Data analysis and visualization

```
In [1]: %matplotlib inline
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import os
        from mpl_toolkits.basemap import Basemap
```

```
In [2]: # Input data from "/data" director
        os.listdir("data")
```

```
Out[2]: ['label_categories.csv',
         'app_labels.csv',
         'sample_submission.csv',
         'phone_brand_device_model.csv',
         'events.csv',
         'gender_age_train.csv',
         'app_events.csv',
         'gender_age_test.csv']
```

```
In [3]: import seaborn as sns
        sns.set(color_codes=True)
        app_event=pd.read_csv("data/events.csv")
        app_event.shape
```

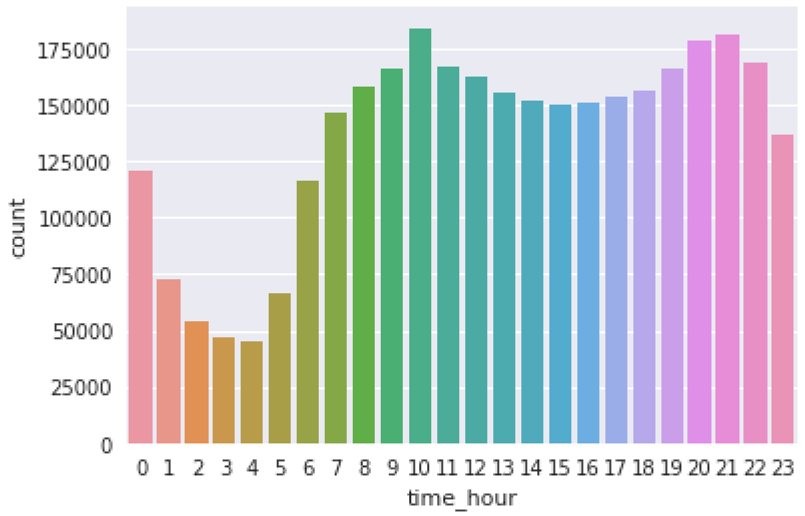
```
Out[3]: (3252950, 5)
```

```
In [4]: app_event.timestamp=pd.to_datetime(app_event.timestamp)
        app_event['time_hour'] = app_event.timestamp.apply(lambda x: x.hour)
```

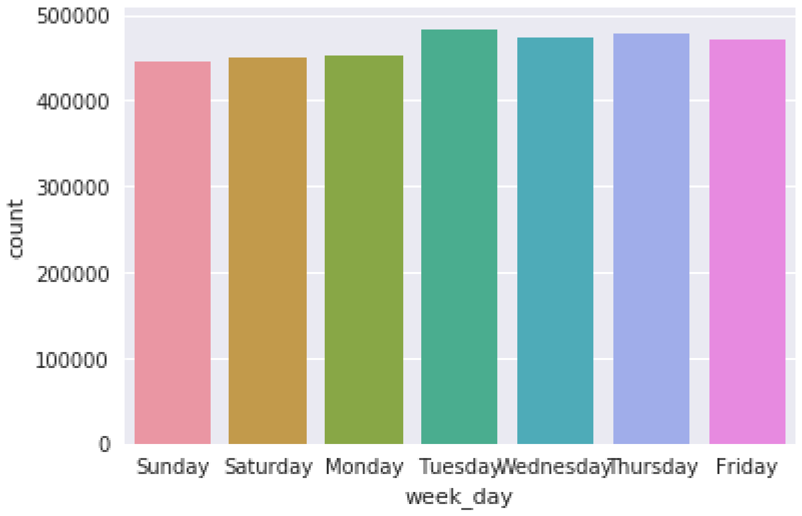
In [5]:
```
# Show frequency of events by hour
app_event['time_hour'].value_counts()
```

Out[5]:
```
10    183839
21    181175
20    178179
22    168246
11    167025
19    166160
9     166061
12    162745
8     157896
18    156209
13    155337
17    153516
14    151379
16    150732
15    149912
7     146667
23    136339
0     120512
6     116370
1      72671
5      66411
2      53764
3      47048
4      44757
Name: time_hour, dtype: int64
```

In [6]:
```
ax = sns.countplot(x="time_hour", data=app_event)
```

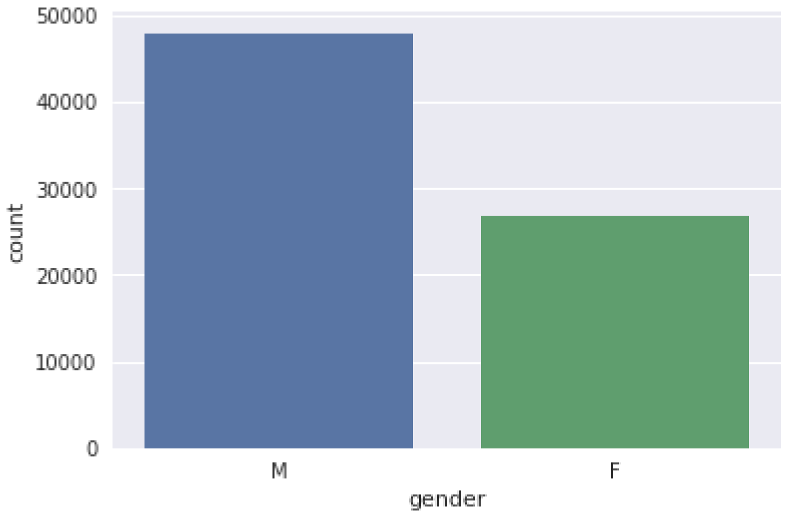


In [7]:
```
import calendar
app_event['week_day'] = app_event.timestamp.apply(lambda x: calendar.day_na
me[x.weekday()])
ax = sns.countplot(x="week_day", data=app_event)
```

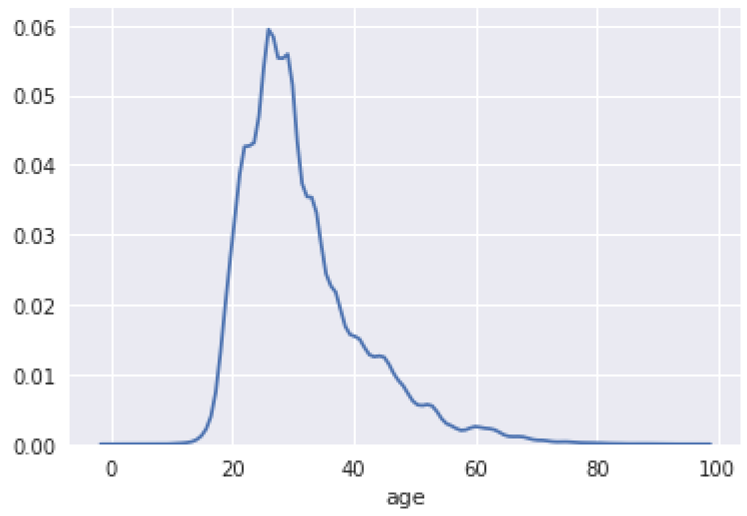


In [8]:
```
gender=pd.read_csv("data/gender_age_train.csv")
print(gender.gender.value_counts())
ax = sns.countplot(x="gender", data=gender)
```

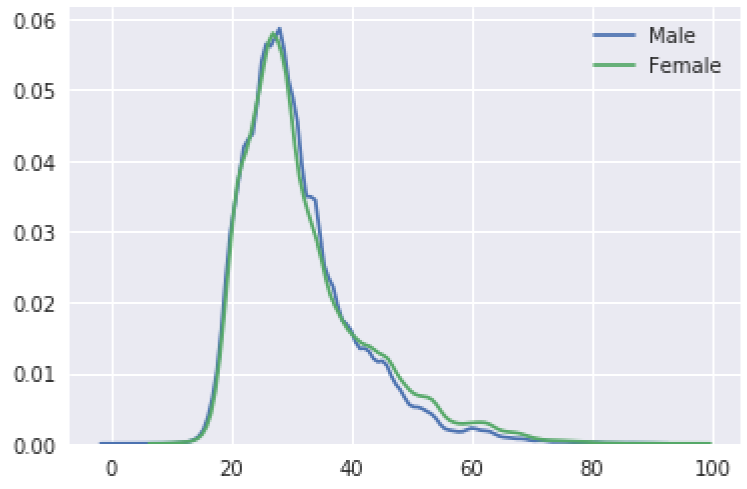
```
M    47904
F    26741
Name: gender, dtype: int64
```



In [9]:
```
# Distribution by age
sns.distplot(gender.age, hist=False);
```



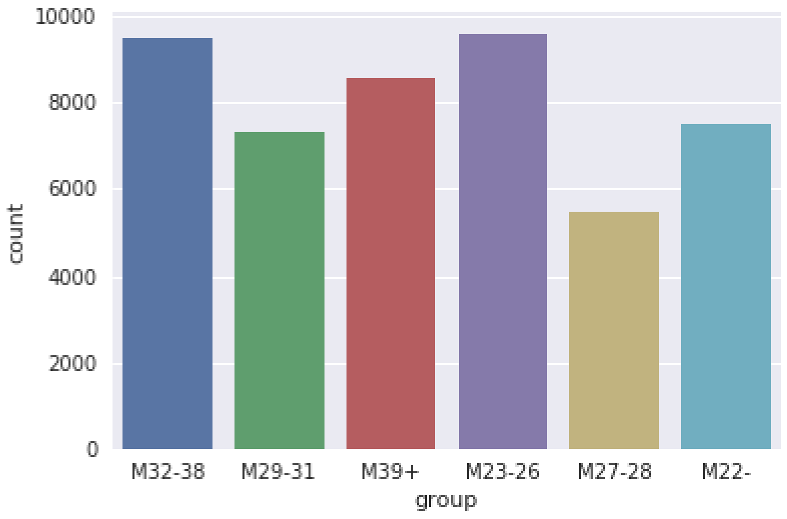
In [10]:
```
# Distribution by sex
sns.kdeplot(gender.age[gender.gender=="M"], label="Male")
sns.kdeplot(gender.age[gender.gender=="F"],  label="Female")
plt.legend();
```



Female at old age are using mobiles little bit more than males at old age

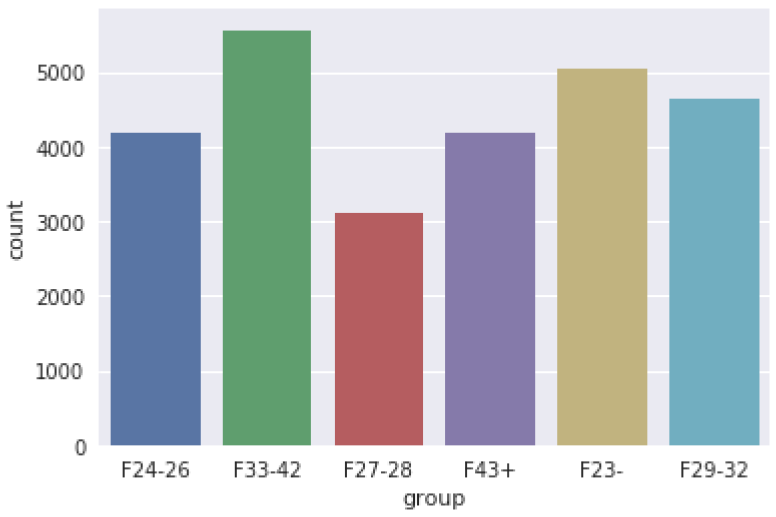
In [11]:
```
print("Male mobile usage count by age")
ax = sns.countplot(x="group", data=gender[gender.gender=="M"])
```

```
Male mobile usage count by age
```



In [12]:
```
print("Female mobile usage count by age")
ax = sns.countplot(x="group", data=gender[gender.gender=="F"])
```

```
Female mobile usage count by age
```



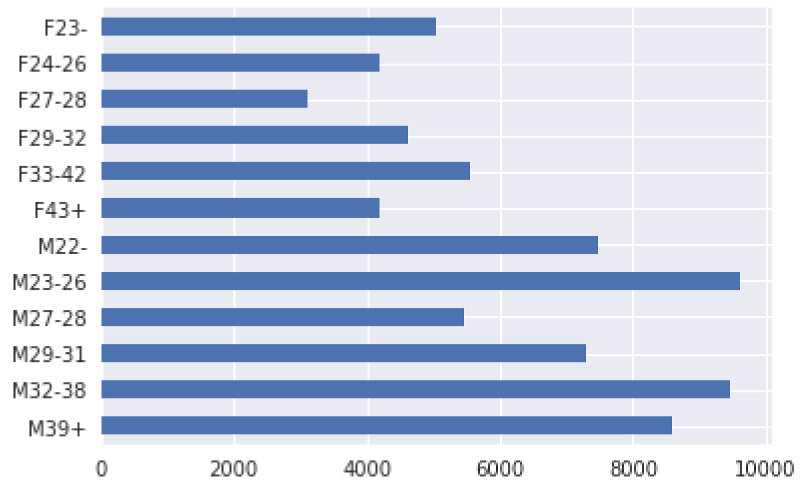
In [13]:
```
appscategories=pd.read_csv("data/label_categories.csv")
print(appscategories.head())
print(appscategories.shape)
```

```
   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
(930, 2)
```

Joint visualisation - male and female

```
In [14]: gender.group.value_counts().sort_index(ascending=False).plot(kind='barh')
```

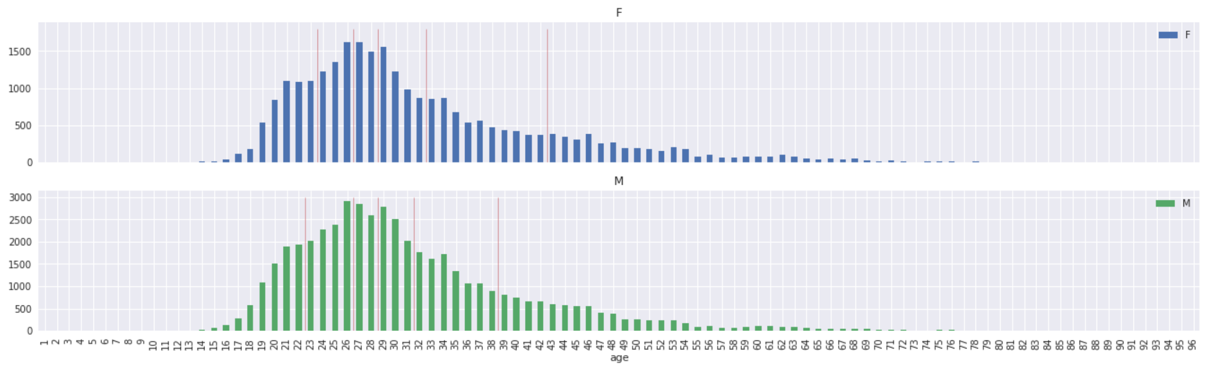
```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8b64c0ceb8>
```



Further break down by age

```
In [15]: c = gender.groupby(['age','gender']).size().unstack().reindex(index=np.aran
         ge(gender.age.min(), gender.age.max()+1)).fillna(0)
         ax1, ax2 = c.plot(kind='bar',figsize=(22,6),subplots=True);
         ax1.vlines(np.array([23,26,28,32,42])-0.5,0,1800,alpha=0.5,linewidth=1,colo
         r='r')
         ax2.vlines(np.array([22,26,28,31,38])-0.5,0,3000,alpha=0.5,linewidth=1,colo
         r='r')
```

```
Out[15]: <matplotlib.collections.LineCollection at 0x7f8b65467668>
```



Locations visualization

```
In [16]: df_events = pd.read_csv("data/events.csv", dtype={'device_id': np.str})
         df_events.head()
```

Out[16]:

	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

Locations of events - World map

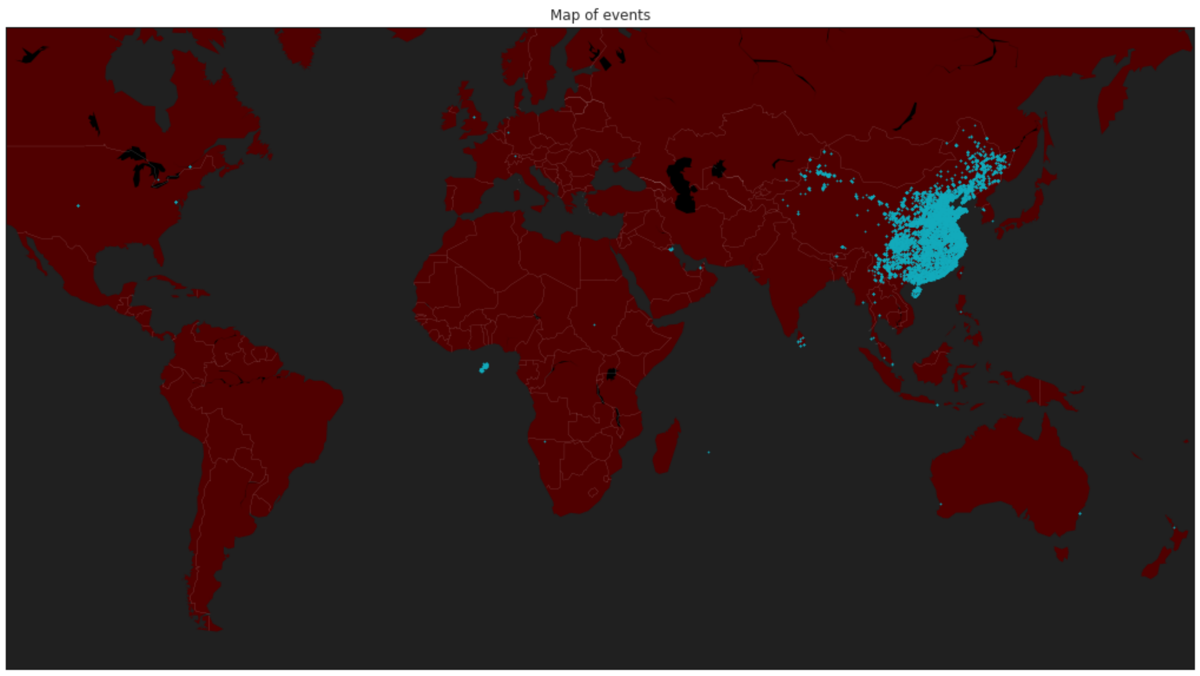
Expand size of the screen so larger map can nicely fit without truncated window with scroller.

```
In [17]: %%html
         <style>
         .output_wrapper, .output {
             height:auto !important;
             max-height:1000px;  /* your desired max-height here */
         }
         .output_scroll {
             box-shadow:none !important;
             webkit-box-shadow:none !important;
         }
         </style>
```

In [18]:

```
# Set plot
df_events_sample = df_events.sample(n=90000)
plt.figure(1, figsize=(20,10))
pd.set_option('display.max_colwidth', -1)

# Map of World
map = Basemap(projection='merc',
             llcrnrlat=-60,
             urcrnrlat=65,
             llcrnrlon=-120,
             urcrnrlon=180,
             lat_ts=0,
             resolution='c')

map.fillcontinents(color='#500000',lake_color='#000000') # grey land, black
 lakes
map.drawmapboundary(fill_color='#202020')                # black background
map.drawcountries(linewidth=0.1, color="w")              # white line of co
untry borders

# Plot the data
mxy = map(df_events_sample["longitude"].tolist(), df_events_sample["latitud
e"].tolist())
map.scatter(mxy[0], mxy[1], s=3, c="#12AABB", lw=0, alpha=1, zorder=5)

plt.title("Map of events")
plt.show()
```

```
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1767: MatplotlibDeprecationWarning: The get_axis_bgcolor function was dep
recated in version 2.0. Use get_facecolor instead.
  axisbgc = ax.get_axis_bgcolor()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1698: MatplotlibDeprecationWarning: The axesPatch function was deprecated
in version 2.1. Use Axes.patch instead.
  limb = ax.axesPatch
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3222: MatplotlibDeprecationWarning: The ishold function was deprecated in
version 2.0.
  b = ax.ishold()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3231: MatplotlibDeprecationWarning: axes.hold is deprecated.
    See the API Changes document (http://matplotlib.org/api/api_changes.htm
l)
    for more details.
  ax.hold(b)
```



As we can see some events have (lat,lon) = (0,0) which probably means that location couldn't be determined. We can find all event on that location and all events that have longitud and latitud less than 1 which means they are really close to that location. That is location is not probable since it's points to sea area close to African cost.

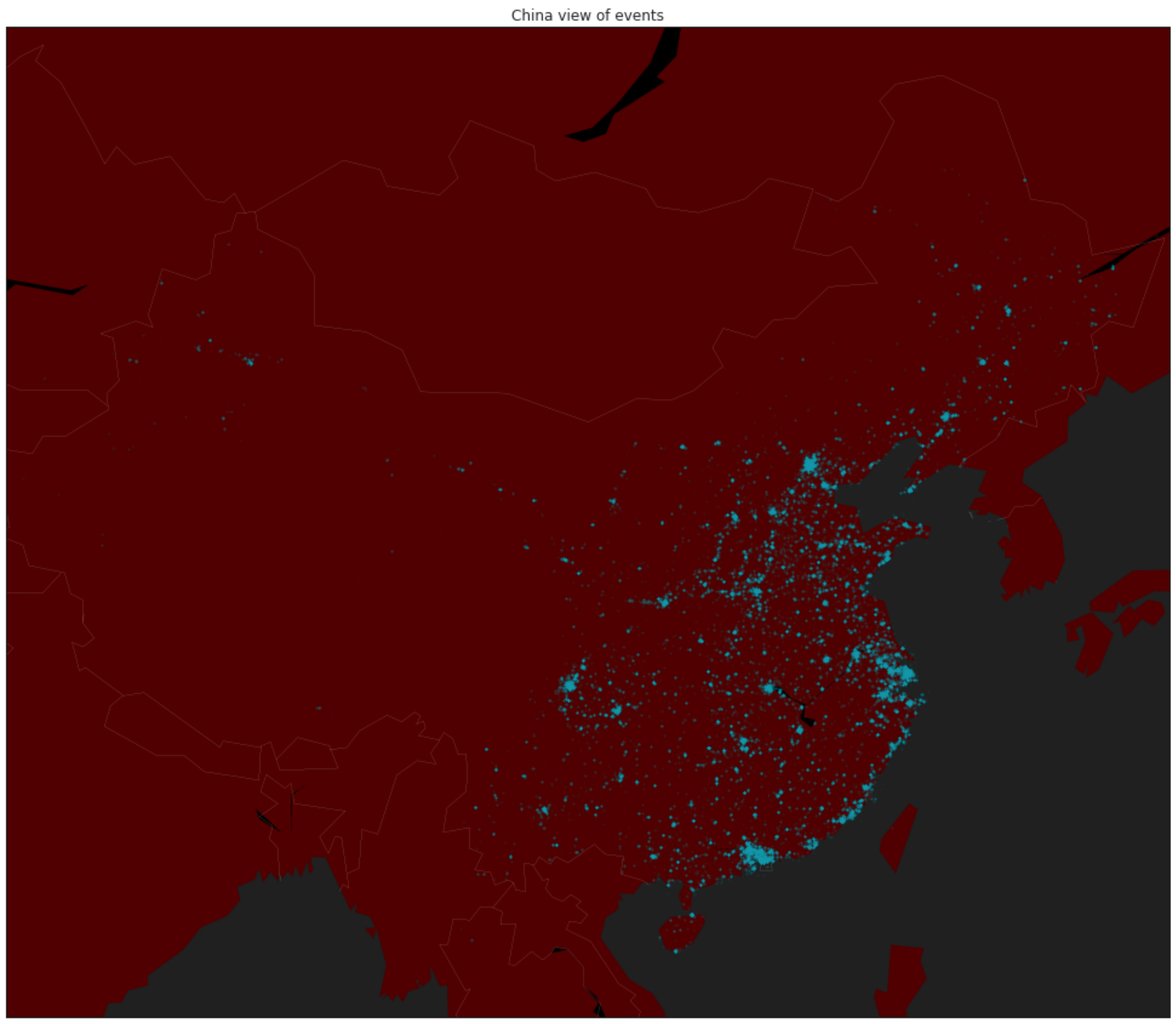
In [19]:
```
df_at0 = df_events[(df_events["longitude"]==0) & (df_events["latitude"]==0
)]
df_near0 = df_events[(df_events["longitude"]>-1) &\
                     (df_events["longitude"]<1) &\
                     (df_events["latitude"]>-1) &\
                     (df_events["latitude"]<1)]

print("Total number of events:", len(df_events))
print("Number of events at (0,0):", len(df_at0))
print("Number of events near (0,0):", len(df_near0))
```

```
Total number of events: 3252950
Number of events at (0,0): 968675
Number of events near (0,0): 969871
```

Locations of events - zooming in region of China

In [20]:
```
# Locate China region
lon_min, lon_max = 75, 135
lat_min, lat_max = 15, 55

idx_china = (df_events["longitude"]>lon_min) &\
            (df_events["longitude"]<lon_max) &\
            (df_events["latitude"]>lat_min) &\
            (df_events["latitude"]<lat_max)

df_events_china = df_events[idx_china].sample(n=100000)

# China
plt.figure(2, figsize=(20,15))

map_zoom = Basemap(projection='merc',
             llcrnrlat=lat_min,
             urcrnrlat=lat_max,
             llcrnrlon=lon_min,
             urcrnrlon=lon_max,
             lat_ts=35,
             resolution='c')

map_zoom.fillcontinents(color='#500000',lake_color='#000000') # dark grey l
and, black lakes
map_zoom.drawmapboundary(fill_color='#202020')                # black backg
round
map_zoom.drawcountries(linewidth=0.1, color="w")              # thin white
 line for country borders


# Plot the data
mxy = map_zoom(df_events_china["longitude"].tolist(), df_events_china["lati
tude"].tolist())
map_zoom.scatter(mxy[0], mxy[1], s=5, c="#12AABB", lw=0, alpha=0.05, zorder
=5)

plt.title("China view of events")
plt.show()
```

```
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1767: MatplotlibDeprecationWarning: The get_axis_bgcolor function was dep
recated in version 2.0. Use get_facecolor instead.
  axisbgc = ax.get_axis_bgcolor()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1698: MatplotlibDeprecationWarning: The axesPatch function was deprecated
in version 2.1. Use Axes.patch instead.
  limb = ax.axesPatch
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3222: MatplotlibDeprecationWarning: The ishold function was deprecated in
version 2.0.
  b = ax.ishold()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3231: MatplotlibDeprecationWarning: axes.hold is deprecated.
    See the API Changes document (http://matplotlib.org/api/api_changes.htm
l)
    for more details.
  ax.hold(b)
```

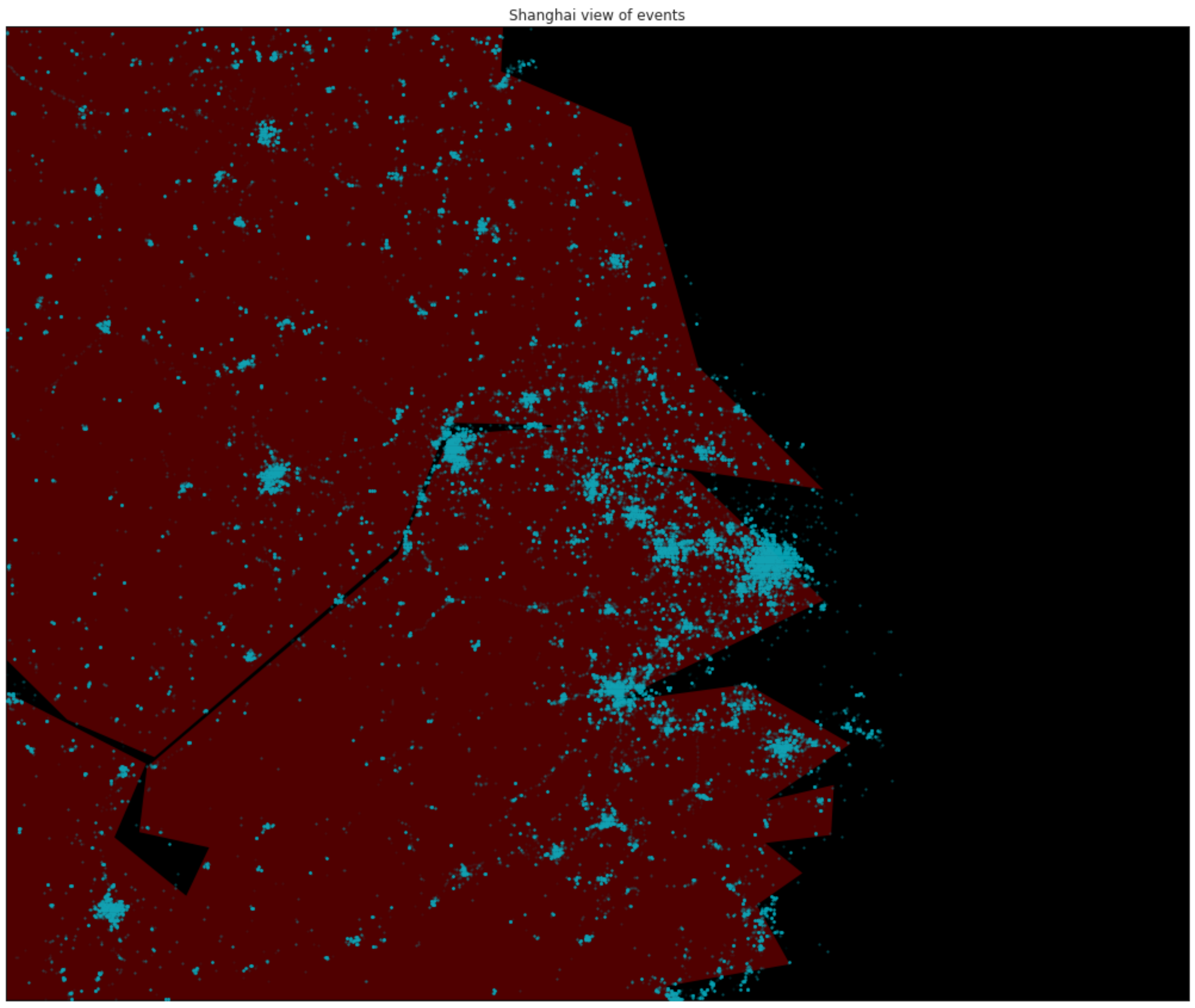


This map nicely shows population density of China. We'll analyze one city region in this case we'll take Shanghai. What follows are maps that are showing longitude and latitude areas. In same way, we can zoom on any area on earth for showing more details in that area.

Locations of applications events - region of Shanghai

In [21]:
```
# Shanghai sits on 31.2304° N, 121.4737° E
# Sampling wider Shanghai region
lon_min, lon_max = 115, 125
lat_min, lat_max = 28, 35

idx_shanghai = (df_events["longitude"]>lon_min) &\
              (df_events["longitude"]<lon_max) &\
              (df_events["latitude"]>lat_min) &\
              (df_events["latitude"]<lat_max)

df_events_shanghai = df_events[idx_shanghai]

# Map of Shanghai region
plt.figure(3, figsize=(20,15))

m_shanghai = Basemap(projection='merc',
             llcrnrlat=lat_min,
             urcrnrlat=lat_max,
             llcrnrlon=lon_min,
             urcrnrlon=lon_max,
             lat_ts=35,
             resolution='c')

m_shanghai.fillcontinents(color='#500000',lake_color='#000000') # dark lan
d, black lakes
m_shanghai.drawmapboundary(fill_color='#000000')                # black bac
kground
m_shanghai.drawcountries(linewidth=0.1, color="w")              # white lin
e for country borders

# Plot the data
mxy = m_shanghai(df_events_shanghai["longitude"].tolist(), df_events_shangh
ai["latitude"].tolist())
m_shanghai.scatter(mxy[0], mxy[1], s=5, c="#12AABB", lw=0, alpha=0.1, zorde
r=5)

plt.title("Shanghai view of events")
plt.show()
```

```
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1767: MatplotlibDeprecationWarning: The get_axis_bgcolor function was dep
recated in version 2.0. Use get_facecolor instead.
  axisbgc = ax.get_axis_bgcolor()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1698: MatplotlibDeprecationWarning: The axesPatch function was deprecated
in version 2.1. Use Axes.patch instead.
  limb = ax.axesPatch
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3222: MatplotlibDeprecationWarning: The ishold function was deprecated in
version 2.0.
  b = ax.ishold()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3231: MatplotlibDeprecationWarning: axes.hold is deprecated.
    See the API Changes document (http://matplotlib.org/api/api_changes.htm
l)
    for more details.
  ax.hold(b)
```



We can see that population around big cities is very disperssed.

Now we'll show male and female app events

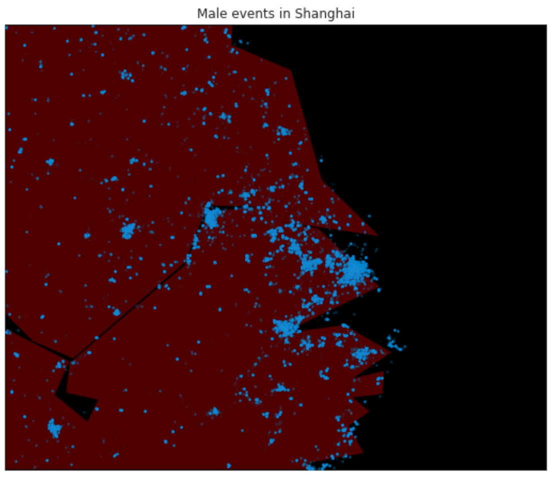
Male and female app events in region of Shanghai

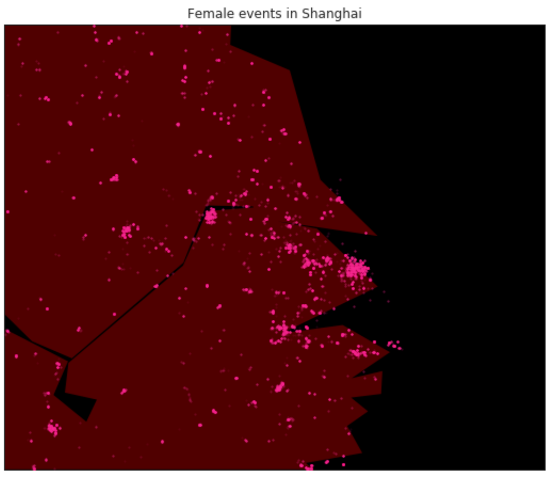
In [22]:
```
# Load the train data and join on the events
df_train = pd.read_csv("data/gender_age_train.csv", dtype={'device_id': np.
str})

df_plot = pd.merge(df_train, df_events_shanghai, on="device_id", how="inne
r")

df_m = df_plot[df_plot["gender"]=="M"]
df_f = df_plot[df_plot["gender"]=="F"]
```

Visualize male and female events in Shanghai

In [23]:
```
# Female and male plot

plt.figure(4, figsize=(20,10))

plt.subplot(121)
m_sh_m = Basemap(projection='merc',
             llcrnrlat=lat_min,
             urcrnrlat=lat_max,
             llcrnrlon=lon_min,
             urcrnrlon=lon_max,
             lat_ts=35,
             resolution='c')
m_sh_m.fillcontinents(color='#500000',lake_color='#000000') # dark grey lan
d, black lakes
m_sh_m.drawmapboundary(fill_color='#000000')                # black backgro
und
m_sh_m.drawcountries(linewidth=0.1, color="w")              # thin white li
ne for country borders
mxy = m_sh_m(df_m["longitude"].tolist(), df_m["latitude"].tolist())
m_sh_m.scatter(mxy[0], mxy[1], s=5, c="#1292db", lw=0, alpha=0.1, zorder=5)
plt.title("Male events in Shanghai")

plt.subplot(122)
m_sh_f = Basemap(projection='merc',
             llcrnrlat=lat_min,
             urcrnrlat=lat_max,
             llcrnrlon=lon_min,
             urcrnrlon=lon_max,
             lat_ts=35,
             resolution='c')
m_sh_f.fillcontinents(color='#500000',lake_color='#000000') # dark grey lan
d, black lakes
m_sh_f.drawmapboundary(fill_color='#000000')                # black backgro
und
m_sh_f.drawcountries(linewidth=0.1, color="w")              # thin white li
ne for country borders
mxy = m_sh_f(df_f["longitude"].tolist(), df_f["latitude"].tolist())
m_sh_f.scatter(mxy[0], mxy[1], s=5, c="#fd3096", lw=0, alpha=0.1, zorder=5)
plt.title("Female events in Shanghai")

plt.show()
```

```
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1767: MatplotlibDeprecationWarning: The get_axis_bgcolor function was dep
recated in version 2.0. Use get_facecolor instead.
  axisbgc = ax.get_axis_bgcolor()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1698: MatplotlibDeprecationWarning: The axesPatch function was deprecated
in version 2.1. Use Axes.patch instead.
  limb = ax.axesPatch
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3222: MatplotlibDeprecationWarning: The ishold function was deprecated in
version 2.0.
  b = ax.ishold()
/root/anaconda3/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:3231: MatplotlibDeprecationWarning: axes.hold is deprecated.
    See the API Changes document (http://matplotlib.org/api/api_changes.htm
l)
    for more details.
  ax.hold(b)
```





For marketing analysis, this might be interesting for further exploration. Which city areas are showing more men activities and which are showing more female activities and in which times of day?

Analysis

Problem classification

Our task is to build a model predicting users' demographic characteristics based on their app usage, geolocation, and mobile device properties. So we need to solv multiclass classification problem This is case where one label needs to be predicted based on several others.

Logistic regression

Logistic regression alghoritham could be obvious choice for that. In the multiclass case, the training algorithm uses the one-vs-rest (OvR) scheme.

In [24]:
```
from sklearn.preprocessing import LabelEncoder
from scipy.sparse import csr_matrix, hstack
from sklearn.linear_model import LogisticRegression
from sklearn.cross_validation import StratifiedKFold
from sklearn.metrics import log_loss
```

```
/root/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favor of
the model_selection module into which all the refactored classes and functi
ons are moved. Also note that the interface of the new CV iterators are dif
ferent from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Loading of data

In [25]:
```
# Read gender Train and Test data
datadir = 'data'
g_a_train = pd.read_csv(os.path.join(datadir,'gender_age_train.csv'),index_
col='device_id')
g_a_test = pd.read_csv(os.path.join(datadir,'gender_age_test.csv'),index_co
l = 'device_id')
phone = pd.read_csv(os.path.join(datadir,'phone_brand_device_model.csv'))

print(g_a_train.head())
print("---------")
print(g_a_test.head())
print("---------")
print(phone.head())
```

```
                     gender  age   group
device_id
-8076087639492063270  M      35   M32-38
-2897161552818060146  M      35   M32-38
-8260683887967679142  M      35   M32-38
-4938849341048082022  M      30   M29-31
 245133531816851882   M      30   M29-31
---------
Empty DataFrame
Columns: []
Index: [1002079943728939269, -1547860181818787117, 7374582448058474277, -62
20210354783429585, -5893464122623104785]
---------
             device_id phone_brand   device_model
0 -8890648629457979026  小米          红米
1  1277779817574759137  小米          MI 2
2  5137427614288105724  三星          Galaxy S4
3  3669464369358936369  SUGAR       时尚手机
4 -5019277647504317457  三星          Galaxy Note 2
```

In [26]:
```
# Remove duplicate device ids in the phones
phone = phone.drop_duplicates(subset=['device_id'], keep='first').set_index
('device_id')
events = pd.read_csv('data/events.csv',parse_dates=['timestamp'],index_col=
'event_id')
appevents = pd.read_csv('data/app_events.csv',usecols=['event_id','app_id',
'is_active'],dtype={'is_active':bool})
applabels = pd.read_csv('data/app_labels.csv')
```

```
/root/anaconda3/lib/python3.6/site-packages/numpy/lib/arraysetops.py:463: F
utureWarning: elementwise comparison failed; returning scalar instead, but
in the future will perform elementwise comparison
  mask |= (ar1 == a)
```

In [27]:
```
print(phone.head())
print("---------")
print(events.head())
print("---------")
print(appevents.head())
print("---------")
print(applabels.head())
print("---------")
```

```
                     phone_brand   device_model
device_id
-8890648629457979026  小米          红米
 1277779817574759137  小米          MI 2
 5137427614288105724  三星          Galaxy S4
 3669464369358936369  SUGAR       时尚手机
-5019277647504317457  三星          Galaxy Note 2
---------
                    device_id           timestamp  longitude  latitude
event_id
1         29182687948017175   2016-05-01 00:55:25  121.38     31.24
2        -6401643145415154744 2016-05-01 00:54:12  103.65     30.97
3        -4833982096941402721 2016-05-01 00:08:05  106.60     29.70
4        -6815121365017318426 2016-05-01 00:06:40  104.27     23.28
5        -5373797595892518570 2016-05-01 00:07:18  115.88     28.66
---------
   event_id               app_id  is_active
0  2         5927333115845830913  True
1  2        -5720078949152207372  False
2  2        -1633887856876571208  False
3  2        -653184325010919369   True
4  2         8693964245073640147  True
---------
                app_id  label_id
0  7324884708820027918  251
1 -4494216993218550286  251
2  6058196446775239644  406
3  6058196446775239644  407
4  8694625920731541625  406
---------
```

Main feature selection

Main features chosen are:

- phone brand
- device model
- installed apps
- app labels

We need to one-hot encode everything and put in sparse matrices which will help deal with a very large number of features. Regarding "Phone brand" feature; we'll make two columns that show which train or test set row a particular device_id belongs to.

In [28]:
```
g_a_train['trainr'] = np.arange(g_a_train.shape[0])
g_a_test['testr'] = np.arange(g_a_test.shape[0])
```

In [29]:
```
print(g_a_train.head())
print("---------")
print(g_a_test.head())
```

```
                      gender  age   group  trainr
device_id
-8076087639492063270   M      35   M32-38  0
-2897161552818060146   M      35   M32-38  1
-8260683887967679142   M      35   M32-38  2
-4938849341048082022   M      30   M29-31  3
 245133531816851882    M      30   M29-31  4
---------
                       testr
device_id
 1002079943728939269   0
-1547860181818787117   1
 7374582448058474277   2
-6220210354783429585   3
-5893464122623104785   4
```

Constructing sparse matrix of features in following wasy:

csr_matrix((data, (row_ind, col_ind)), [shape=(M, N)]) where `data`, `row_ind` and `col_ind` satisfy the relationship `a[row_ind[k], col_ind[k]] = data[k]`

This allows us to define what values to put into certain places in a sparse matrix. For phone brand data the data array will be all ones, row_ind will be the row number of a device and col_ind will be the number of brand.

Brand features

In [30]:
```
brand_encoder = LabelEncoder().fit(phone.phone_brand)
phone['brand'] = brand_encoder.transform(phone['phone_brand'])
g_a_train['brand'] = phone['brand']
g_a_test['brand'] = phone['brand']
Xtr_brand = csr_matrix((np.ones(g_a_train.shape[0]),(g_a_train.trainr, g_a_
train.brand)))
Xte_brand = csr_matrix((np.ones(g_a_test.shape[0]),(g_a_test.testr,g_a_test
.brand)))
print('Brand features: train shape {}, test shape {}'.format(Xtr_brand.shap
e, Xte_brand.shape))
```

```
Brand features: train shape (74645, 131), test shape (112071, 131)
```

Device model

In [70]:
```
phone_model = phone.phone_brand.str.cat(phone.device_model)
model_encoder = LabelEncoder().fit(phone_model)
phone['model'] = model_encoder.transform(phone_model)
g_a_train['model'] = phone['model']
g_a_test['model'] = phone['model']
Xtr_model = csr_matrix((np.ones(g_a_train.shape[0]),
                       (g_a_train.trainr, g_a_train.model)))
Xte_model = csr_matrix((np.ones(g_a_test.shape[0]),
                       (g_a_test.testr, g_a_test.model)))
print('Device model features: train shape {}, test shape {}'.format(Xtr_mod
el.shape, Xte_model.shape))
```

```
Device model features: train shape (74645, 1667), test shape (112071, 1667)
```

Installed apps features

For each device we want to have list of installed applications. So we'll have as many feature columns as there are distinct apps.

Apps are linked to devices through events. So we'll do the following:

merge device_id column from events table to app_events group the resulting dataframe by device_id and app and aggregate merge in trainrow and testrow columns to know at which row to put each device in the features matrix

In [32]:
```
apps_encoder = LabelEncoder().fit(appevents.app_id)
appevents['app'] = apps_encoder.transform(appevents.app_id)
napps = len(apps_encoder.classes_)
deviceapps = (appevents.merge(events[['device_id']], how='left',left_on='ev
ent_id',right_index=True)
                       .groupby(['device_id','app'])['app'].agg(['size'])
                       .merge(g_a_train[['trainr']], how='left', left_index
=True, right_index=True)
                       .merge(g_a_test[['testr']], how='left', left_index=T
rue, right_index=True)
                       .reset_index())
```

In [33]:
```
deviceapps.head()
```

Out[33]:

	device_id	app	size	trainr	testr
0	-9222956879900151005	548	18	21594.0	NaN
1	-9222956879900151005	1096	18	21594.0	NaN
2	-9222956879900151005	1248	26	21594.0	NaN
3	-9222956879900151005	1545	12	21594.0	NaN
4	-9222956879900151005	1664	18	21594.0	NaN

Next step is to build a feature matrix. Data will be all ones, row_ind comes from trainr or testr and col_ind is the label-encoded app_id.

In [36]:
```
dfm = deviceapps.dropna(subset=['trainr'])
Xtr_app = csr_matrix((np.ones(dfm.shape[0]), (dfm.trainr, dfm.app)),
                      shape=(g_a_train.shape[0],napps))
dfm = deviceapps.dropna(subset=['testr'])
Xte_app = csr_matrix((np.ones(dfm.shape[0]), (dfm.testr, dfm.app)),
                      shape=(g_a_test.shape[0],napps))
print('Apps data: train shape {}, test shape {}'.format(Xtr_app.shape, Xte_
app.shape))
```

```
Apps data: train shape (74645, 19237), test shape (112071, 19237)
```

App labels features

We can create app labels merging app_labels with the deviceapps dataframe.

In [40]:
```
applabels = applabels.loc[applabels.app_id.isin(appevents.app_id.unique())]
applabels['app'] = apps_encoder.transform(applabels.app_id)
labelencoder = LabelEncoder().fit(applabels.label_id)
applabels['label'] = labelencoder.transform(applabels.label_id)
nlabels = len(labelencoder.classes_)
```

In [41]:
```
devicelabels = (deviceapps[['device_id','app']]
                .merge(applabels[['app','label']])
                .groupby(['device_id','label'])['app'].agg(['size'])
                .merge(g_a_train[['trainr']], how='left', left_index=True,
right_index=True)
                .merge(g_a_test[['testr']], how='left', left_index=True, ri
ght_index=True)
                .reset_index())
```

In [42]:
```
devicelabels.head()
```

Out[42]:

	device_id	label	size	trainr	testr
0	-9222956879900151005	117	1	21594.0	NaN
1	-9222956879900151005	120	1	21594.0	NaN
2	-9222956879900151005	126	1	21594.0	NaN
3	-9222956879900151005	138	2	21594.0	NaN
4	-9222956879900151005	147	2	21594.0	NaN

In [45]:
```
dfm = devicelabels.dropna(subset=['trainr'])
Xtr_label = csr_matrix((np.ones(dfm.shape[0]), (dfm.trainr, dfm.label)),
                      shape=(g_a_train.shape[0],nlabels))
dfm = devicelabels.dropna(subset=['testr'])
Xte_label = csr_matrix((np.ones(dfm.shape[0]), (dfm.testr, dfm.label)),
                      shape=(g_a_test.shape[0],nlabels))
print('Labels data: train shape {}, test shape {}'.format(Xtr_label.shape,
Xte_label.shape))
```

```
Labels data: train shape (74645, 492), test shape (112071, 492)
```

Features concatenation

In [46]:
```
Xtrain = hstack((Xtr_brand, Xtr_model, Xtr_app, Xtr_label), format='csr')
Xtest =  hstack((Xte_brand, Xte_model, Xte_app, Xte_label), format='csr')
print('All features: train shape {}, test shape {}'.format(Xtrain.shape, Xt
est.shape))
```

```
All features: train shape (74645, 21527), test shape (112071, 21527)
```

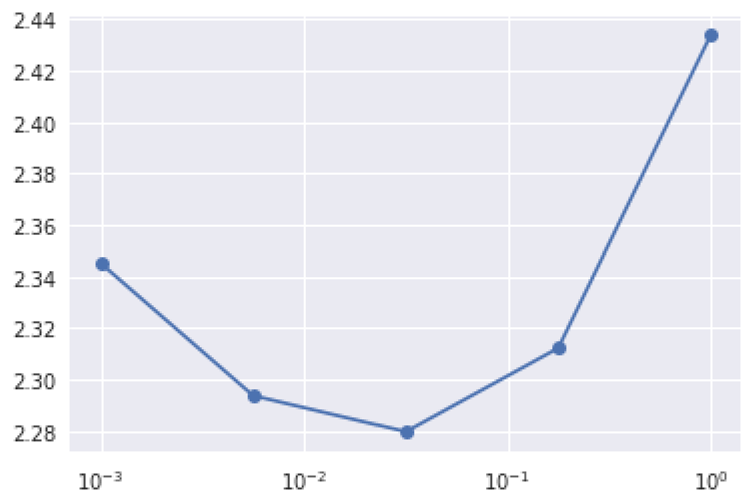
Performing cross-validation

In [48]:
```
targ_encoder = LabelEncoder().fit(g_a_train.group)
y = targ_encoder.transform(g_a_train.group)
nclasses = len(targ_encoder.classes_)
```

```
In [50]: # Defining loss- score function
         def score(clf, random_state = 0):
             kf = StratifiedKFold(y, n_folds=5, shuffle=True, random_state=random_st
         ate)
             pred = np.zeros((y.shape[0],nclasses))
             for itrain, itest in kf:
                 Xtr, Xte = Xtrain[itrain, :], Xtrain[itest, :]
                 ytr, yte = y[itrain], y[itest]
                 clf.fit(Xtr, ytr)
                 pred[itest,:] = clf.predict_proba(Xte)

                 # Resize to one fold (for kernels)
                 return log_loss(yte, pred[itest, :])
                 print("{:.5f}".format(log_loss(yte, pred[itest,:])), end=' ')
             print('')
             return log_loss(y, pred)
```

We've tested values for regularization constant C. Since there is probably a lot of columns which are not so important (rare apps or models of brands) we are probably going to get better score with stronger regularization which means that C value will probably going to be below 1.

```
In [61]: cvalue = np.logspace(-3,0,5)
         res = []
         for C in cvalue:
             res.append(score(LogisticRegression(C = C)))
         plt.semilogx(cvalue, res,'-o');
```



So it looks like the best value for C could between 0.01 and 0.1.

```
In [63]: score(LogisticRegression(C=0.01))

Out[63]: 2.2848755470140127
```

```
In [55]: score(LogisticRegression(C=0.02))

Out[55]: 2.2797068236722908
```

```
In [64]: score(LogisticRegression(C=0.03))

Out[64]: 2.2796060828323981
```

```
In [65]: score(LogisticRegression(C=0.04))

Out[65]: 2.2809556715503021
```

```
In [66]: score(LogisticRegression(C=0.05))

Out[66]: 2.2828903616369471
```

LogisticRegression classifier solves multiclass classification problem -in form of one versus rest fashion. But we can also fit a multinomial model that optimizes the multiclass logloss like in our case. We could improve results using this scenario since this is our exact setup.

```
In [62]: score(LogisticRegression(C=0.02, multi_class='multinomial',solver='saga'))

         /root/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/sag.py:32
         6: ConvergenceWarning: The max_iter was reached which means the coef_ did n
         ot converge
           "the coef_ did not converge", ConvergenceWarning)

Out[62]: 2.2733450166849916
```

```
In [67]: score(LogisticRegression(C=0.02, multi_class='multinomial',solver='lbfgs'))

Out[67]: 2.273326572493398
```

```
In [68]: score(LogisticRegression(C=0.02, multi_class='multinomial',solver='newton-c
         g'))

Out[68]: 2.2731559680466482
```

```
In [69]: score(LogisticRegression(C=0.02, multi_class='multinomial',solver='sag'))

         /root/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/sag.py:32
         6: ConvergenceWarning: The max_iter was reached which means the coef_ did n
         ot converge
           "the coef_ did not converge", ConvergenceWarning)

Out[69]: 2.273158162504858
```

Test data predictions

```
In [57]: clf = LogisticRegression(C=0.02, multi_class='multinomial',solver='lbfgs')
         clf.fit(Xtrain, y)
         pred = pd.DataFrame(clf.predict_proba(Xtest), index = g_a_test.index, colum
         ns=targ_encoder.classes_)
```

In [58]:
```
pred.head()
```

Out[58]:

	F23-	F24-26	F27-28	F29-32	F33-42	F43+	M2
device_id							
1002079943728939269	0.001424	0.005998	0.013605	0.013286	0.025313	0.046103	0.01
-1547860181818787117	0.007414	0.013299	0.031228	0.058677	0.072686	0.151391	0.00
7374582448058474277	0.023158	0.036713	0.036233	0.158343	0.162774	0.079852	0.01
-6220210354783429585	0.003474	0.030860	0.008801	0.012351	0.050697	0.172943	0.04
-5893464122623104785	0.046952	0.065640	0.042578	0.062522	0.056329	0.043467	0.09

Storing best predictions in CSV file

In [59]:
```
pred.to_csv('predictions.csv',index=True)
```