How many days_plan is being used by maximum number of customers ?

In [40]:

In [40]:

```
plt.figure(figsize=(18,6))
sns.countplot(x="payment_plan_days", data=transaction_logs)
plt.ylabel('Count', fontsize=10)
plt.xlabel('payment_method_id', fontsize=12)
plt.xticks(rotation='vertical')
plt.title("counts of payment_plan_id ", fontsize=12)
plt.show()
```



- Maximum number of people takes 30 days plan

- As we have seen that data of same user listening to different numbers of song on different day

Q) In which plan churn rate is Maximum ?

In [ ]:

```
all_Plans =  train_transaction_logs['payment_plan_days'].unique()
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

Q) Which gender churned more ?

In [16]:

```
## Merging the train data and members data
train_member = pd.merge(train,members,on='msno',how='left')
```

In [17]:

```
train_member.head(-1)
```

Out[17]:

	msno	is_churn	city	bd	gender	registered_via	registration_init_time
0	waLDQMmcOu2jLDaV1ddDkgCrB/jl6sD66Xzs0Vqax1Y=	1	18.0	36.0	female	9.0	20050406.0
1	QA7uiXy8vIbUSPOkCf9RwQ3FsT8jVq2OxDr8zqa7bRQ=	1	10.0	38.0	male	9.0	20050407.0
2	fGwBva6hikQmTJzrbz/2Ezjm5Cth5jZUNvXigKK2AFA=	1	11.0	27.0	female	9.0	20051016.0
3	mT5V8rEpa+8wuqi6x0DoVd3H5icMKkE9Prt49UlmK+4=	1	13.0	23.0	female	9.0	20051102.0
4	XaPhtGLk/5UvvOYHcONTwsnH97P4eGECeq+BARGItRw=	1	3.0	27.0	male	9.0	20051228.0
...	...	...	...	...	...	...	...
992925	+vvehvMxda8/6O4Yf+Aq9PELkx5mlsb1wtcuTb9PsR4=	0	NaN	NaN	NaN	NaN	NaN
992926	tUM0yxAj50Vc35vQZ++xMlomdyeLJUW9lEcoPnt3H+g=	0	12.0	24.0	male	4.0	20170201.0
992927	KQS8etmfGgvE/7Y9gK+E9wdLnRTI0lyyPXaXL3I8E4c=	0	15.0	17.0	female	4.0	20170210.0
992928	8/jDLgNREuWI9hcKVYp8723nmavn01T+AuMWkK3uM7g=	0	NaN	NaN	NaN	NaN	NaN
992929	iNV99F1Rml7EMndOeLI0Y/iek6aCj/Qp1Z4dZvR+sak=	0	1.0	0.0	NaN	7.0	20170215.0

992930 rows × 7 columns

In [61]:

```
def change(x):
    if x=='female':
        return 0
    elif x=='male':
        return 1
```

In [62]:

```
Gender = train_member['gender']
converted = Gender.map(change)
train_member['gender'] = converted
```

In [63]:

```
train_member.head(5)
```

Out[63]:

	msno	is_churn	city	bd	gender	registered_via	registration_init_time
0	waLDQMmcOu2jLDaV1ddDkgCrB/jl6sD66Xzs0Vqax1Y=	1	18.0	36.0	0.0	9.0	20050406.0
1	QA7uiXy8vIbUSPOkCf9RwQ3FsT8jVq2OxDr8zqa7bRQ=	1	10.0	38.0	1.0	9.0	20050407.0
2	fGwBva6hikQmTJzrbz/2Ezjm5Cth5jZUNvXigKK2AFA=	1	11.0	27.0	0.0	9.0	20051016.0
3	mT5V8rEpa+8wuqi6x0DoVd3H5icMKkE9Prt49UlmK+4=	1	13.0	23.0	0.0	9.0	20051102.0
4	XaPhtGLk/5UvvOYHcONTwsnH97P4eGECeq+BARGItRw=	1	3.0	27.0	1.0	9.0	20051228.0

In [65]:

```
train_member.shape
```

Out[65]:

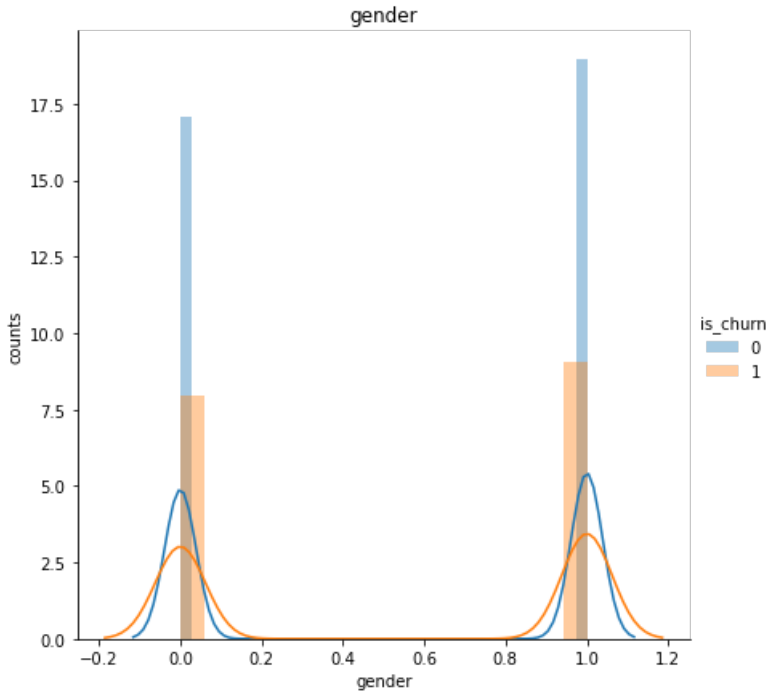
```
(992931, 7)
```

In [67]:

```
sns.FacetGrid(train_member,hue="is_churn",size=6) \
    .map(sns.distplot,"gender") \
    .add_legend();
plt.title("gender")
plt.ylabel("counts")
plt.plot()
```

Out[67]:

```
[]
```



- There is not much difference in the churn rate of male and female

In [71]:

```
train_member.head()
```

Out[71]:

	msno	is_churn	city	bd	gender	registered_via	registration_init_time
0	waLDQMmcOu2jLDaV1ddDkgCrB/jl6sD66Xzs0Vqax1Y=	1	18.0	36.0	0.0	9.0	20050406.0
1	QA7uiXy8vIbUSPOkCf9RwQ3FsT8jVq2OxDr8zqa7bRQ=	1	10.0	38.0	1.0	9.0	20050407.0
2	fGwBva6hikQmTJzrbz/2Ezjm5Cth5jZUNvXigKK2AFA=	1	11.0	27.0	0.0	9.0	20051016.0
3	mT5V8rEpa+8wuqi6x0DoVd3H5icMKkE9Prt49UlmK+4=	1	13.0	23.0	0.0	9.0	20051102.0
4	XaPhtGLk/5UvvOYHcONTwsnH97P4eGECeq+BARGItRw=	1	3.0	27.0	1.0	9.0	20051228.0

Q) Whats the main age group of customers ?

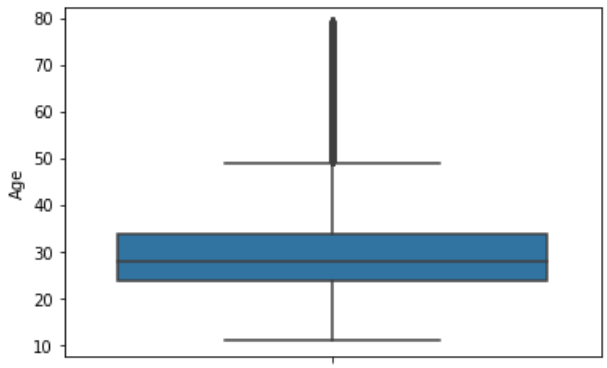
In [47]:

```
age_member =train_member.bd[(train_member.bd > 10 )& (train_member.bd < 80)]
```

```
sns.boxplot(y = age_member, data = train_member)
plt.ylabel('Age')
```

Out[47]:

```
Text(0, 0.5, 'Age')
```



- The majority customer age group of customers are 25 to 35

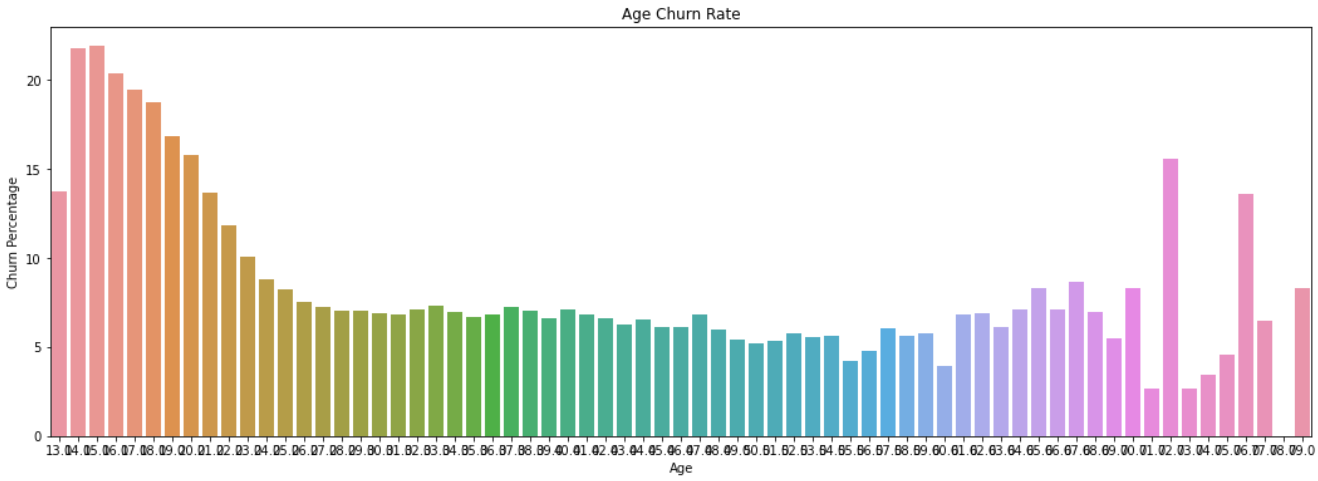
Q) Which age group of customers churn more ?

In [48]:

```
plt.figure(figsize=(18,6))
age_group = train_member[(train_member.bd>12)& (train_member.bd<80)]
b = age_group.groupby(['bd','is_churn'])['msno'].count().reset_index()
b = pd.pivot_table(b, values='msno', index='bd',columns=['is_churn'])
b['churn_percentage'] = (b[1]/(b[0] + b[1]))*100
b = b.reset_index()
sns.barplot(x = 'bd', y = 'churn_percentage',data = b)
plt.xlabel('Age')
plt.ylabel('Churn Percentage')
plt.title('Age Churn Rate')
```

Out[48]:

```
Text(0.5, 1.0, 'Age Churn Rate')
```

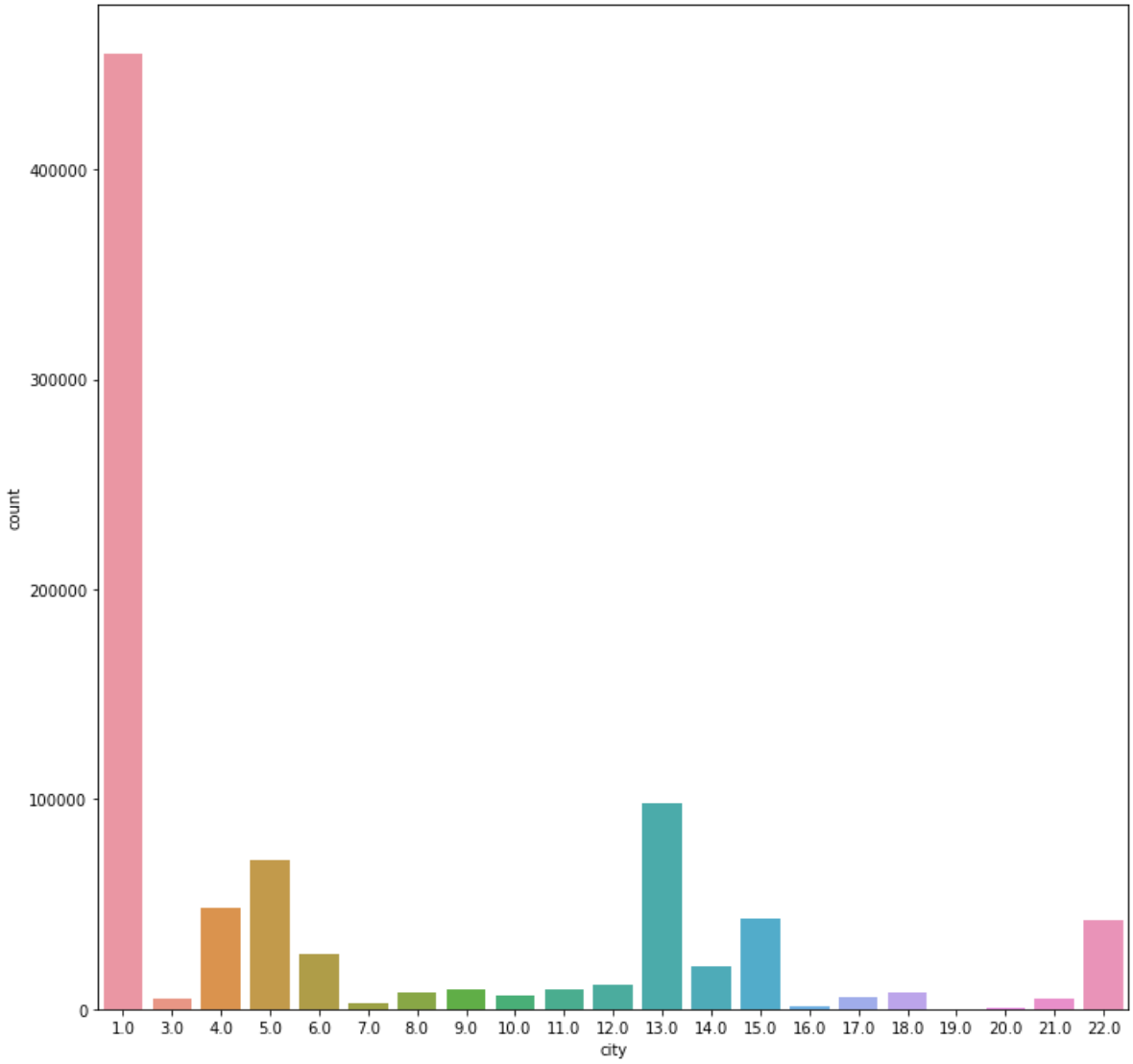


- Younger people and older poeple are more likely to churn

Q.) Which city has the largest number of customer ?

In [72]:

```
plt.figure(figsize=(12,12))
sns.countplot(x='city',data=train_member)
plt.show()
```



- City 1 has largest nuber of customer
- City 20 has smallest number of customer

Q.) Which city maximum number of customer churn ?

In [73]:

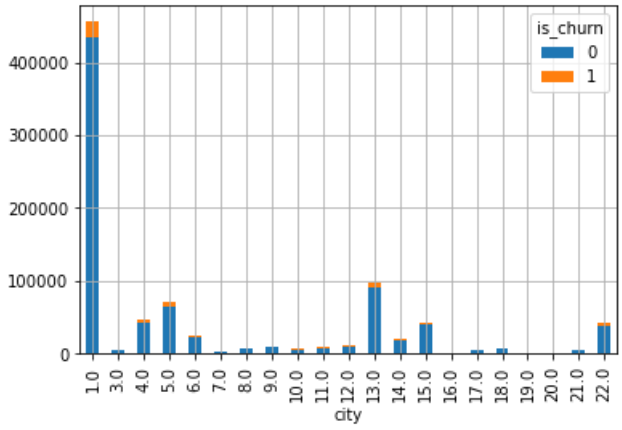
```
plt.figure(figsize=(18,6))
city_crosstab=pd.crosstab(train_member['city'],train_member['is_churn'])
city_crosstab.plot(kind='bar', stacked=True, grid=True)
city_crosstab["Ratio"] =  city_crosstab[1] / city_crosstab[0]
city_crosstab
```

Out[73]:

is_churn	0	1	Ratio
city			
1.0	433343	22046	0.050874
3.0	4667	422	0.090422
4.0	43681	4264	0.097617
5.0	65051	6248	0.096048
6.0	23783	2239	0.094143

is_churn	0	1	Ratio
city			
1.0	2480	186	0.075000
3.0	6946	744	0.107112
4.0	8790	768	0.087372
5.0	5938	595	0.100202
6.0	8276	760	0.091832
7.0	10431	1123	0.107660
8.0	90543	7738	0.085462
9.0	18585	1582	0.085122
10.0	39704	3652	0.091981
11.0	877	79	0.090080
12.0	5130	416	0.081092
13.0	7197	645	0.089621
14.0	130	10	0.076923
15.0	621	56	0.090177
16.0	4753	533	0.112140
17.0	38580	3549	0.091991

<Figure size 1296x432 with 0 Axes>



In [74]:

```
city_crosstab[city_crosstab['Ratio']<0.085] ## Choosing a random threshold to find results
```

Out[74]:

is_churn	0	1	Ratio
city			
1.0	433343	22046	0.050874
7.0	2480	186	0.075000
17.0	5130	416	0.081092
19.0	130	10	0.076923

The maximum churn is from city 1,7,17,19

Q)Whats the trend of churn every year ?

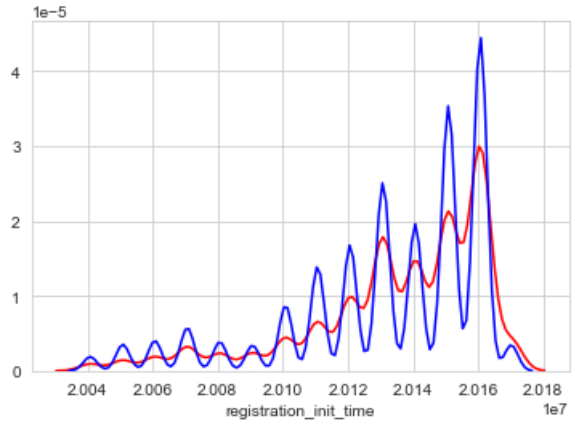
In [71]:

```
## Finding the inights of
sns.set_style('whitegrid')
sns.distplot(train_data['registration_init_time'][train_data['is_churn']==1],hist = False, color ='
```

```
red')
sns.distplot(train_data['registration_init_time'][train_data['is_churn']==0], hist= False, color ='
blue')
```

Out[71]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f523bb8b88>
```



- Every year the max value of churn is increasing

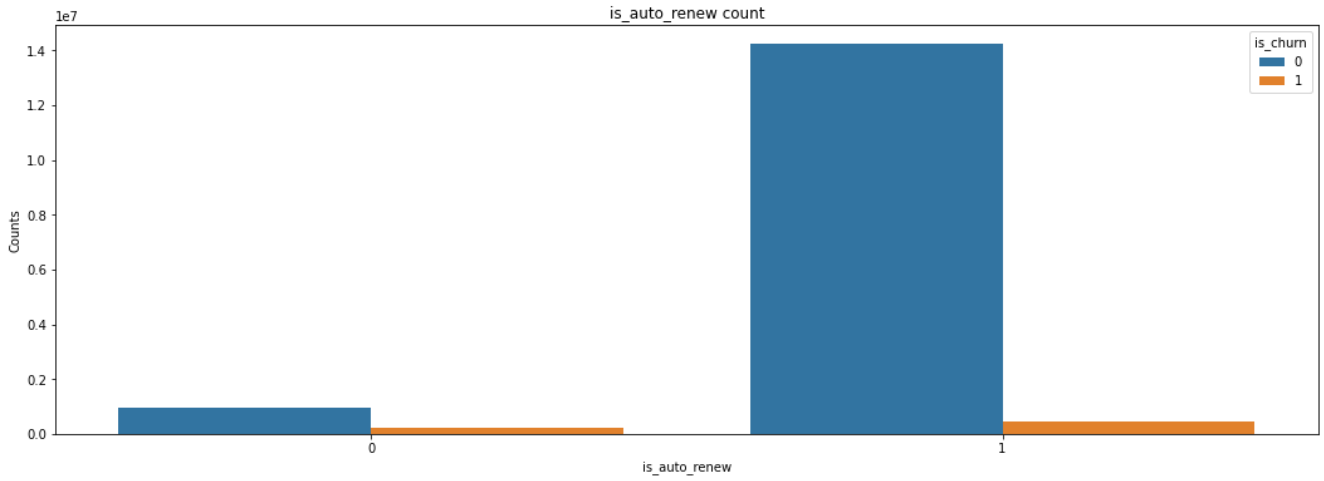
Q) Is there any relationship between customer churn and auto_renew ?

In [28]:

```
plt.figure(figsize=(18,6))
sns.countplot(x='is_auto_renew',hue='is_churn',data=train_transaction_logs)
plt.xlabel('is_auto_renew')
plt.ylabel('Counts')
plt.title('is_auto_renew count')
```

Out[28]:

```
Text(0.5, 1.0, 'is_auto_renew count')
```



- People who has not enabeled the auto_renew mode are more likely to churn , as compared to people who use auto_renew

Q) Whats the day-wise , monthly and yearly trends registration ?

In [18]:

```
train_member.head(1)
```

Out[18]:

	msno	is_churn	city	bd	gender	registered_via	registration_init_time
0	waLDQMmcOu2jLDaV1ddDkgCrB/jl6sD66Xzs0Vqax1Y=	1	18.0	36.0	female	9.0	20050406.0

In [25]:

```
## Convert the registration time to yyyy/mm/dd Format
train_member['registration_init_time'] = train_member.registration_init_time.apply(lambda x: dateti
me.strptime(str(int(x)), "%Y%m%d").date() if pd.notnull(x) else "NAN" )
```

In [27]:

```
train_member.head(1)
```

Out[27]:

	msno	is_churn	city	bd	gender	registered_via	registration_init_time
0	waLDQMmcOu2jLDaV1ddDkgCrB/jl6sD66Xzs0Vqax1Y=	1	18.0	36.0	female	9.0	2005-04-06

In [57]:

```
train_member['registration_time_year'] = pd.DatetimeIndex(train_member['registration_init_time']).
year
train_member['registration_time_year'] = train_member['registration_time_year'].apply(lambda x: int
(x) if pd.notnull(x) else "NaN")
year_count=train_member['registration_time_year'].value_counts()
year_order = train_member['registration_time_year'].unique()
year_order=sorted(year_order, key=lambda x: str(x))
plt.figure(figsize=(18,6))
sns.barplot(year_count.index,year_count.values,order=year_order)
plt.xlabel('Year')
plt.ylabel('counts')
plt.title("year vs Registration")
```

Out[57]:

```
Text(0.5, 1.0, 'year vs Registration')
```

- Maximum registration were done in 2016

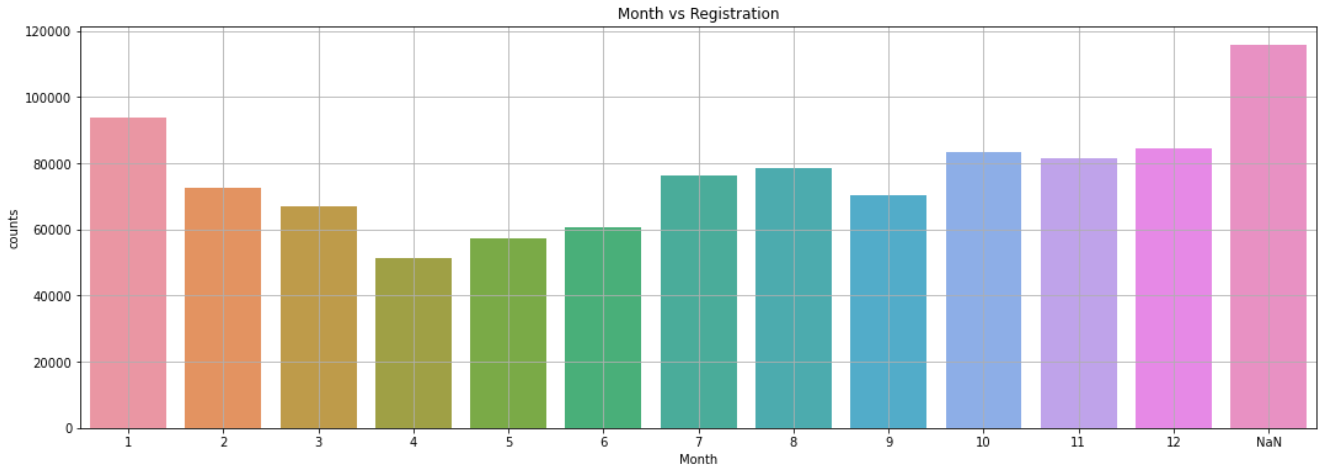
In [64]:

```
### Monthly registration

train_member['registration_time_month'] = pd.DatetimeIndex(train_member['registration_init_time'])
.month
train_member['registration_time_month'] = train_member['registration_time_month'].apply(lambda x: i
nt(x) if pd.notnull(x) else "NaN")
```

```
month_count=train_member['registration_time_month'].value_counts()
month_order = train_member['registration_time_month'].unique()
month_order=sorted(month_order, key=lambda x: str(x))
month_order=sorted(month_order, key=lambda x: float(x))

plt.figure(figsize=(18,6))
sns.barplot(month_count.index,month_count.values,order=month_order)
plt.grid()
plt.xlabel('Month')
plt.ylabel('counts')
plt.title("Month vs Registration")
```

Out[64]:

```
Text(0.5, 1.0, 'Month vs Registration')
```



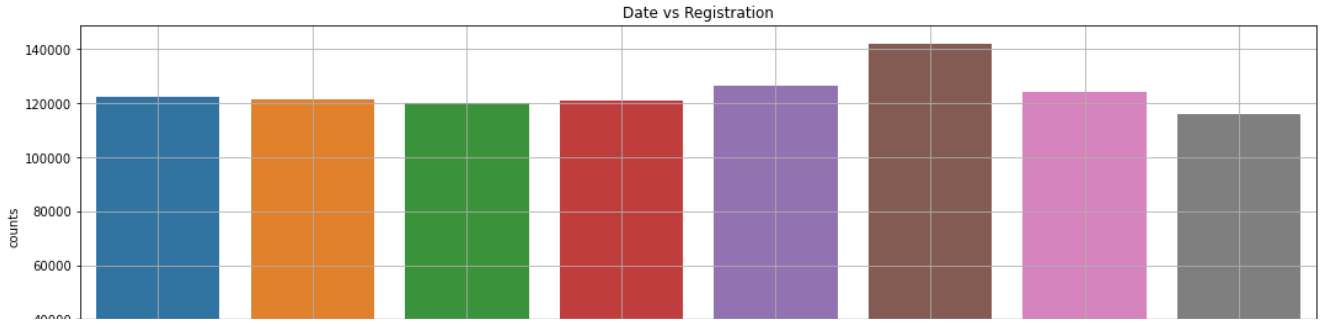
- There is not very much difference in the registration during in any particular month , but if we see there are more than 80000 registration in 1th,10th,11th,12th month of the year

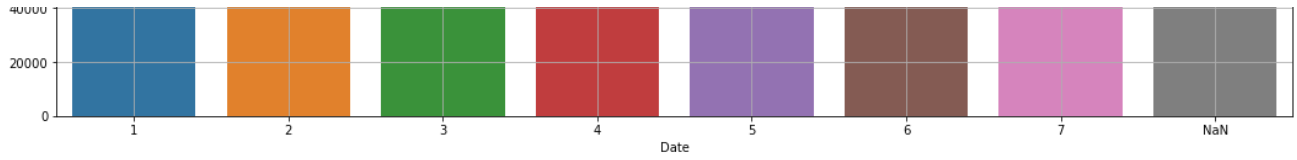
In [72]:

```
## registration on a particular day

train_member['registration_time_date'] = pd.DatetimeIndex(train_member['registration_init_time']).
dayofweek + 1
train_member['registration_time_date'] = train_member['registration_time_date'].apply(lambda x: int
(x) if pd.notnull(x) else "NaN")
date_count=train_member['registration_time_date'].value_counts()
date_order = train_member['registration_time_date'].unique()
date_order=sorted(date_order, key=lambda x: str(x))
date_order=sorted(date_order, key=lambda x: float(x))

plt.figure(figsize=(18,6))
sns.barplot(date_count.index,date_count.values,order=date_order)
plt.grid()
plt.xlabel('Date')
plt.ylabel('counts')
plt.title("Date vs Registration")
```

Out[72]:

```
Text(0.5, 1.0, 'Date vs Registration')
```





- There is not much difference of registration on particuar week day , but only day 6 has registration above 140000

Q) Number of unique songs vs Churning

In [11]:

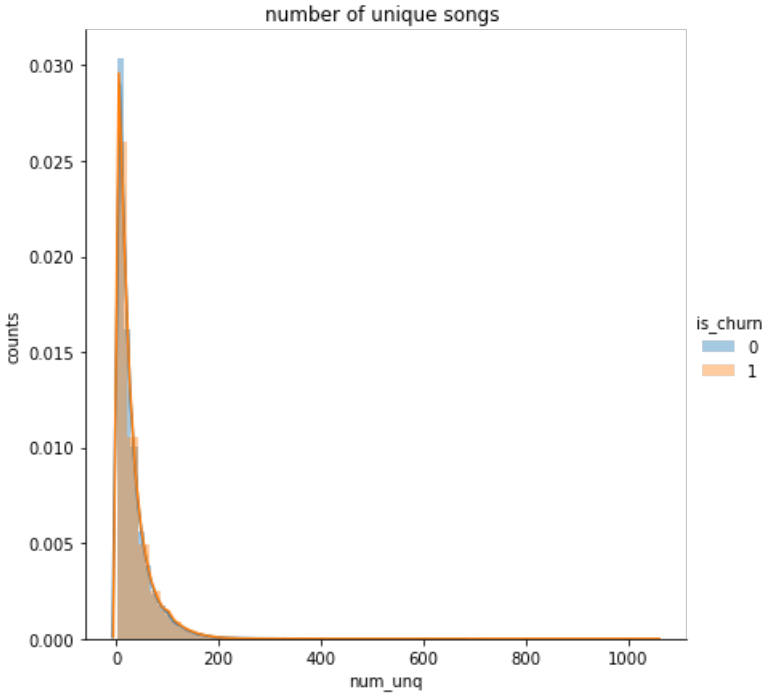
```
train_user_logs = pd.merge(train,user_logs_rows,on='msno',how='left')
```

In [19]:

```
sns.FacetGrid(train_user_logs[:1000000],hue="is_churn",size=6) \
    .map(sns.distplot,"num_unq") \
    .add_legend();
plt.title("number of unique songs ")
plt.ylabel("counts")
plt.plot()
```

Out[19]:

```
[]
```



- Majority of the people are listening 0 to 200 unique songs

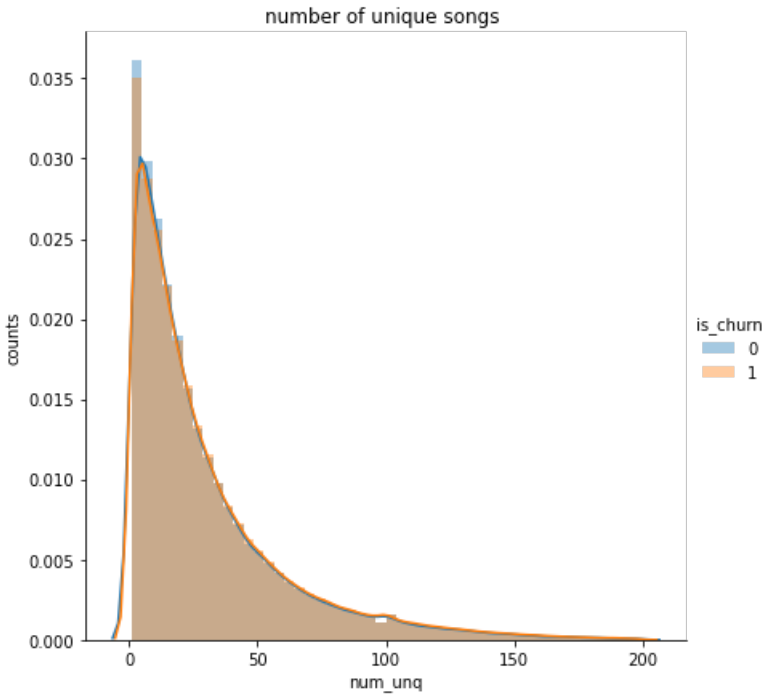
In [22]:

```
sns.FacetGrid(train_user_logs[(train_user_logs['num_unq']<200)&(train_user_logs['num_unq']>0)][:10
00000],hue="is_churn",size=6) \
    .map(sns.distplot,"num_unq") \
    .add_legend();
plt.title("number of unique songs ")
plt.ylabel("counts")
plt.plot()
```

Out[22]:

```
[]
```

[ ]

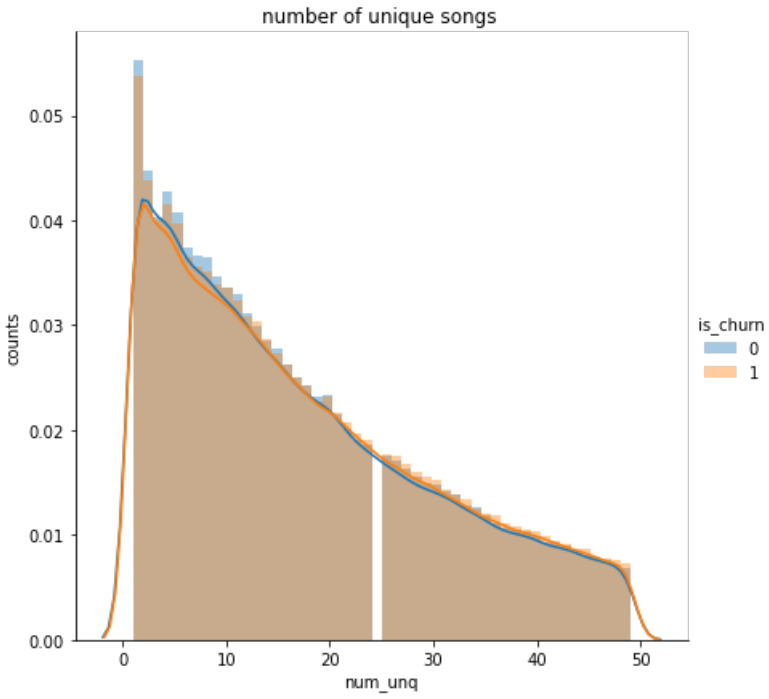


In [24]:

```
sns.FacetGrid(train_user_logs[(train_user_logs['num_unq']<50)&(train_user_logs['num_unq']>0)][:100
0000],hue="is_churn",size=6) \
    .map(sns.distplot,"num_unq") \
    .add_legend();
plt.title("number of unique songs ")
plt.ylabel("counts")
plt.plot()
```

Out[24]:

[]



- Majority of the people are listening 1 to 20 unique songs

- There is no relationship between listening to unique songs and churning rate of customers because they almost overlaping each

other

Number of unique songs vs is_churn

In [31]:

```
Numer_of_unique_songs_churned = train_user_logs['num_unq'][train_user_logs['is_churn']==1]
Numer_of_unique_songs_stayed =  train_user_logs['num_unq'][train_user_logs['is_churn']==0]
```

In [33]:

```
Numer_of_unique_songs_churned =
Numer_of_unique_songs_churned[np.logical_not(np.isnan(Numer_of_unique_songs_churned))]
Numer_of_unique_songs_stayed=
Numer_of_unique_songs_stayed[np.logical_not(np.isnan(Numer_of_unique_songs_stayed))]
```

In [35]:

```
print(f'Median of number of songs played by customer who churned :
{np.median(Numer_of_unique_songs_churned)}')
print(f'Median of number of songs played by customer who stayed :
{np.median(Numer_of_unique_songs_stayed)}')
```

```
Median of number of songs played by customer who churned : 20.0
Median of number of songs played by customer who stayed : 19.0
```

- There's not much difference between number of unique songs played by customer who churned and customer who stayed

observation

- There is not much difference of registration on particuar week day , but only day 6 has registration above 140000
- There is not very much difference in the registration during in any particular month , but if we see there are more than 80000 registration in 1th,10th,11th,12th month of the year
- Maximum registration were done in 2016
- Every year the max value of churn is increasing
- City 1 has largest nuber of customer
- City 20 has smallest number of customer
- Younger people and older poeple are more likely to churn
- The majority customer age group of customers are 25 to 35
- There is not much difference in the churn rate of male and female
- As we have seen that data of same user listening to different numbers of song on different day
- About 93.6% of customer stayed and 6.3% of churned
- Maximum number of people takes 30 days plan
- People who has not enabeled the auto_renew mode are more likely to churn , as compared to people who use auto_renew