In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import os
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import KFold
from sklearn.metrics import log_loss
```

LOADING THE DATA

In [2]:

```
gen_train = pd.read_csv(r"C:\Users\Venki\talkingdata-mobile-user-demographics\gender_ag
e_train.csv\gender_age_train.csv")
gen_test = pd.read_csv(r"C:\Users\Venki\talkingdata-mobile-user-demographics\gender_age
_test.csv\gender_age_test.csv")
gen_train.head(3)
```

Out[2]:

	device_id	gender	age	group
0	-8076087639492063270	M	35	M32-38
1	-2897161552818060146	M	35	M32-38
2	-8260683887967679142	M	35	M32-38

In [3]:

```
print(gen_train.shape)
print(gen_test.shape)
```

```
(74645, 4)
(112071, 1)
```

In [4]:

```
#https://www.kaggle.com/c/talkingdata-mobile-user-demographics/discussion/22186
phone = pd.read_csv("English_phone_brand_device_model.csv")
print(phone.shape)
phone.head()
```

(187245, 3)

Out[4]:

	device_id	phone_brand	device_model
0	-8890648629457979026	xiaomi	??
1	1277779817574759137	xiaomi	MI 2
2	5137427614288105724	samsung	Galaxy S4
3	3669464369358936369	SUGAR	????
4	-5019277647504317457	samsung	Galaxy Note 2

In [5]:

```
app_label = pd.read_csv(r"C:\Users\Venki\talkingdata-mobile-user-demographics\app_label
s.csv\app_labels.csv")
print(app_label.shape)
app_label.head()
```

(459943, 2)

Out[5]:

	app_id	label_id
0	7324884708820027918	251
1	-4494216993218550286	251
2	6058196446775239644	406
3	6058196446775239644	407
4	8694625920731541625	406

In [6]:

```
events = pd.read_csv(r"C:\Users\Venki\talkingdata-mobile-user-demographics\events.csv\e
vents.csv",parse_dates=['timestamp'])
print(events.shape)
events.head()
```

```
(3252950, 5)
```

Out[6]:

	event_id	device_id	timestamp	longitude	latitude
0	1	29182687948017175	2016-05-01 00:55:25	121.38	31.24
1	2	-6401643145415154744	2016-05-01 00:54:12	103.65	30.97
2	3	-4833982096941402721	2016-05-01 00:08:05	106.60	29.70
3	4	-6815121365017318426	2016-05-01 00:06:40	104.27	23.28
4	5	-5373797595892518570	2016-05-01 00:07:18	115.88	28.66

In [7]:

```
#tying up active hours with devices
tm = events['timestamp']
hours = [g.hour for g in tm]
events['hour'] = hours
```

In [8]:

```
events.head()
```

Out[8]:

	event_id	device_id	timestamp	longitude	latitude	hour
0	1	29182687948017175	2016-05-01 00:55:25	121.38	31.24	0
1	2	-6401643145415154744	2016-05-01 00:54:12	103.65	30.97	0
2	3	-4833982096941402721	2016-05-01 00:08:05	106.60	29.70	0
3	4	-6815121365017318426	2016-05-01 00:06:40	104.27	23.28	0
4	5	-5373797595892518570	2016-05-01 00:07:18	115.88	28.66	0

In [9]:

```
#https://stackoverflow.com/questions/28009370/get-weekday-day-of-week-for-datetime-colu
mn-of-dataframe
#events = events.reset_index()
events['weekday'] = events['timestamp'].dt.dayofweek
events.head()
```

Out[9]:

	event_id	device_id	timestamp	longitude	latitude	hour	weekday
0	1	29182687948017175	2016-05-01 00:55:25	121.38	31.24	0	6
1	2	-6401643145415154744	2016-05-01 00:54:12	103.65	30.97	0	6
2	3	-4833982096941402721	2016-05-01 00:08:05	106.60	29.70	0	6
3	4	-6815121365017318426	2016-05-01 00:06:40	104.27	23.28	0	6
4	5	-5373797595892518570	2016-05-01 00:07:18	115.88	28.66	0	6

In [10]:

```
app_events = pd.read_csv(r"C:\Users\Venki\talkingdata-mobile-user-demographics\app_even
ts.csv\app_events.csv")
print(app_events.shape)
app_events.head()
```

```
(32473067, 4)
```

Out[10]:

	event_id	app_id	is_installed	is_active
0	2	5927333115845830913	1	1
1	2	-5720078949152207372	1	0
2	2	-1633887856876571208	1	0
3	2	-653184325010919369	1	1
4	2	8693964245073640147	1	1

In [11]:

```
label_categories = pd.read_csv(r"C:\Users\Venki\talkingdata-mobile-user-demographics\label_categories.csv\label_categories.csv")
print(label_categories.shape)
label_categories.head()
```

```
(930, 2)
```

Out[11]:

	label_id	category
0	1	NaN
1	2	game-game type
2	3	game-Game themes
3	4	game-Art Style
4	5	game-Leisure time

DATA PREPROCESSING

CHECKING FOR DUPLICATE VALUES

In [12]:

```
print('Numbers of duplicated data:', gen_train.duplicated('device_id').sum())
```

```
Numbers of duplicated data: 0
```

In [13]:

```
print('Numbers of duplicated data:', gen_test.duplicated('device_id').sum())
```

```
Numbers of duplicated data: 0
```

In [14]:

```
print('Numbers of duplicated data:', phone.duplicated('device_id').sum())
phone.drop_duplicates('device_id', keep='first', inplace=True)
phone.shape
```

```
Numbers of duplicated data: 529
```

Out[14]:

```
(186716, 3)
```

In [15]:

```
print(label_categories.duplicated().sum())
label_categories.drop_duplicates(keep='first', inplace=True)
label_categories.shape
```

```
0
```

Out[15]:

```
(930, 2)
```

In [16]:

```
print(app_label.duplicated().sum())
app_label.drop_duplicates(keep='first', inplace=True)
app_label.shape
```

```
491
```

Out[16]:

```
(459452, 2)
```

CHECKING FOR MISSING DATA

In [17]:

```
gen_train.isnull().any()
```

Out[17]:

```
device_id    False
gender       False
age          False
group        False
dtype: bool
```

In [18]:

```
gen_test.isnull().any()
```

Out[18]:

```
device_id    False
dtype: bool
```

In [19]:

```
phone.isnull().any()
```

Out[19]:

```
device_id       False
phone_brand     False
device_model    False
dtype: bool
```

In [20]:

```
print(label_categories[label_categories['category'].isnull()])
label_categories.dropna(inplace=True)
label_categories.shape
```

```
     label_id category
0           1      NaN
229       248      NaN
245       264      NaN
```

Out[20]:

```
(927, 2)
```

In [21]:

```
app_label.isnull().any()
```

Out[21]:

```
app_id      False
label_id    False
dtype: bool
```

In [22]:

```
app_events.isnull().any()
```

Out[22]:

```
event_id        False
app_id          False
is_installed    False
is_active       False
dtype: bool
```

In [23]:

```
events.isnull().any()
```

Out[23]:

```
event_id     False
device_id    False
timestamp    False
longitude    False
latitude     False
hour         False
weekday      False
dtype: bool
```

In [24]:

```
print('THE FINAL SHAPES ARE')
print(gen_train.shape)
print(gen_test.shape)
print(app_label.shape)
print(events.shape)
print(phone.shape)
print(app_events.shape)
```

```
THE FINAL SHAPES ARE
(74645, 4)
(112071, 1)
(459452, 2)
(3252950, 7)
(186716, 3)
(32473067, 4)
```

EDA

MERGING ALL FILES INTO 1 DATAFRAME

MERGING GENDER TRAIN AND TEST WITH PHONE BRAND

In [25]:

```
assert (gen_test.shape[0] + gen_train.shape[0]) == phone.shape[0]
```

In [26]:

```
train_brand = gen_train.merge(phone, on='device_id', how='left')
#train_brand.set_index('device_id', inplace=True)
print(train_brand.shape)
train_brand.head()
```

```
(74645, 6)
```

Out[26]:

	device_id	gender	age	group	phone_brand	device_model
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2
3	-4938849341048082022	M	30	M29-31	xiaomi	??note
4	245133531816851882	M	30	M29-31	xiaomi	MI 3

In [27]:

```
test_brand = gen_test.merge(phone, on='device_id', how='left')
#test_brand.set_index('device_id', inplace=True)
print(test_brand.shape)
test_brand.head()
```

(112071, 3)

Out[27]:

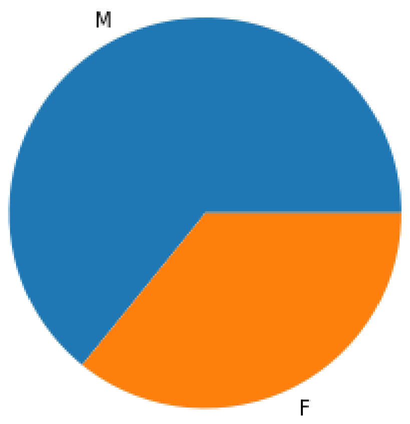
	device_id	phone_brand	device_model
0	1002079943728939269	xiaomi	xiaominote
1	-1547860181818787117	xiaomi	??2
2	7374582448058474277	huawei	Y523-L176
3	-6220210354783429585	huawei	??6
4	-5893464122623104785	xiaomi	MI 2

In [28]:

```
#Create a pie chart for visualization
genders = train_brand.gender.value_counts()
print(genders);

plt.pie(genders.values, labels=genders.keys())
plt.axis('equal')
plt.show()
```

```
M    47904
F    26741
Name: gender, dtype: int64
```



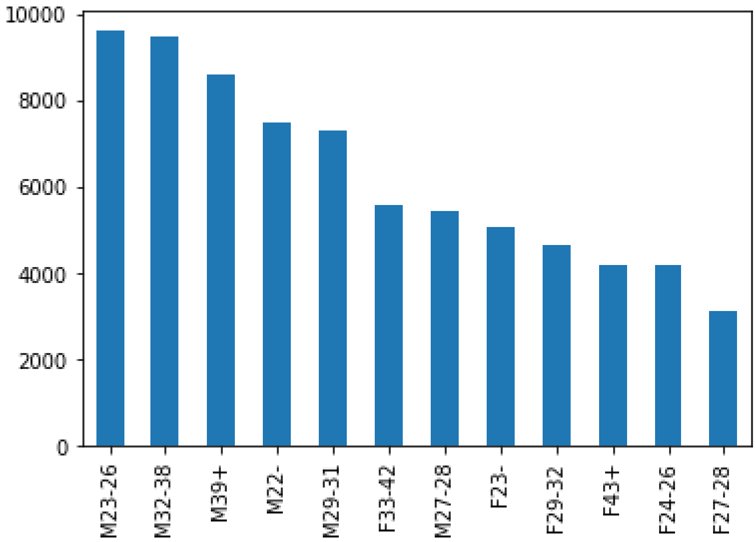
In [29]:

```
#checking how many users belong to each group
train_brand.group.value_counts().sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
```

Out[29]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dbb67d4c88>
```



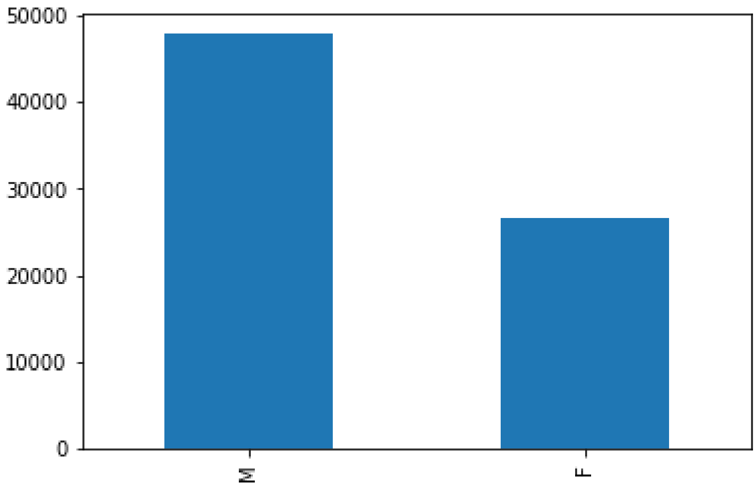
In [30]:

```
train_brand.gender.value_counts().sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[30]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dbbd3dae48>
```



THE FEMALE USERS ARE LESS WHEN COMPARED TO MALE USERS

In [31]:

```
len(train_brand['phone_brand'].unique())
```

Out[31]:

```
80
```

In [32]:

```
len(test_brand['phone_brand'].unique())
```

Out[32]:

```
80
```

In [33]:

```
train_brand['phone_brand'].value_counts()
```

Out[33]:

```
xiaomi     17299
samsung    13669
huawei     12960
OPPO        5783
vivo        5637
           ...  
MIL            1
pner           1
fs             1
mole           1
ZOYE           1
Name: phone_brand, Length: 80, dtype: int64
```

In [34]:

```
test_brand['phone_brand'].value_counts()
```

Out[34]:

```
xiaomi     25808
samsung    20522
huawei     19505
vivo        8705
OPPO        8456
           ...  
?Q             4
PPTV           2
fs             1
MIL            1
E?E?           1
Name: phone_brand, Length: 80, dtype: int64
```

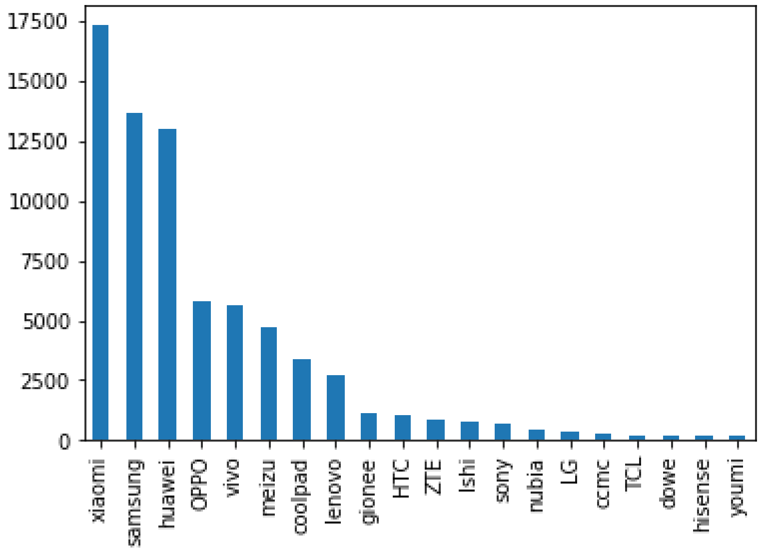
In [35]:

```
#checking which are more often used in train data
train_brand.phone_brand.value_counts()[:20].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
```

Out[35]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dbb9dfd4a8>
```



THE MAJORITY OF THE USERS 20 OF THE ALL THE 120 BRANDS GIVEN IN THE DATASET

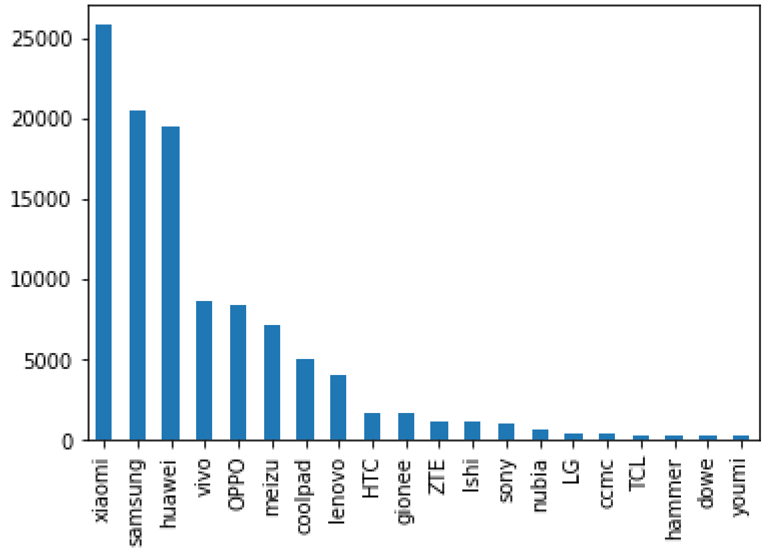
In [36]:

```
#checking which are more often used in test data
test_brand.phone_brand.value_counts()[:20].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
```

Out[36]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba6671240>
```



THE MAJORITY OF THE USERS 20 OF THE ALL THE 126 BRANDS GIVEN IN THE TEST DATASET

APP EVENTS

In [37]:

```
print(app_events.shape)
app_events.head()
```

```
(32473067, 4)
```

Out[37]:

	event_id	app_id	is_installed	is_active
0	2	5927333115845830913	1	1
1	2	-5720078949152207372	1	0
2	2	-1633887856876571208	1	0
3	2	-653184325010919369	1	1
4	2	8693964245073640147	1	1

In [38]:

```
app_events['is_active'].value_counts()
```

Out[38]:

```
0    19740071
1    12732996
Name: is_active, dtype: int64
```

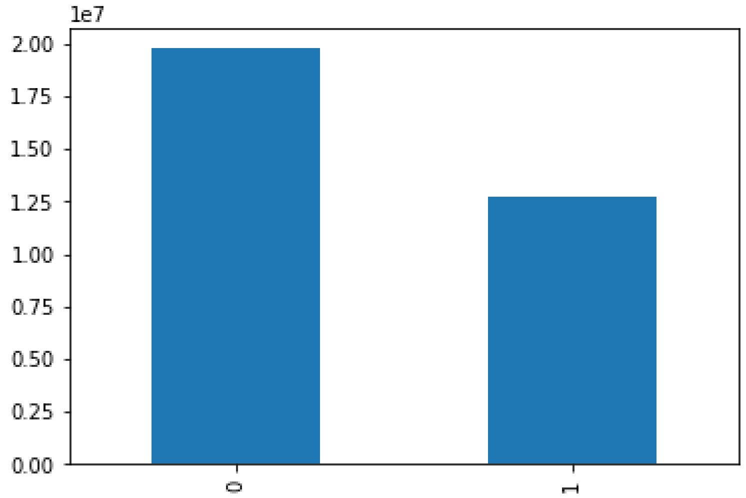
In [39]:

```
app_events.is_active.value_counts().sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba6722208>
```



In [40]:

```
len(app_events['app_id'].unique())
```

Out[40]:

```
19237
```

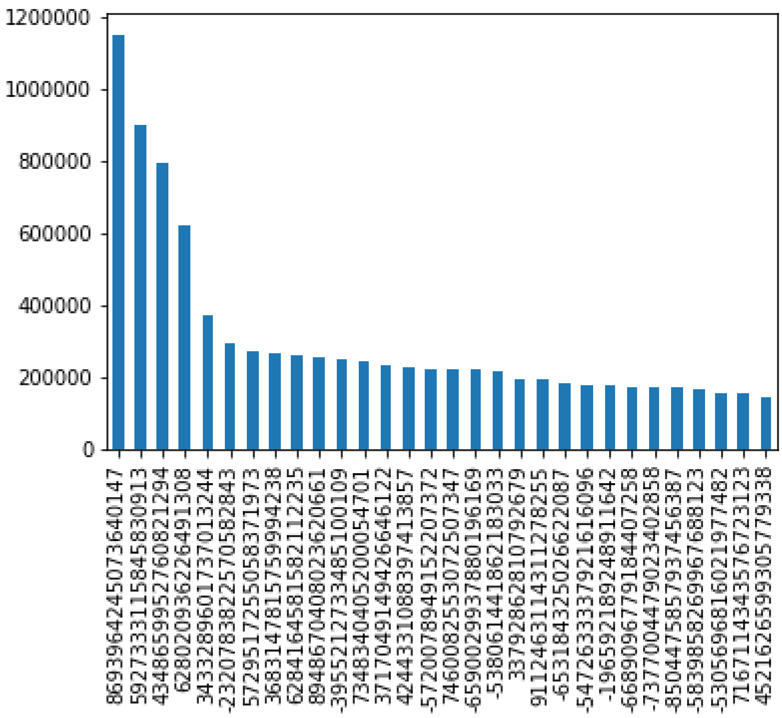
In [41]:

```
app_events.app_id.value_counts()[:30].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba67084e0>
```



In [42]:

```
len(app_events['event_id'].unique())
```

Out[42]:

```
1488096
```

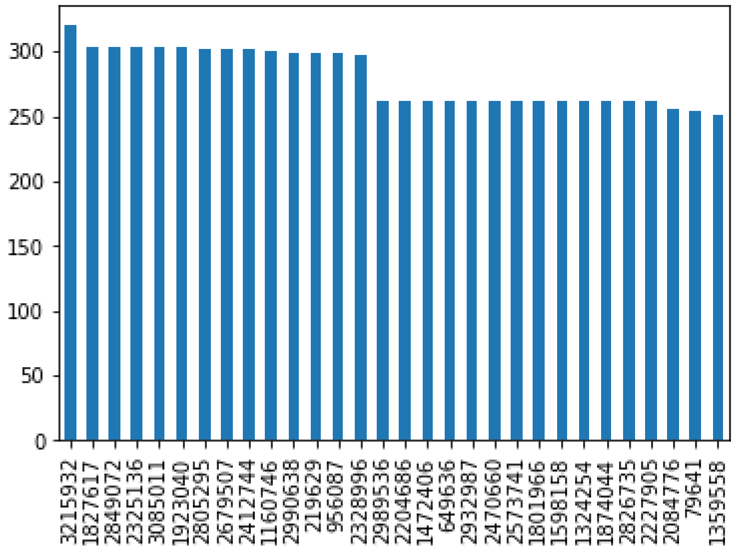
In [43]:

```
#checking which events are more popular
app_events.event_id.value_counts()[:30].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba6750e80>
```



AS THE MAJORITY OF THE APPS ARE NOT ACTIVE SO WE ARE TAKING ONLY THE APPS WHICH ARE ACTIVE

In [44]:

```
app_events = app_events[app_events.is_active == 1]
app_events.head()
```

Out[44]:

	event_id	app_id	is_installed	is_active
0	2	5927333115845830913	1	1
3	2	-653184325010919369	1	1
4	2	8693964245073640147	1	1
5	2	4775896950989639373	1	1
9	2	7167114343576723123	1	1

In [45]:

```
#total active apps
len(app_events['app_id'].unique())
```

Out[45]:

```
10582
```

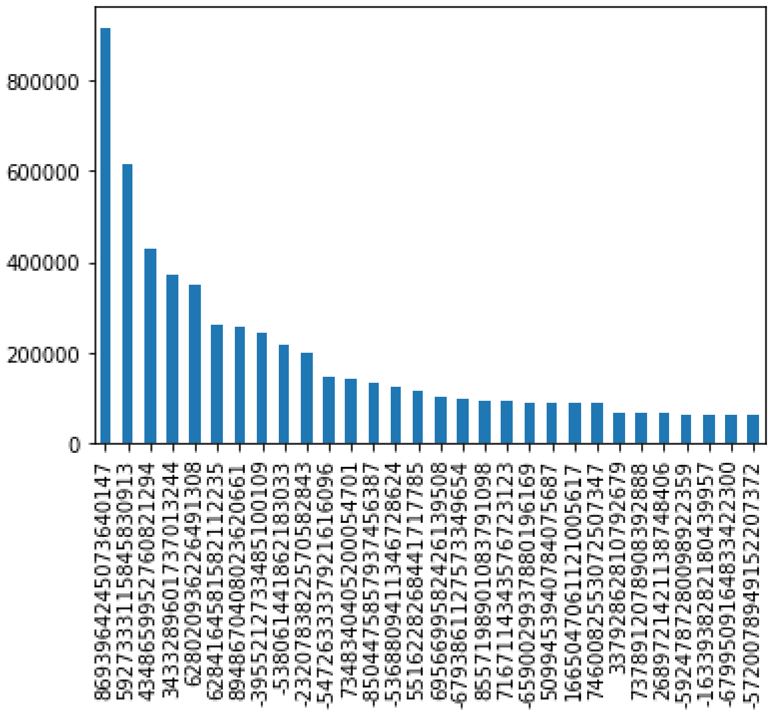
In [46]:

```
#top 30 apps
app_events.app_id.value_counts()[:30].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
```

Out[46]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba6cf0b38>
```



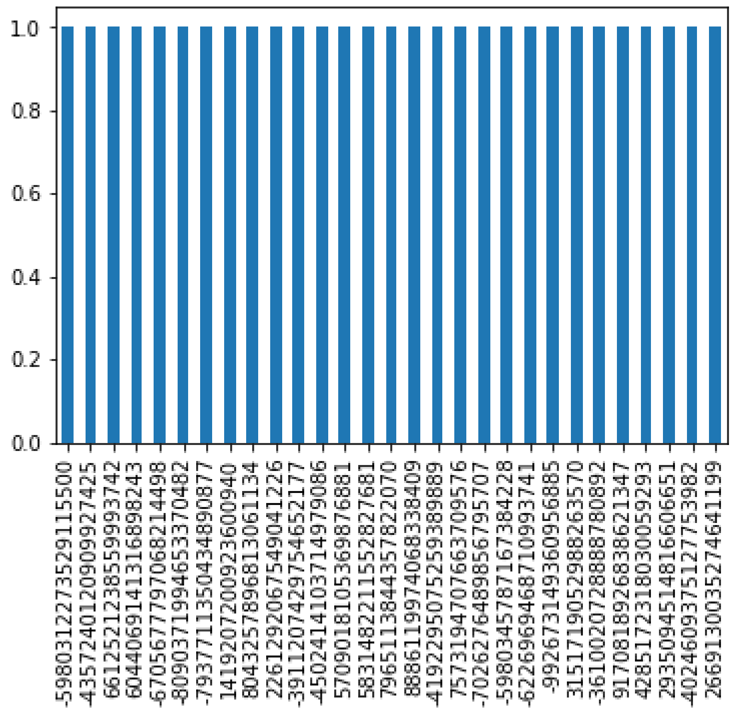
In [47]:

```
app_events.app_id.value_counts()[-30:-1].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[47]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba6cb8048>
```



EVENTS

In [48]:

```
print(events.shape)
events.head()
```

(3252950, 7)

Out[48]:

	event_id	device_id	timestamp	longitude	latitude	hour	weekday
0	1	29182687948017175	2016-05-01 00:55:25	121.38	31.24	0	6
1	2	-6401643145415154744	2016-05-01 00:54:12	103.65	30.97	0	6
2	3	-4833982096941402721	2016-05-01 00:08:05	106.60	29.70	0	6
3	4	-6815121365017318426	2016-05-01 00:06:40	104.27	23.28	0	6
4	5	-5373797595892518570	2016-05-01 00:07:18	115.88	28.66	0	6

In [49]:

```
len(events['device_id'].unique())
```

Out[49]:

60865

In [50]:

```
len(events['event_id'].unique())
```

Out[50]:

3252950

In [51]:

```
events['device_id'].value_counts()
```

Out[51]:

```
 1186608308763918427    33426
 3915082290673137129    14568
-1656894751624916732     6731
-6242501228649113250     4150
-8340098378141155823     3973
                        ...
 781851599932550953         1
-8126302119835621758        1
-803242747247619527         1
 709247865516551294         1
 4224710574768605050        1
Name: device_id, Length: 60865, dtype: int64
```

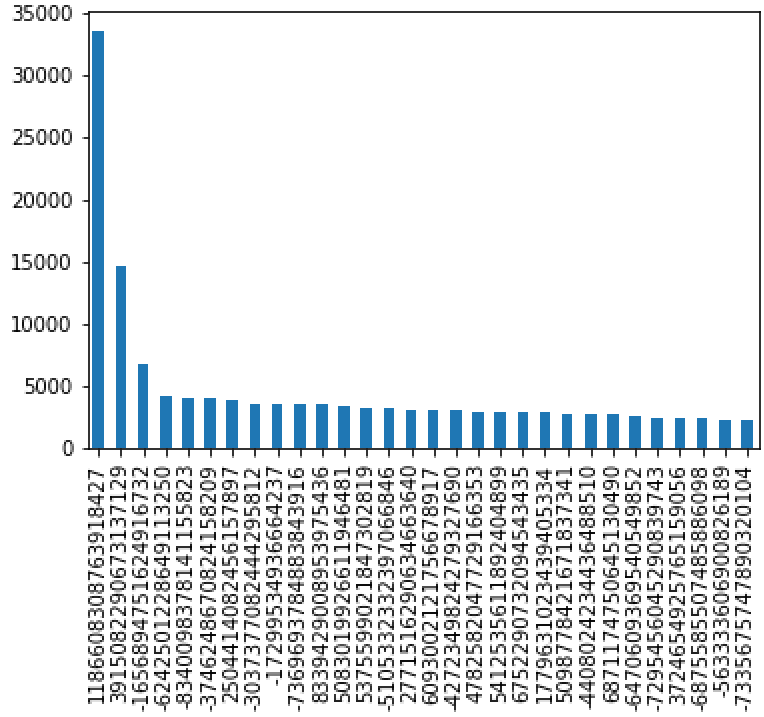
In [52]:

```
#top 30 devices
events.device_id.value_counts()[:30].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
```

Out[52]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba6e89470>
```



In [53]:

```
for i in range(0,100,10):
    var =events["device_id"].value_counts()
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 1
10 percentile value is 1
20 percentile value is 3
30 percentile value is 6
40 percentile value is 9
50 percentile value is 15
60 percentile value is 24
70 percentile value is 40
80 percentile value is 67
90 percentile value is 130
100 percentile value is  33426
```

In [54]:

```
for i in range(90,100):
    var =events["device_id"].value_counts()
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 130
91 percentile value is 141
92 percentile value is 155
93 percentile value is 170
94 percentile value is 190
95 percentile value is 216
96 percentile value is 248
97 percentile value is 297
98 percentile value is 373
99 percentile value is 525
100 percentile value is  33426
```

In [55]:

```
#calculating speed values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.
8,99.9,100
for i in np.arange(0.0, 1.0, 0.1):
    var =events["device_id"].value_counts()
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100
))]))
print("100 percentile value is ",var[-1])
```

```
99.0 percentile value is 525
99.1 percentile value is 553
99.2 percentile value is 587
99.3 percentile value is 635
99.4 percentile value is 701
99.5 percentile value is 773
99.6 percentile value is 853
99.7 percentile value is 959
99.8 percentile value is 1145
99.9 percentile value is 1511
100 percentile value is  33426
```

99.9% OF THE DEVICES HAVE EVENTS LESS THAN 1511

MERGING TRAIN BRAND AND EVENTS ON DEVICE ID

In [56]:

```
train_brand_2 = train_brand.merge(events, on ='device_id',how = 'left')
train_brand_2.shape
```

Out[56]:

```
(1266931, 12)
```

In [57]:

```
train_brand_2.head()
```

Out[57]:

	device_id	gender	age	group	phone_brand	device_model	event_id	times
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	NaN	
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	NaN	
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	201 14:
3	-4938849341048082022	M	30	M29-31	xiaomi	??note	NaN	
4	245133531816851882	M	30	M29-31	xiaomi	MI 3	NaN	

In [58]:

```
len(train_brand_2['device_id'].unique())
```

Out[58]:

```
74645
```

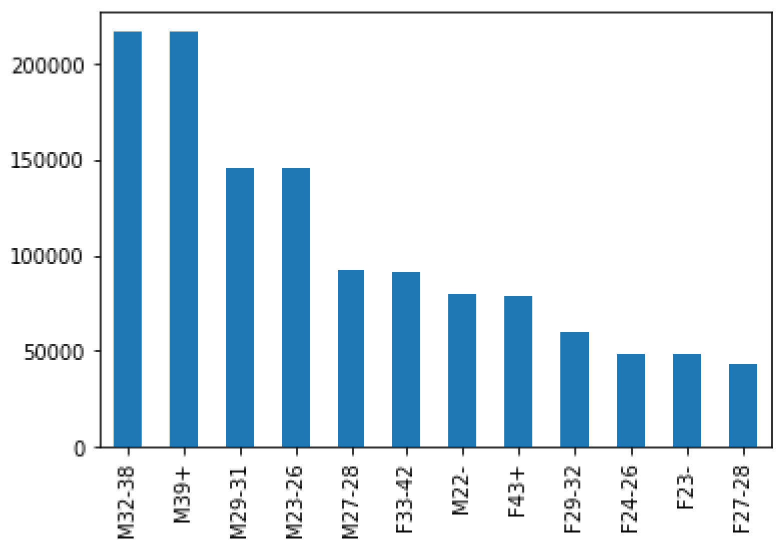
In [59]:

```
train_brand_2.group.value_counts().sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[59]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba6f7b6a0>
```



In [60]:

```
train_brand_3 = train_brand_2.drop(['timestamp','longitude','latitude'],axis=1)
print(train_brand_3.shape)
train_brand_3.head()
```

(1266931, 9)

Out[60]:

	device_id	gender	age	group	phone_brand	device_model	event_id	hour
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	NaN	NaN
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	NaN	NaN
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
3	-4938849341048082022	M	30	M29-31	xiaomi	??note	NaN	NaN
4	245133531816851882	M	30	M29-31	xiaomi	MI 3	NaN	NaN

MERGING TRAIN BRAND WITH APP EVENTS ON EVENT ID

In [61]:

```
train_brand_4 = train_brand_3.merge(app_events, on = 'event_id',how = 'left')
print(train_brand_4.shape)
train_brand_4.head()
```

(5502490, 12)

Out[61]:

	device_id	gender	age	group	phone_brand	device_model	event_id	hour
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	NaN	NaN
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	NaN	NaN
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
3	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
4	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0

In [62]:

```
len(train_brand_4['device_id'].unique())
```

Out[62]:

```
74645
```

In [63]:

```
len(train_brand_4['app_id'].unique())
```

Out[63]:

```
6914
```

In [64]:

```
len(train_brand_4['event_id'].unique())
```

Out[64]:

```
1215596
```

In [65]:

```
len(train_brand_4['phone_brand'].unique())
```

Out[65]:

```
80
```

MERGING APP LABEL WITH LABEL CATEGORY

In [66]:

```
app_label_category = app_label.merge(label_categories,on = 'label_id',how = 'left')
print(app_label_category.shape)
app_label_category.head()
```

```
(459452, 3)
```

Out[66]:

	app_id	label_id	category
0	7324884708820027918	251	Finance
1	-4494216993218550286	251	Finance
2	6058196446775239644	406	unknown
3	6058196446775239644	407	DS_P2P net loan
4	8694625920731541625	406	unknown

In [67]:

```
len(app_label_category['app_id'].unique())
```

Out[67]:

113211

In [68]:

```
len(app_label_category['category'].unique())
```

Out[68]:

473

In [69]:

```
app_label_category_1 = app_label_category.drop(['label_id'],axis = 1)
app_label_category_1.shape
```

Out[69]:

(459452, 2)

MERGING TRAIN BRAND 4 WITH APP LABEL CATEGORY 1

In [70]:

```
train_brand_5 = train_brand_4.merge(app_label_category_1,on = 'app_id',how = 'left')
print(train_brand_5.shape)
train_brand_5.head()
```

(5686499, 13)

Out[70]:

	device_id	gender	age	group	phone_brand	device_model	event_id	hour
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	NaN	NaN
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	NaN	NaN
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
3	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
4	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0

In [71]:

```
print('THE NUMBER OF UNIQUE DEVICES ARE ',len(train_brand_5['device_id'].unique()))
print('THE NUMBER OF UNIQUE PHONE BRANDS  ARE ',len(train_brand_5['phone_brand'].unique
()))
print('THE NUMBER OF UNIQUE DEVICE MODELS  ARE ',len(train_brand_5['device_model'].uniq
ue()))
print('THE NUMBER OF UNIQUE APPS  ARE ',len(train_brand_5['app_id'].unique()))
print('THE NUMBER OF UNIQUE EVENTS  ARE ',len(train_brand_5['event_id'].unique()))
print('THE NUMBER OF UNIQUE CATEGORIES   ARE ',len(train_brand_5['category'].unique()))
```

```
THE NUMBER OF UNIQUE DEVICES ARE  74645
THE NUMBER OF UNIQUE PHONE BRANDS  ARE  80
THE NUMBER OF UNIQUE DEVICE MODELS  ARE  1404
THE NUMBER OF UNIQUE APPS  ARE  6914
THE NUMBER OF UNIQUE EVENTS  ARE  1215596
THE NUMBER OF UNIQUE CATEGORIES   ARE  95
```

In [72]:

```
final_train = train_brand_5.drop(['is_installed','is_active'],axis = 1)
print(final_train.shape)
final_train.head()
```

```
(5686499, 11)
```

Out[72]:

	device_id	gender	age	group	phone_brand	device_model	event_id	hour
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	NaN	NaN
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	NaN	NaN
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
3	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
4	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0

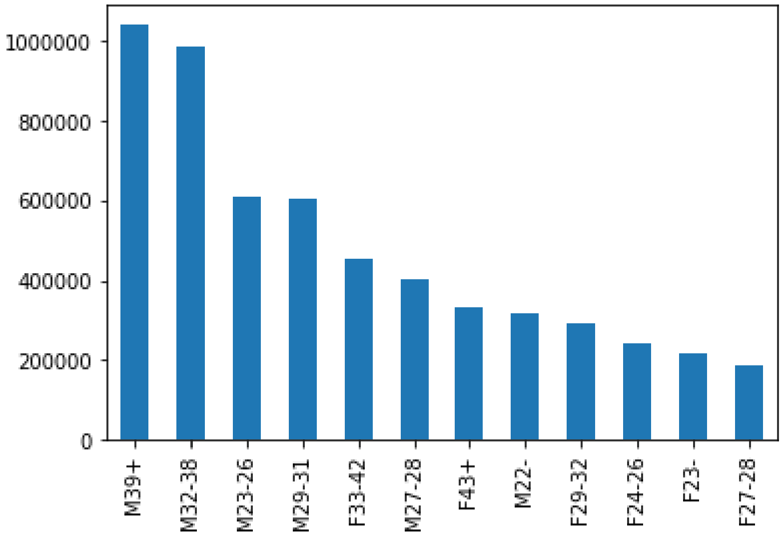
In [73]:

```
final_train.group.value_counts().sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[73]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba7002908>
```



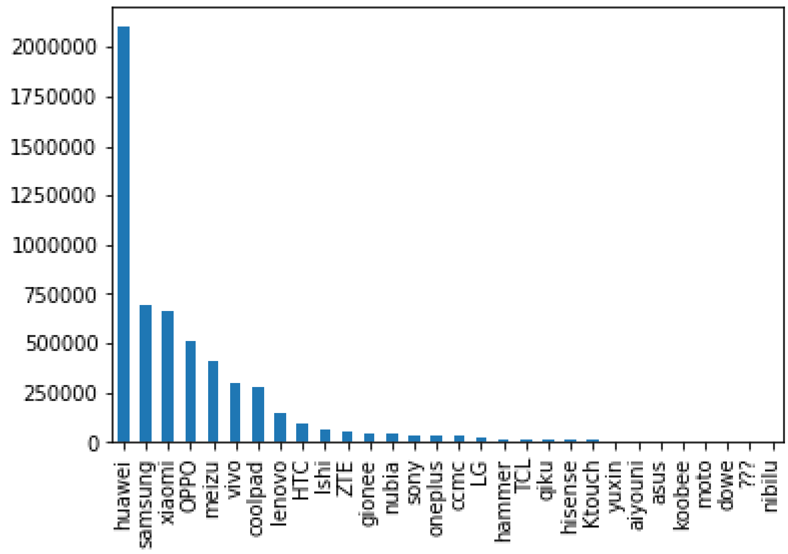
In [74]:

```
final_train.phone_brand.value_counts()[:30].sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[74]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dba722ee80>
```



THE MIX OF THE DATA WAS NOT CHANGED AFTER MERGING ALL THE DATASETS.THE GROUP CATEGORY WHERE MALE GROUPS ARE COMPARABLY MORE TO THE FEMALE GROUPS AND THE TOP PHONE BRANDS USED WHICH ARE RELATIVELY SAME AS TRAIN BRAND DATAFRAME

CHECKING FOR MISSING VALUES

In [75]:

```
final_train.isnull().any()
```

Out[75]:

```
device_id       False
gender          False
age             False
group           False
phone_brand     False
device_model    False
event_id         True
hour             True
weekday          True
app_id           True
category         True
dtype: bool
```

In [76]:

```
final_train['weekday'].value_counts()
```

Out[76]:

```
4.0    845763
3.0    834779
1.0    829610
2.0    807250
5.0    785758
0.0    772764
6.0    759239
Name: weekday, dtype: int64
```

FILLING THE MISSING VALUES WITH ZERO

In [77]:

```
final_train_1 = final_train.fillna(0)
print(final_train_1.shape)
final_train_1.head()
```

(5686499, 11)

Out[77]:

	device_id	gender	age	group	phone_brand	device_model	event_id	hour
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	0.0	0.0
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	0.0	0.0
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
3	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
4	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0

In [78]:

```
final_train_1.isnull().any()
```

Out[78]:

```
device_id       False
gender          False
age             False
group           False
phone_brand     False
device_model    False
event_id        False
hour            False
weekday         False
app_id          False
category        False
dtype: bool
```

In [79]:

```
len(final_train_1['device_id'].unique())
```

Out[79]:

```
74645
```

In [80]:

```
len(final_train_1['phone_brand'].unique())
```

Out[80]:

```
80
```

In [81]:

```
len(final_train_1['app_id'].unique())
```

Out[81]:

```
6914
```

In [82]:

```
len(final_train_1['event_id'].unique())
```

Out[82]:

```
1215596
```

In [83]:

```
len(final_train_1['weekday'].unique())
```

Out[83]:

```
7
```

In [84]:

```
final_train_1['weekday'].value_counts()
```

Out[84]:

```
4.0    845763
3.0    834779
1.0    829610
0.0    824100
2.0    807250
5.0    785758
6.0    759239
Name: weekday, dtype: int64
```

In [85]:

```
final_train_1['hour'].value_counts()
```

Out[85]:

```
10.0    310627
21.0    309312
20.0    299452
9.0     295306
12.0    293420
11.0    289158
19.0    289126
22.0    284831
8.0     281081
18.0    273913
13.0    273517
17.0    269075
14.0    267037
16.0    263872
15.0    260326
7.0     256069
0.0     251439
23.0    234726
6.0     202852
1.0     122895
5.0     113275
2.0      90684
3.0      77836
4.0      76670
Name: hour, dtype: int64
```

MERGING ALL FILES WITH TEST BRAND

In [86]:

```
test_brand_2 = test_brand.merge(events, on ='device_id',how = 'left')
test_brand_2.shape
```

Out[86]:

```
(2021699, 9)
```

In [87]:

```
test_brand_3 = test_brand_2.drop(['longitude','latitude'],axis = 1)
print(test_brand_3.shape)
test_brand_3.head()
```

(2021699, 7)

Out[87]:

	device_id	phone_brand	device_model	event_id	timestamp	hour	weekday
0	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
1	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
2	1002079943728939269	xiaomi	xiaominote	1171252.0	2016-05-02 08:20:02	8.0	0.0
3	1002079943728939269	xiaomi	xiaominote	1805074.0	2016-05-01 16:33:52	16.0	6.0
4	1002079943728939269	xiaomi	xiaominote	2145937.0	2016-05-05 08:28:20	8.0	3.0

In [88]:

```
test_brand_4 = test_brand_3.merge(app_events, on = 'event_id',how = 'left')
print(test_brand_4.shape)
test_brand_4.head()
```

(8755527, 10)

Out[88]:

	device_id	phone_brand	device_model	event_id	timestamp	hour	weekday
0	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
1	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
2	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
3	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
4	1002079943728939269	xiaomi	xiaominote	1171252.0	2016-05-02 08:20:02	8.0	0.0

In [89]:

```
len(test_brand_4['device_id'].unique())
```

Out[89]:

112071

In [90]:

```
len(test_brand_4['phone_brand'].unique())
```

Out[90]:

80

In [91]:

```
test_brand_5 = test_brand_4.merge(app_label_category_1,on = 'app_id',how = 'left')
print(test_brand_5.shape)
test_brand_5.head()
```

(9044860, 11)

Out[91]:

	device_id	phone_brand	device_model	event_id	timestamp	hour	weekday
0	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
1	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
2	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
3	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
4	1002079943728939269	xiaomi	xiaominote	1171252.0	2016-05-02 08:20:02	8.0	0.0

In [92]:

```
final_test = test_brand_5.drop(['is_installed','is_active'],axis = 1)
print(final_test.shape)
final_test.head()
```

(9044860, 9)

Out[92]:

	device_id	phone_brand	device_model	event_id	timestamp	hour	weekday
0	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
1	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
2	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
3	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
4	1002079943728939269	xiaomi	xiaominote	1171252.0	2016-05-02 08:20:02	8.0	0.0

In [93]:

```
len(final_test['device_id'].unique())
```

Out[93]:

112071

In [94]:

```
len(final_test['app_id'].unique())
```

Out[94]:

8726

In [95]:

```
len(final_test['event_id'].unique())
```

Out[95]:

1944823

In [96]:

```
len(final_test['phone_brand'].unique())
```

Out[96]:

80

In [97]:

```
len(final_test['weekday'].unique())
```

Out[97]:

```
8
```

In [98]:

```
len(final_test['category'].unique())
```

Out[98]:

```
114
```

In [99]:

```
final_test['weekday'].value_counts()
```

Out[99]:

```
4.0    1343551
1.0    1320830
3.0    1307059
2.0    1276168
5.0    1252253
0.0    1237271
6.0    1230851
Name: weekday, dtype: int64
```

In [100]:

```
final_test['hour'].value_counts()
```

Out[100]:

```
10.0    490682
21.0    489601
20.0    485832
11.0    466452
12.0    463079
19.0    461742
22.0    457795
9.0     457141
18.0    441020
13.0    437804
8.0     437703
14.0    426853
17.0    425805
15.0    419874
16.0    417840
7.0     403636
23.0    366818
6.0     324823
0.0     316640
1.0     193061
5.0     187445
2.0     144980
3.0     127111
4.0     124246
Name: hour, dtype: int64
```

CHECKING FOR MISSING VALUES AND FILLING WITH ZEROES

In [101]:

```
final_test.isnull().any()
```

Out[101]:

```
device_id       False
phone_brand     False
device_model    False
event_id         True
timestamp        True
hour             True
weekday          True
app_id           True
category         True
dtype: bool
```

In [102]:

```
final_test_1 = final_test.fillna(0)
print(final_test_1.shape)
final_test_1.head()
```

(9044860, 9)

Out[102]:

	device_id	phone_brand	device_model	event_id	timestamp	hour	weekday
0	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
1	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
2	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
3	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
4	1002079943728939269	xiaomi	xiaominote	1171252.0	2016-05-02 08:20:02	8.0	0.0

THE MIX OF THE DATA WAS NOT CHANGED AFTER MERGING ALL THE DATASETS.THE TOP PHONE BRANDS USED WHICH ARE RELATIVELY SAME AS Test BRAND DATAFRAME AND NUMBER OF UNIQUE DEVICE ID'S ARE SAME AS GIVEN IN TEST DATA.

In [103]:

```
import pickle
with open('train', 'wb') as fp:
     pickle.dump(final_train_1, fp)
```

In [104]:

```
import pickle
with open('test', 'wb') as fp:
     pickle.dump(final_test_1, fp)
```

In [1]:

```
import pickle
with open('train', 'rb') as fp:
    final_train_1 = pickle.load(fp)
```

In [2]:

```
import pickle
with open('test', 'rb') as fp:
    final_test_1 = pickle.load(fp)
```

In [3]:

```
print(final_train_1.shape)
print(final_test_1.shape)
```

```
(5686499, 11)
(9044860, 9)
```

EDA

In [106]:

```
final_train_1.head()
```

Out[106]:

	device_id	gender	age	group	phone_brand	device_model	event_id	hour
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	0.0	0.0
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	0.0	0.0
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
3	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
4	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0

In [107]:

```
final_train_1['group'].value_counts()
```

Out[107]:

```
M39+      1041412
M32-38     988546
M23-26     608801
M29-31     604152
F33-42     453849
M27-28     402929
F43+       330655
M22-       316813
F29-32     291727
F24-26     243302
F23-       218119
F27-28     186194
Name: group, dtype: int64
```

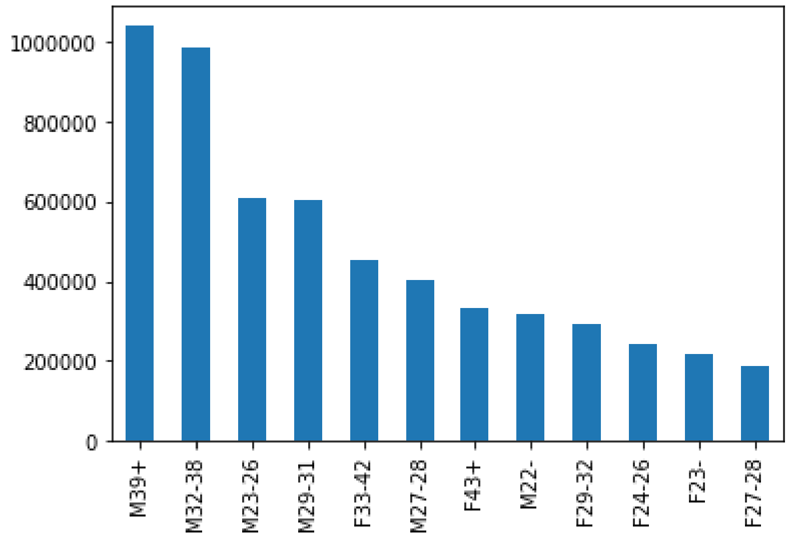
In [108]:

```
final_train_1.group.value_counts().sort_values(ascending=False).plot('bar')
```

```
C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: `Se
ries.plot()` should not be called with positional arguments, only keyword
arguments. The order of positional arguments will change in the future. Us
e `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  """Entry point for launching an IPython kernel.
```

Out[108]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2ddeffcf400>
```



MALE USERS ARE MORE COMPARED TO FEMALE USERS

CATEGORIES

In [109]:

```
unique_categories = final_train_1['category'].value_counts()
print('Number of Unique categories :', unique_categories.shape[0])
# the top 10 brands that occured most
print(unique_categories.head(10))
```

```
Number of Unique categories : 95
0                      5479280
Wealth Management        11801
P2P                      11483
P2P net loan             11354
Custom label             11338
And the Church           11096
Internet banking         11073
Low liquidity            10956
Financial Services       10944
Low income               10944
Name: category, dtype: int64
```

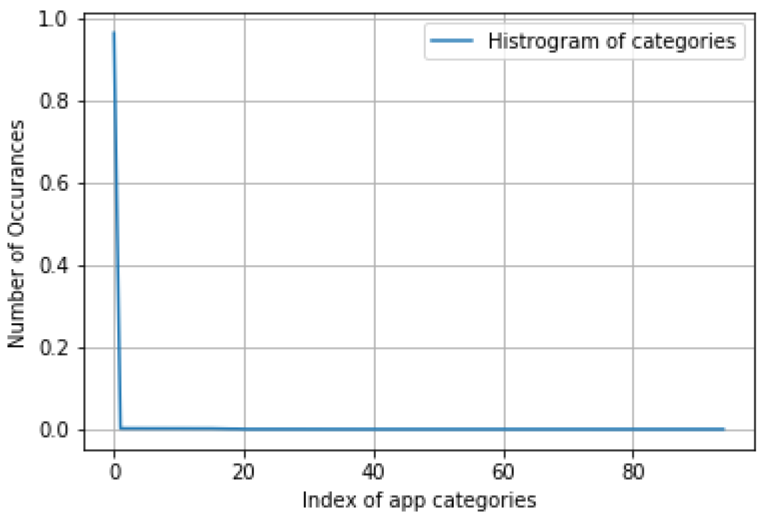
In [110]:

```
unique_test_categories = final_test_1['category'].value_counts()
print('Number of Unique categories :', unique_test_categories.shape[0])
# the top 10 brands that occured most
print(unique_test_categories.head(10))
```

```
Number of Unique categories : 114
0                      8717585
Wealth Management        17977
P2P                      17813
Custom label             17698
P2P net loan             17543
And the Church           17191
Internet banking         17067
Low liquidity            16891
Low Risk                 16797
Low income               16797
Name: category, dtype: int64
```

In [111]:

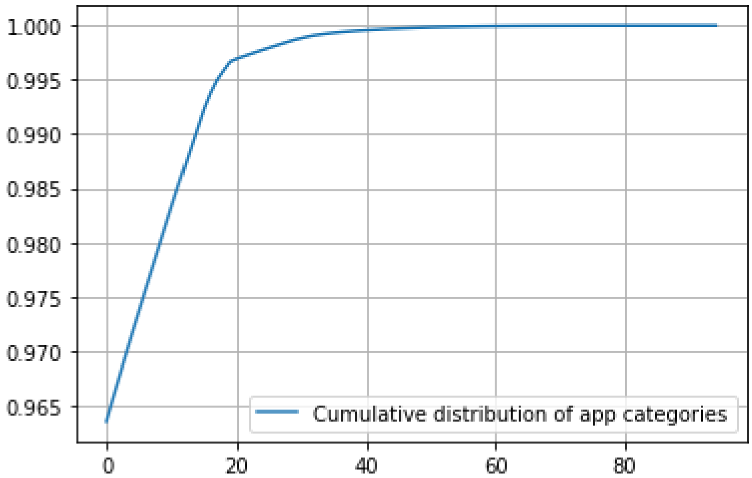
```
#pdf of categories
s = sum(unique_categories.values);
h = unique_categories.values/s;
plt.plot(h, label="Histrogram of categories")
plt.xlabel('Index of app categories')
plt.ylabel('Number of Occurances')
plt.legend()
plt.grid()
plt.show()
```



In [112]:

```
#cdf of phone brand
c = np.cumsum(h)
print(c)
plt.plot(c,label='Cumulative distribution of app categories')
plt.grid()
plt.legend()
plt.show()
```

```
[0.96355948 0.96563474 0.96765409 0.96965075 0.97164459 0.97359588
 0.97554312 0.97746979 0.97939435 0.98131891 0.98324347 0.98511562
 0.98692992 0.98874017 0.99055042 0.99233799 0.99381711 0.99499956
 0.99585932 0.99666473 0.99693379 0.99714288 0.99734599 0.99754805
 0.99774888 0.99794337 0.998134   0.99832111 0.99850822 0.99868935
 0.99883162 0.99897389 0.99909276 0.99917788 0.99926088 0.99932577
 0.99938838 0.99944078 0.99948984 0.9995324  0.99957496 0.99960925
 0.99964354 0.99967783 0.9997072  0.99973323 0.99975767 0.99978088
 0.9998041  0.99982713 0.99984507 0.99985826 0.99987092 0.99988306
 0.99989519 0.99990715 0.99991612 0.99992491 0.9999323  0.99993933
 0.99994619 0.99995182 0.99995744 0.99996219 0.99996624 0.99997028
 0.99997292 0.99997556 0.99997784 0.99998013 0.99998224 0.99998417
 0.99998611 0.99998804 0.99998962 0.99999103 0.99999191 0.99999279
 0.99999367 0.99999437 0.9999949  0.99999543 0.99999596 0.99999648
 0.99999701 0.99999754 0.99999807 0.99999842 0.99999877 0.99999912
 0.9999993  0.99999947 0.99999965 0.99999982 1.        ]
```



20 CATEGORIES ACCOUNT FOR MORE THAN 99.5% USERS

APP IDS

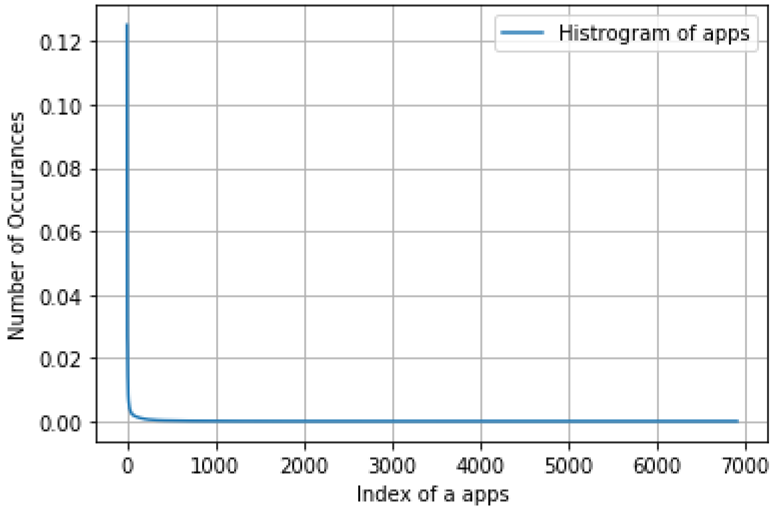
In [113]:

```
unique_apps = final_train_1['app_id'].value_counts()
print('Number of Unique categories :', unique_apps.shape[0])
# the top 10 brands that occured most
print(unique_apps.head(10))
```

```
Number of Unique categories : 6914
 0.000000e+00    711652
 8.693964e+18    350672
 5.927333e+18    235059
 4.348660e+18    164969
-4.986140e+15    152475
 3.433290e+18    147057
 6.280209e+17    136099
 6.284165e+18    103677
 8.948670e+18     99963
-3.955213e+18     93338
Name: app_id, dtype: int64
```

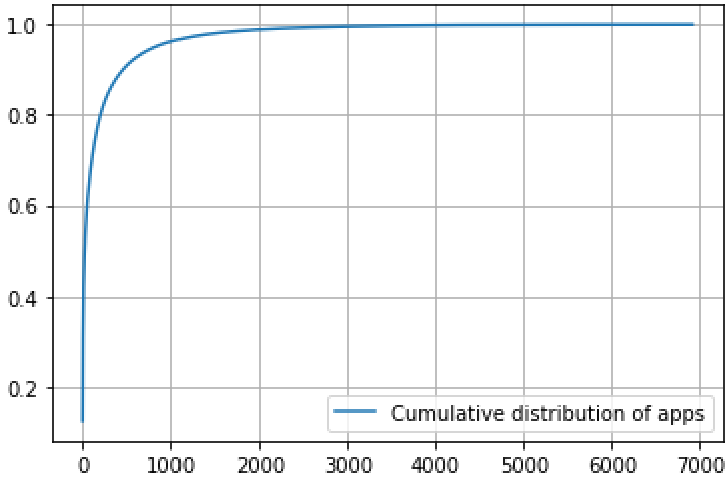
In [114]:

```
#pdf of app
s = sum(unique_apps.values);
h = unique_apps.values/s;
plt.plot(h, label="Histrogram of apps")
plt.xlabel('Index of a apps')
plt.ylabel('Number of Occurances')
plt.legend()
plt.grid()
plt.show()
```



In [115]:

```
#cdf of phone brand
c = np.cumsum(h)
#print(c)
plt.plot(c,label='Cumulative distribution of apps')
plt.grid()
plt.legend()
plt.show()
```



1000 APPS ACCOUNT FOR MORE THAN 95% OF USERS

PHONE BRAND

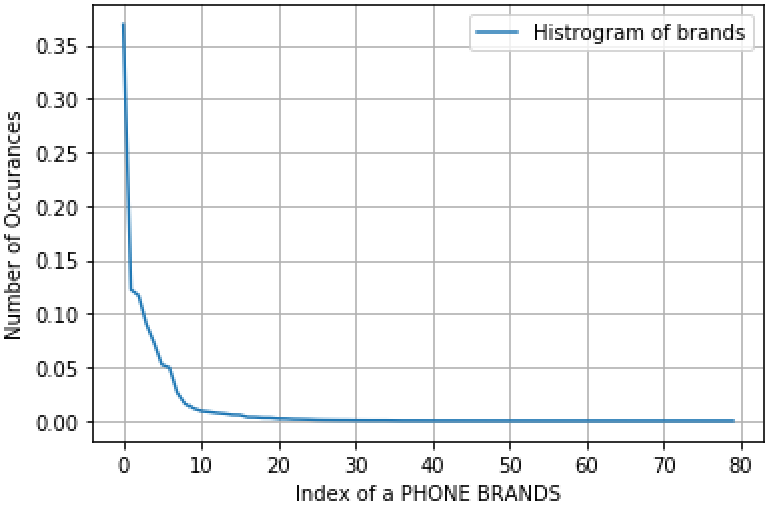
In [116]:

```
unique_brands = final_train_1['phone_brand'].value_counts()
print('Number of Unique brands :', unique_brands.shape[0])
# the top 10 brands that occured most
print(unique_brands.head(10))
```

```
Number of Unique brands : 80
huawei     2100132
samsung     697319
xiaomi      665984
OPPO        513802
meizu       414998
vivo        299541
coolpad     282937
lenovo      150074
HTC          91801
lshi         66013
Name: phone_brand, dtype: int64
```

In [117]:

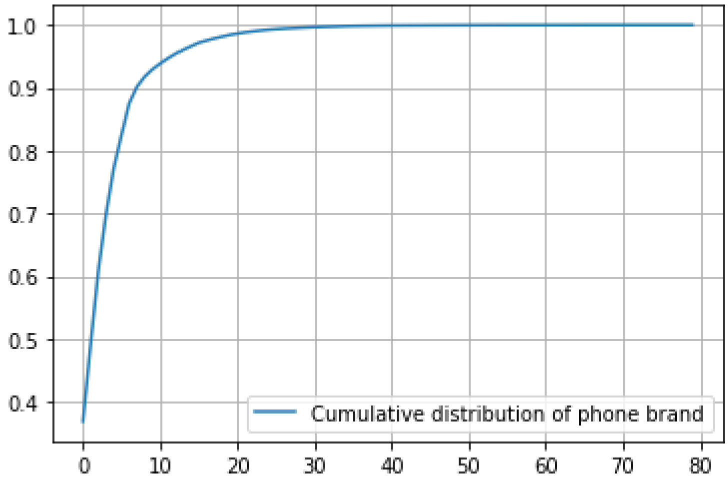
```
#pdf of phone brand
s = sum(unique_brands.values);
h = unique_brands.values/s;
plt.plot(h, label="Histrogram of brands")
plt.xlabel('Index of a PHONE BRANDS')
plt.ylabel('Number of Occurances')
plt.legend()
plt.grid()
plt.show()
```



In [118]:

```
#cdf of phone brand
c = np.cumsum(h)
print(c)
plt.plot(c,label='Cumulative distribution of phone brand')
plt.grid()
plt.legend()
plt.show()
```

```
[0.36931898 0.4919461  0.6090628  0.69941752 0.77239704 0.82507286
 0.87482878 0.90122007 0.91736374 0.92897247 0.93819818 0.94660106
 0.95398979 0.96071924 0.96637738 0.97181289 0.97530572 0.97864275
 0.98149441 0.9842775  0.98635769 0.98828928 0.98983522 0.99124646
 0.99247076 0.99338011 0.99416284 0.99487417 0.99551499 0.99614191
 0.99661233 0.99703209 0.99742671 0.99782063 0.99820733 0.99847463
 0.99863396 0.99878396 0.99892746 0.99905214 0.9991566  0.99923134
 0.99930572 0.99937448 0.99943498 0.99948826 0.99954067 0.99958903
 0.99963686 0.99968135 0.99971564 0.99974712 0.99977737 0.9998048
 0.9998259  0.99984454 0.99986125 0.9998762  0.99989079 0.99990539
 0.99991911 0.99993159 0.99994302 0.99995428 0.99996536 0.99997151
 0.99997749 0.99998294 0.99998628 0.99998945 0.99999226 0.99999455
 0.99999648 0.99999771 0.99999877 0.9999993  0.99999947 0.99999965
 0.99999982 1.        ]
```



10 BRANDS ACCOUNT FOR MORE THAN 95% OF USERS

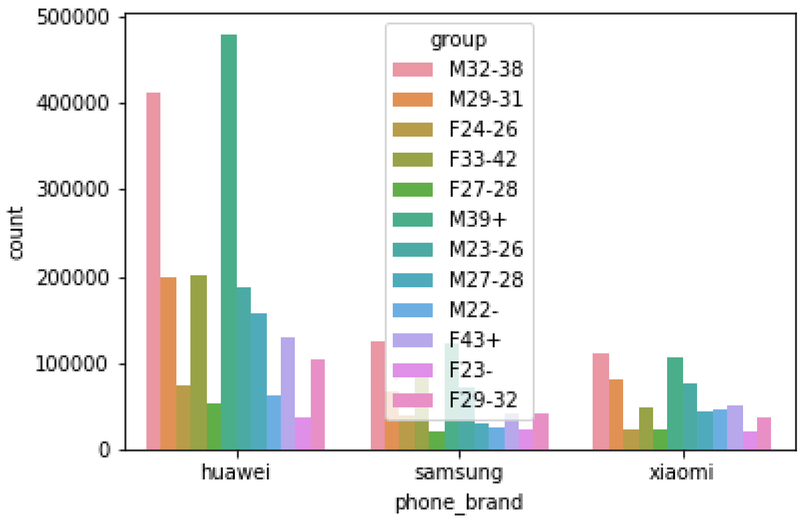
PLOTTING HISTOGRAM FOR TOP 10 BRANDS

In [119]:

```
sns.countplot(data = final_train_1, x = 'phone_brand',hue = 'group' ,order=['huawei','s
amsung','xiaomi'])
```

Out[119]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2de1193ec18>
```

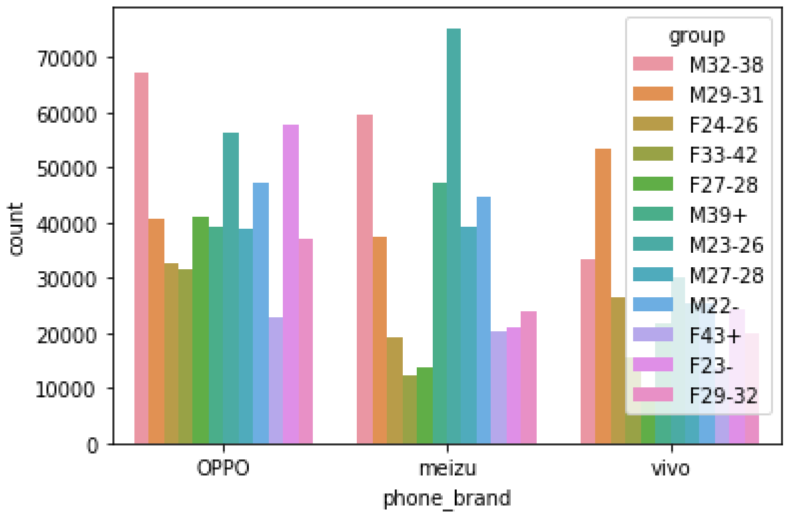


In [120]:

```
sns.countplot(data = final_train_1, x = 'phone_brand',hue = 'group' ,order=['OPPO','mei
zu','vivo'])
```

Out[120]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2ddf191dd30>
```

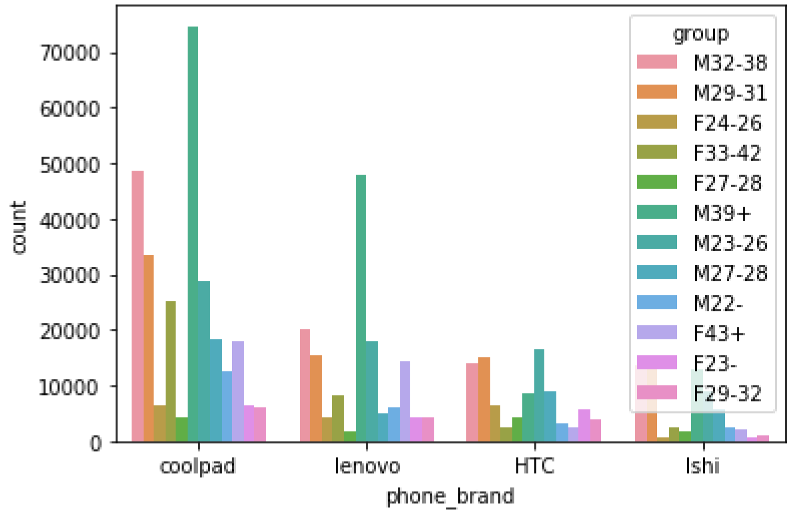


In [121]:

```
sns.countplot(data = final_train_1, x = 'phone_brand',hue = 'group' ,order=['coolpad',
'lenovo','HTC','lshi'])
```

Out[121]:

<matplotlib.axes._subplots.AxesSubplot at 0x2dded561ac8>

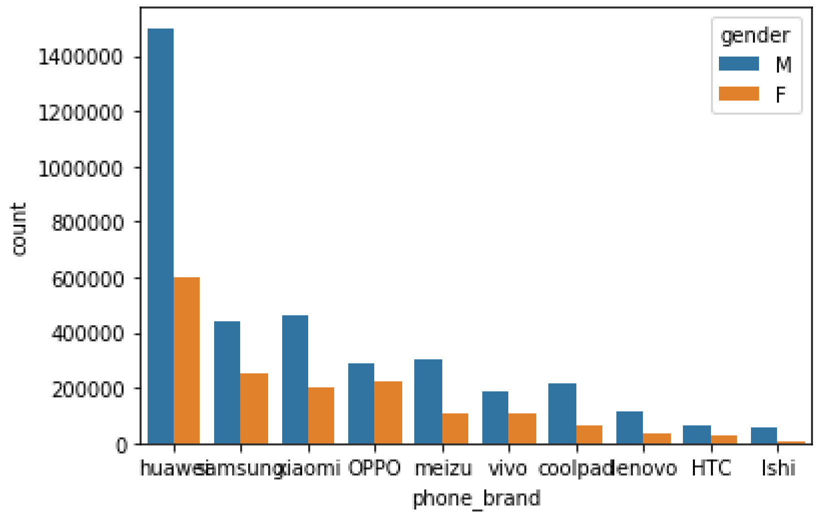


In [122]:

```
sns.countplot(data = final_train_1, x = 'phone_brand',hue = 'gender' ,order=['huawei',
'samsung','xiaomi','OPPO','meizu','vivo','coolpad','lenovo','HTC','lshi'])
```

Out[122]:

<matplotlib.axes._subplots.AxesSubplot at 0x2ddf556a9e8>

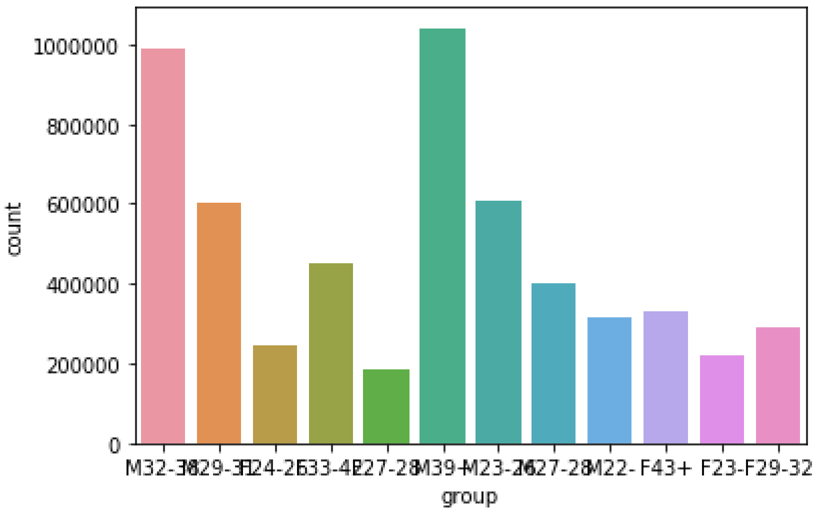


In [123]:

```
sns.countplot(data = final_train_1, x = 'group')
```

Out[123]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2de646d4c50>
```

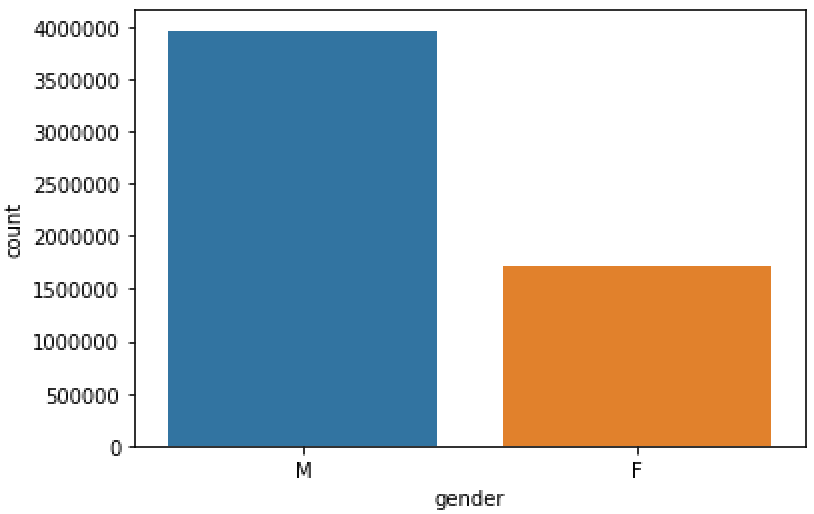


In [124]:

```
sns.countplot(data = final_train_1, x = 'gender')
```

Out[124]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2ddc2acd4e0>
```



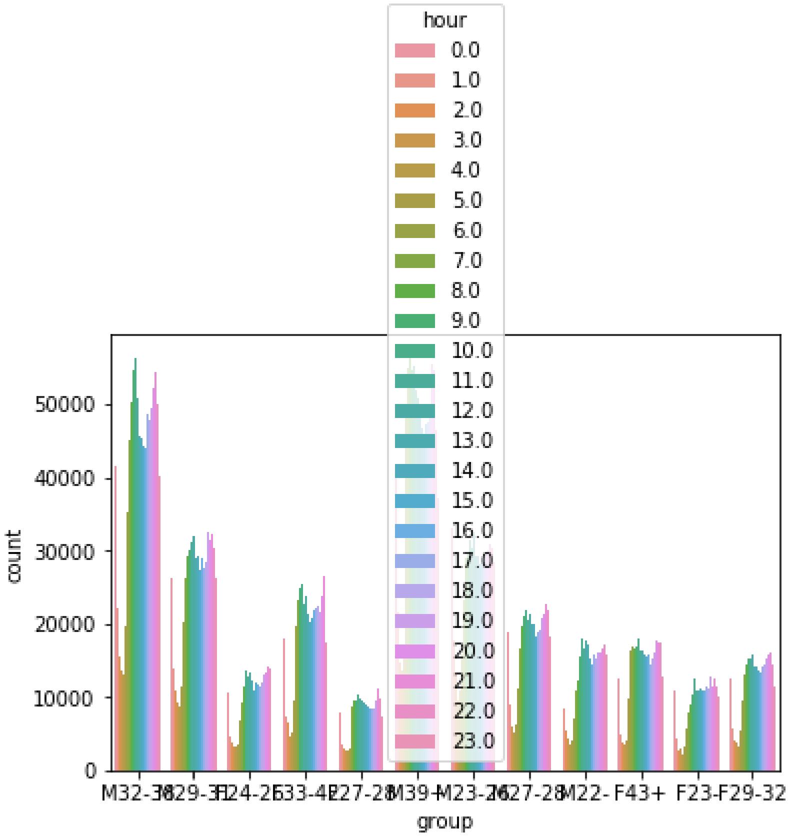
BOX PLOT OF HOUR VS AGE

In [125]:

```
sns.countplot(x='group', hue='hour', data=final_train_1)
```

Out[125]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2ddc7ff6eb8>
```

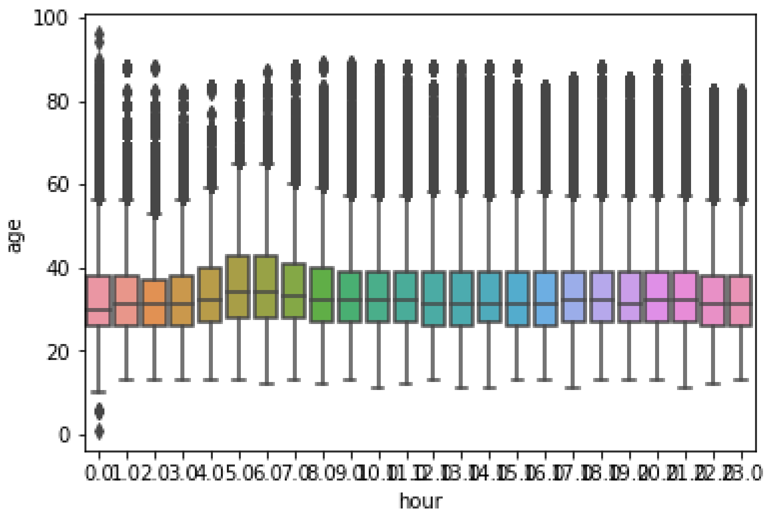


In [126]:

```
sns.boxplot(data = final_train_1, x='hour', y='age')
```

Out[126]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2ddc80e9d30>
```



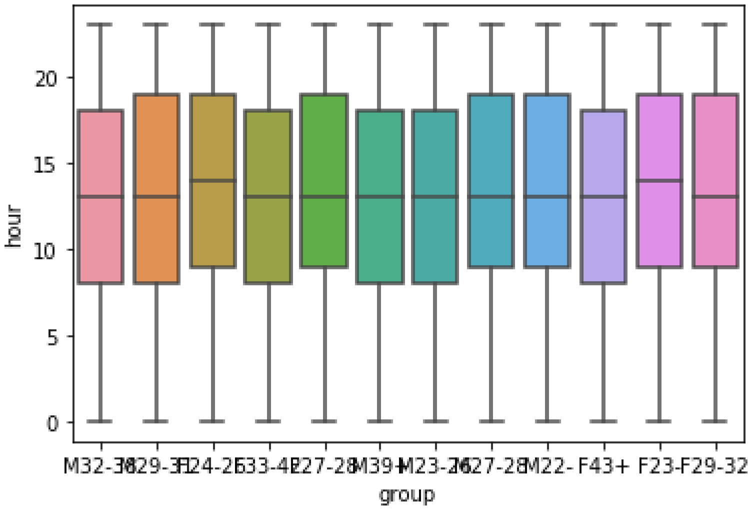
BOX PLOT OF HOUR VS GROUP

In [127]:

```
sns.boxplot(data = final_train_1, y='hour', x='group')
```

Out[127]:

<matplotlib.axes._subplots.AxesSubplot at 0x2ddee6b0198>

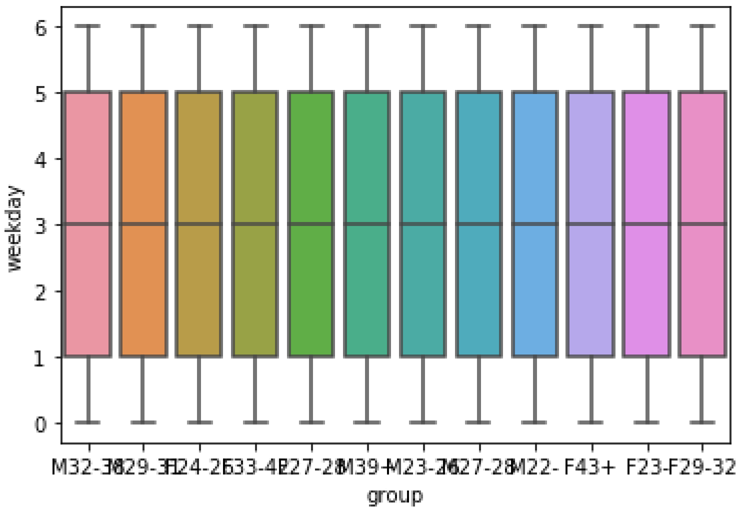


In [128]:

```
sns.boxplot(data = final_train_1, y='weekday', x='group')
```

Out[128]:

<matplotlib.axes._subplots.AxesSubplot at 0x2dd4eddf518>



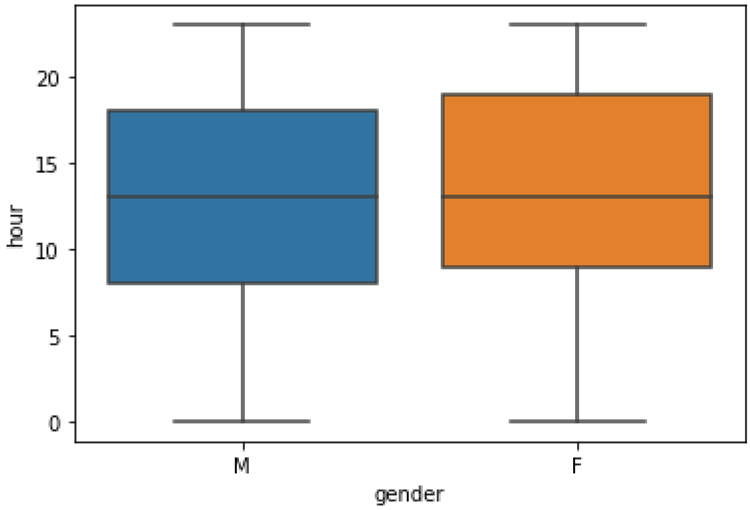
BOX PLOT OF GENDER VS HOUR

In [129]:

```
sns.boxplot(data = final_train_1, y='hour', x='gender')
```

Out[129]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dde918f048>
```



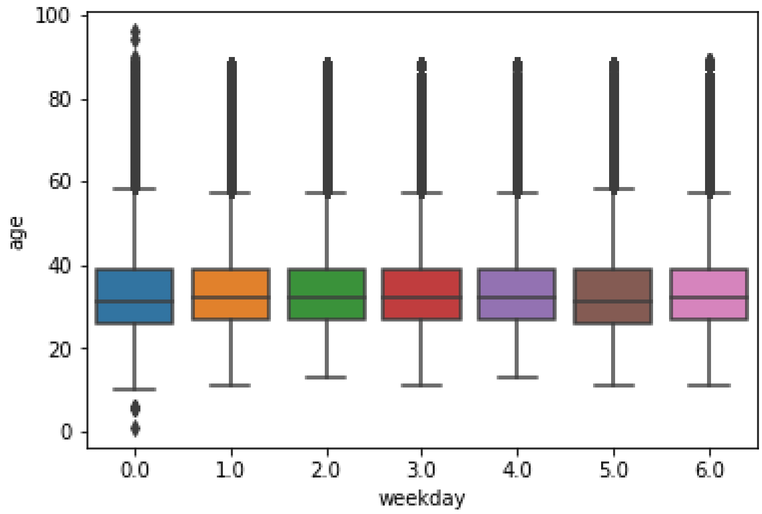
BOXPLOT OF WEEKDAY VS AGE

In [130]:

```
sns.boxplot(data = final_train_1, x='weekday', y='age')
```

Out[130]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2dde66b8e10>
```



FROM THE PLOTS WE CANNOT DRAW ANY CONCLUSIONS AS ALL THE FEATURES ARE OVERLAPPING

ONE HOT ENCODING OF CATEGORICAL VARIABLES IN TRAIN DATA and TEST DATA

In [4]:

```
print(final_train_1.shape)
final_train_1.head()
```

(5686499, 11)

Out[4]:

	device_id	gender	age	group	phone_brand	device_model	event_id	hour
0	-8076087639492063270	M	35	M32-38	xiaomi	MI 2	0.0	0.0
1	-2897161552818060146	M	35	M32-38	xiaomi	MI 2	0.0	0.0
2	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
3	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0
4	-8260683887967679142	M	35	M32-38	xiaomi	MI 2	2479656.0	14.0

In [5]:

```
print(final_test_1.shape)
final_test_1.head()
```

(9044860, 9)

Out[5]:

	device_id	phone_brand	device_model	event_id	timestamp	hour	weekday
0	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
1	1002079943728939269	xiaomi	xiaominote	460577.0	2016-05-03 21:06:29	21.0	1.0
2	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
3	1002079943728939269	xiaomi	xiaominote	755837.0	2016-05-05 22:15:16	22.0	3.0
4	1002079943728939269	xiaomi	xiaominote	1171252.0	2016-05-02 08:20:02	8.0	0.0

In [6]:

```
y = final_train_1['group']
print(y.shape)
```

(5686499,)

In [7]:

```
train_data = final_train_1.drop(['age','gender'],axis = 1)
print(train_data.shape)
train_data.head()
```

(5686499, 9)

Out[7]:

	device_id	group	phone_brand	device_model	event_id	hour	weekday	
0	-8076087639492063270	M32-38	xiaomi	MI 2	0.0	0.0	0.0	0.C
1	-2897161552818060146	M32-38	xiaomi	MI 2	0.0	0.0	0.0	0.C
2	-8260683887967679142	M32-38	xiaomi	MI 2	2479656.0	14.0	6.0	8.7
3	-8260683887967679142	M32-38	xiaomi	MI 2	2479656.0	14.0	6.0	8.C
4	-8260683887967679142	M32-38	xiaomi	MI 2	2479656.0	14.0	6.0	1.6

In [8]:

```
test_data = final_test_1.drop(['timestamp'],axis = 1)
print(test_data.shape)
test_data.head()
```

(9044860, 8)

Out[8]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app_
0	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	6.965654e+
1	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	-5.380614e+
2	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	6.965654e+
3	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	-5.380614e+
4	1002079943728939269	xiaomi	xiaominote	1171252.0	8.0	0.0	6.965654e+

In [9]:

```
len(train_data['phone_brand'].unique())
```

Out[9]:

80

In [10]:

```
len(test_data['phone_brand'].unique())
```

Out[10]:

80

In [11]:

```
len(train_data['device_model'].unique())
```

Out[11]:

1404

In [12]:

```
len(test_data['device_model'].unique())
```

Out[12]:

1488

In [13]:

```
len(test_data['category'].unique())
```

Out[13]:

114

In [14]:

```
len(train_data['category'].unique())
```

Out[14]:

95

In [15]:

```
import pandas as pd
train_data_1 = pd.get_dummies(train_data,columns = ['group'])
print(train_data_1.shape)
train_data_1.head()
```

(5686499, 20)

Out[15]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app
0	-8076087639492063270	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
1	-2897161552818060146	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
2	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.772885e+
3	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.096758e+
4	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	1.665047e+

LABEL ENCODING OF PHONE BRAND

In [18]:

```
from sklearn import preprocessing
import pandas as pd
le = preprocessing.LabelEncoder()

train_data_1['phone_brand_en'] = le.fit_transform(train_data_1.phone_brand.values)
train_data_1.head()
```

Out[18]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app_
0	-8076087639492063270	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
1	-2897161552818060146	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
2	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.772885e+
3	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.096758e+
4	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	1.665047e+

5 rows × 21 columns

In [23]:

```
from sklearn import preprocessing
import pandas as pd
le = preprocessing.LabelEncoder()

test_data['phone_brand_en'] = le.fit_transform(test_data.phone_brand.values)
test_data.head()
```

Out[23]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app_
0	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	6.965654e+
1	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	-5.380614e+
2	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	6.965654e+
3	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	-5.380614e+
4	1002079943728939269	xiaomi	xiaominote	1171252.0	8.0	0.0	6.965654e+

LABEL ENCODING OF DEVICE MODEL

In [19]:

```
le = preprocessing.LabelEncoder()
train_data_1['device_model_en'] = le.fit_transform(train_data_1.device_model.values)
train_data_1.head()
```

Out[19]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app_
0	-8076087639492063270	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
1	-2897161552818060146	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
2	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.772885e+
3	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.096758e+
4	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	1.665047e+

5 rows × 22 columns

In [24]:

```
le = preprocessing.LabelEncoder()
test_data['device_model_en'] = le.fit_transform(test_data.device_model.values)
print(test_data.shape)
test_data.head()
```

```
(9044860, 10)
```

Out[24]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app_
0	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	6.965654e+
1	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	-5.380614e+
2	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	6.965654e+
3	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	-5.380614e+
4	1002079943728939269	xiaomi	xiaominote	1171252.0	8.0	0.0	6.965654e+

LABEL ENCODING OF CATEGORY

In [21]:

```
train_data_1['category'] = train_data_1['category'].astype(str)
```

In [22]:

```
le = preprocessing.LabelEncoder()
train_data_1['category_en'] = le.fit_transform(train_data_1.category.values)
train_data_1.head()
```

Out[22]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app_
0	-8076087639492063270	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
1	-2897161552818060146	xiaomi	MI 2	0.0	0.0	0.0	0.000000e+
2	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.772885e+
3	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	8.096758e+
4	-8260683887967679142	xiaomi	MI 2	2479656.0	14.0	6.0	1.665047e+

5 rows × 23 columns

In [25]:

```
test_data['category'] = test_data['category'].astype(str)
```

In [26]:

```
le = preprocessing.LabelEncoder()
test_data['category_en'] = le.fit_transform(test_data.category.values)
print(test_data.shape)
test_data.head()
```

```
(9044860, 11)
```

Out[26]:

	device_id	phone_brand	device_model	event_id	hour	weekday	app_
0	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	6.965654e+
1	1002079943728939269	xiaomi	xiaominote	460577.0	21.0	1.0	-5.380614e+
2	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	6.965654e+
3	1002079943728939269	xiaomi	xiaominote	755837.0	22.0	3.0	-5.380614e+
4	1002079943728939269	xiaomi	xiaominote	1171252.0	8.0	0.0	6.965654e+

GROUPBY DEVICEID AND SUM

In [32]:

```
final_train_data = train_data_1.groupby('device_id').sum()
```

In [33]:

```
print(final_train_data.shape)
```

(74645, 19)

In [30]:

```
final_test_data = test_data.groupby('device_id').sum()
```

In [31]:

```
print(final_test_data.shape)
```

(112071, 7)

In [ ]:

```

```