Mounting GDrive directory

In [ ]:
```
from google.colab import drive
drive.mount('/content/gdrive')
%cd '/content/gdrive/MyDrive/Colab Notebooks/UoA_MSDS/Course_8/Capstone1_Ad_
```

```
Mounted at /content/gdrive
/content/gdrive/MyDrive/Colab Notebooks/UoA_MSDS/Course_8/Capstone1_Ad_Campa
ign_Recommender
```

Import libraries

In [ ]:
```
%pip install basemap awscli --quiet
```

```
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 860.7/860.7 kB 5.9 MB/s eta 0:
00:00
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00
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 30.5/30.5 MB 37.8 MB/s eta 0:0
0:00
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11.3/11.3 MB 94.2 MB/s eta 0:0
0:00
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 548.2/548.2 kB 45.7 MB/s eta
0:00:00
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 79.8/79.8 kB 9.3 MB/s eta 0:0
0:00
ERROR: pip's dependency resolver does not currently take into account all th
e packages that are installed. This behaviour is the source of the following
dependency conflicts.
llmx 0.0.15a0 requires cohere, which is not installed.
llmx 0.0.15a0 requires openai, which is not installed.
llmx 0.0.15a0 requires tiktoken, which is not installed.
```

In [ ]:
```
import os
import csv

from IPython.core.display import display, HTML

import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline

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

Subtask 1: Reading data

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- app_events.csv
- train_event_data.csv
- app_events_meta_data.csv
- train_mobile_brand.csv

In [ ]:
```
datasets = {
  'app_events.csv' : 's3://uoacapstone/app_events.csv',
  'train_event_data.csv' : 's3://uoacapstone/train_event_data.csv',
  'app_events_meta_data.csv' : 's3://uoacapstone/app_events_meta_data.csv',
  'train_mobile_brand.csv' : 's3://uoacapstone/train_mobile_brand.csv',
}
```

In [ ]:
```
# Download datasets if not already downloaded
for k,v in datasets.items():
  if not os.path.exists(f'data/{k}'):
    !aws s3 cp "$v" "data/$k" --no-sign-request
```

```
download: s3://uoacapstone/app_events.csv to data/app_events.csv
download: s3://uoacapstone/train_event_data.csv to data/train_event_data.csv
download: s3://uoacapstone/app_events_meta_data.csv to data/app_events_meta_
data.csv
download: s3://uoacapstone/train_mobile_brand.csv to data/train_mobile_bran
d.csv
```

In [ ]:
```
# Load into dataframes, disble quote parsing inside strings when loading
# Ref: https://stackoverflow.com/a/29857126

app_events = pd.read_csv('data/app_events.csv', quoting=csv.QUOTE_NONE)
train_event_data = pd.read_csv('data/train_event_data.csv', quoting=csv.QUOT
app_events_meta_data = pd.read_csv('data/app_events_meta_data.csv', quoting=
train_mobile_brand = pd.read_csv('data/train_mobile_brand.csv', quoting=csv.
```

Subtask 2: Cleaning data

Show some records

In [ ]:
```
for df, label in zip(
    [
        app_events,
        train_event_data,
        app_events_meta_data,
        train_mobile_brand,
    ],
    [
        'app_events',
        'train_event_data',
        'app_events_meta_data',
        'train_mobile_brand',
    ],
):
```

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```
l}</h2>'))
```

```
    display(df.head(5))
    display(HTML('<hr/>'))
```

app_events

	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

---

train_event_data

	device_id	gender	age	group_train	event_id	datetimestamp	latituc
0	-7548291590301750000	M	33	M32+	2369465.0	2016-05-03 15:55:35	33.9
1	-7548291590301750000	M	33	M32+	1080869.0	2016-05-03 06:07:16	33.9
2	-7548291590301750000	M	33	M32+	1079338.0	2016-05-04 03:28:02	33.9
3	-7548291590301750000	M	33	M32+	1078881.0	2016-05-04 02:53:08	33.9
4	-7548291590301750000	M	33	M32+	1068711.0	2016-05-03 15:59:35	33.9

---

app_events_meta_data

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

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train_mobile_brand

	device_id	gender	age	group_train	phone_brand	device_model
0	-7548291590301750000	M	33	M32+	Huawei	è £è€€3C
1	6943568600617760000	M	37	M32+	Xiaomi	xnote
2	5441349705980020000	M	40	M32+	OPPO	R7s
3	-5393876656119450000	M	33	M32+	Xiaomi	MI 4
4	4543988487649880000	M	53	M32+	samsung	Galaxy S4

Check data types and missing values

In [ ]:
```
for df, label in zip(
    [
        app_events,
        train_event_data,
        app_events_meta_data,
        train_mobile_brand,
    ],
    [
        'app_events',
        'train_event_data',
        'app_events_meta_data',
        'train_mobile_brand',
    ],
):
  display(HTML(f'<h2>{label}</h2>'))
  display(df.info())
  display(HTML('<hr/>'))
```

app_events

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32473067 entries, 0 to 32473066
Data columns (total 4 columns):
 #   Column        Dtype
---  ------        -----
 0   event_id      int64
 1   app_id        int64
 2   is_installed  int64
 3   is_active     int64
dtypes: int64(4)
memory usage: 991.0 MB
None
```

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train_event_data

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1266933 entries, 0 to 1266932
Data columns (total 8 columns):
 #   Column         Non-Null Count    Dtype  
---  ------         --------------    -----  
 0   device_id      1266933 non-null  int64  
 1   gender         1266933 non-null  object 
 2   age            1266933 non-null  int64  
 3   group_train    1266933 non-null  object 
 4   event_id       1215598 non-null  float64
 5   datetimestamp  1215598 non-null  object 
 6   latitude       1215598 non-null  float64
 7   longitude      1215598 non-null  float64
dtypes: float64(3), int64(2), object(3)
memory usage: 77.3+ MB
None
```

---

app_events_meta_data

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 459944 entries, 0 to 459943
Data columns (total 3 columns):
 #   Column    Non-Null Count   Dtype 
---  ------    --------------   ----- 
 0   app_id    459944 non-null  object
 1   label_id  459944 non-null  object
 2   category  459944 non-null  object
dtypes: object(3)
memory usage: 10.5+ MB
None
```

---

train_mobile_brand

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74840 entries, 0 to 74839
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   device_id     74840 non-null  int64 
 1   gender        74840 non-null  object
 2   age           74840 non-null  int64 
 3   group_train   74840 non-null  object
 4   phone_brand   74840 non-null  object
 5   device_model  74840 non-null  object
dtypes: int64(2), object(4)
memory usage: 3.4+ MB
None
```

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For labels columns `gender` and `age`, assume there is no mismatch of labels in records with the same device id.

For other columns in the datasets, only `train_event_data` has missing values, and we can easily see that for many records there aren't associated events with them. Let's check again to make sure the missing events and related data are on the same records.

In [ ]:
```
train_event_data[train_event_data['event_id'].isna()].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 51335 entries, 1215595 to 1266932
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   device_id      51335 non-null  int64  
 1   gender         51335 non-null  object 
 2   age            51335 non-null  int64  
 3   group_train    51335 non-null  object 
 4   event_id       0 non-null      float64
 5   datetimestamp  0 non-null      object 
 6   latitude       0 non-null      float64
 7   longitude      0 non-null      float64
dtypes: float64(3), int64(2), object(3)
memory usage: 3.5+ MB
```

That is correct, so there is no missing data in the input datasets

Let's see how many unique device ids that we have:

In [ ]:
```
for df, label in zip(
    [
        train_event_data,
        train_mobile_brand,
        pd.merge(train_event_data, train_mobile_brand, on='device_id', how='
    ],
    [
        'train_event_data',
        'train_mobile_brand',
        'merged',
    ],
):
  display(HTML(f'<h2>{label} unique devices:</h2>'))
  display(df['device_id'].nunique())
  display(HTML('<hr/>'))
```

train_event_data unique devices:

74645

---

train_mobile_brand unique devices:

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merged unique devices:

74645

The devices are the same in both train datasets.

The remaining cleaning is to cast datetime to correct data type

In [ ]:
```
train_event_data['datetimestamp'] = pd.to_datetime(train_event_data['datetim
```

In [ ]:
```
train_event_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1266933 entries, 0 to 1266932
Data columns (total 8 columns):
 #   Column         Non-Null Count    Dtype
---  ------         --------------    -----
 0   device_id      1266933 non-null  int64
 1   gender         1266933 non-null  object
 2   age            1266933 non-null  int64
 3   group_train    1266933 non-null  object
 4   event_id       1215598 non-null  float64
 5   datetimestamp  1215598 non-null  datetime64[ns]
 6   latitude       1215598 non-null  float64
 7   longitude      1215598 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(2), object(2)
memory usage: 77.3+ MB
```

Check statistics for invalid records

In [ ]:
```
for df, label in zip(
    [
        app_events,
        train_event_data,
        app_events_meta_data,
        train_mobile_brand,
    ],
    [
        'app_events',
        'train_event_data',
        'app_events_meta_data',
        'train_mobile_brand',
    ],
):
  display(HTML(f'<h2>{label}</h2>'))
  display(df.describe())
  display(HTML('<h3>unique values:</h3>'))
  display(df.nunique())
  display(HTML('<hr/>'))
```

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app_events

	event_id	app_id	is_installed	is_active
count	3.247307e+07	3.247307e+07	32473067.0	3.247307e+07
mean	1.625564e+06	1.182779e+18	1.0	3.921094e-01
std	9.384682e+05	5.360173e+18	0.0	4.882209e-01
min	2.000000e+00	-9.221157e+18	1.0	0.000000e+00
25%	8.134720e+05	-3.474568e+18	1.0	0.000000e+00
50%	1.626907e+06	1.387044e+18	1.0	0.000000e+00
75%	2.441106e+06	6.043001e+18	1.0	1.000000e+00
max	3.252948e+06	9.222488e+18	1.0	1.000000e+00

unique values:

```
event_id        1488096
app_id            19237
is_installed          1
is_active             2
dtype: int64
```

---

train_event_data

	device_id	age	event_id	latitude	longitude
count	1.266933e+06	1.266933e+06	1.215598e+06	1.215598e+06	1.215598e+06
mean	-2.967925e+16	3.340051e+01	1.626675e+06	2.182751e+01	7.839380e+01
std	5.322606e+18	9.762003e+00	9.396631e+05	1.564827e+01	5.381246e+01
min	-9.223067e+18	1.000000e+00	1.000000e+00	-3.380000e+01	-1.800000e+02
25%	-4.668347e+18	2.600000e+01	8.123205e+05	0.000000e+00	0.000000e+00
50%	-1.115514e+17	3.100000e+01	1.627310e+06	2.857000e+01	1.127500e+02
75%	4.631837e+18	3.900000e+01	2.440380e+06	3.401000e+01	1.171700e+02
max	9.222849e+18	9.600000e+01	3.252948e+06	5.364000e+01	1.511800e+02

unique values:

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```
device_id          74645
gender                 2
age                   85
group_train            6
event_id         1215598
datetimestamp     497663
latitude            2707
longitude           2914
dtype: int64
```

---

app_events_meta_data

	app_id	label_id	category
count	459944	459944	459944
unique	165044	554	472
top	-4550209074213737101	405	Industry tag
freq	22	49391	56902

unique values:

```
app_id      165044
label_id       554
category       472
dtype: int64
```

---

train_mobile_brand

	device_id	age
count	7.484000e+04	74840.000000
mean	2.381650e+14	31.407924
std	5.327486e+18	9.867279
min	-9.223067e+18	1.000000
25%	-4.617637e+18	25.000000
50%	-1.831665e+16	29.000000
75%	4.638645e+18	36.000000
max	9.222849e+18	96.000000

unique values:

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```
device_id       74645
gender              2
age                85
group_train         6
phone_brand        97
device_model     1438
dtype: int64
```

The input data contains valid values but the age range is questionable since minimum age in data is 1 year old.

For coordinate, latitude is within range of [-90, 90] and longitude is withing range [-180, 180] so they are valid values (reference: https://developers.google.com/maps/documentation/javascript/reference/coordinates).

Subtask 3: Basic EDA and visualization and feature engineering ideas

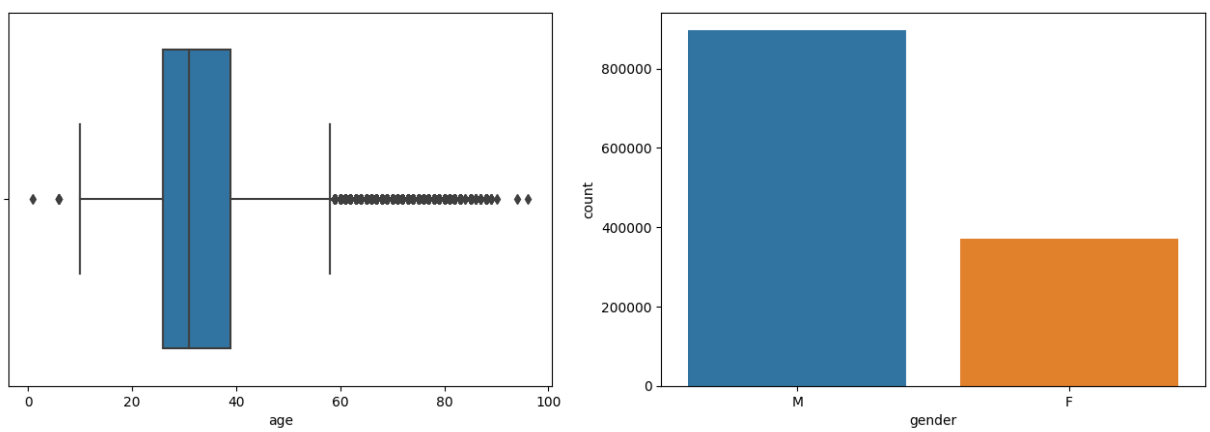
1. Age and gender distribution

In [ ]:
```
# Univariate analysis of age and gender

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16,5))

sns.boxplot(train_event_data, x="age", ax=ax1)
sns.countplot(train_event_data, x='gender', ax=ax2)

plt.show()
```



Most of the data points are people of young age around 20 - 40. Although there is a questionable outliers of "baby" users, we will ignore it for now as it may still be a valid label depends on the domain and labeling rules.

There is an imbalance in gender between male and female. The data points from male

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s from female.

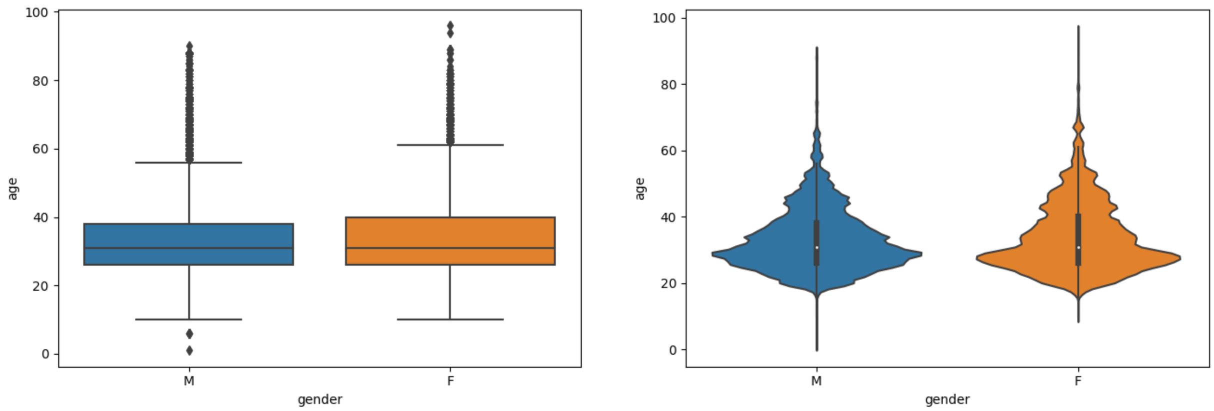
In [ ]:

```
# Bivariate analysis between age and gender

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16,5))

sns.boxplot(train_event_data, x='gender', y='age', ax=ax1)
sns.violinplot(train_event_data, x='gender', y='age', ax=ax2)

plt.show()
```



Male users tend to be a little younger than female users. The majority of users in both male and female groups are young ones.

There are some "baby" users in the male group, possibly due to wrong label. Since they are outliers, we may ignore them for now.

2. Trends in event data

a) Percentage of device ids with and without event data

In [ ]:

```
# Filter out records with empty event_id
devices_with_event_data = (~train_event_data['event_id'].isna())
ax = (
    devices_with_event_data.value_counts() * 100 / devices_with_event_data.c
).plot.bar()
ax.bar_label(ax.containers[0], fmt='%g%%')
plt.title('Percentage of devices with event data')
plt.show()
```

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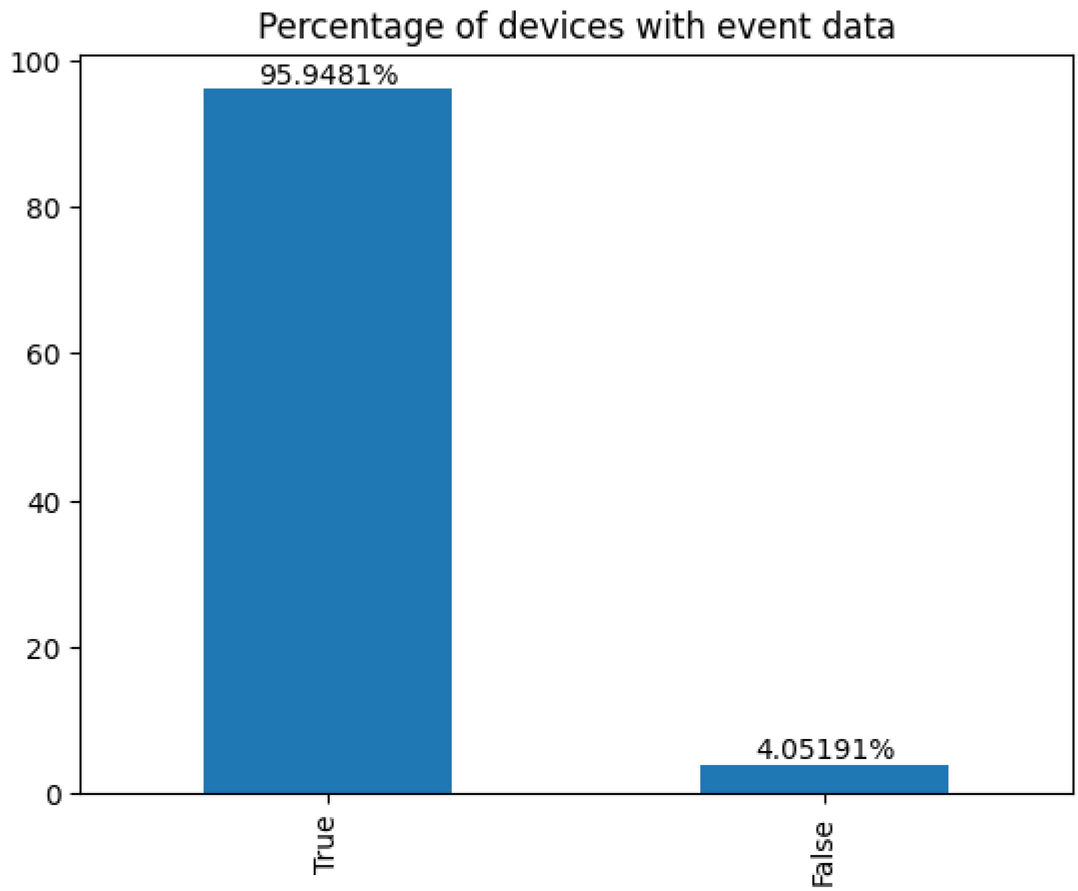

There is only around 4.05% of devices are without event data

b) Distribution of events on different days of week

In [ ]:
```
# Filter out records with empty event_id
events_per_weekday = train_event_data[~train_event_data['event_id'].isna()]
# Get day of week from timestamp
events_per_weekday['Day of week'] = (
    events_per_weekday['datetimestamp']
      .apply(lambda d: d.dayofweek)
)
# Count events on each day of week
events_per_weekday = events_per_weekday.groupby('Day of week')['event_id'].c
# Reset index after grouping to flatten columns
events_per_weekday = events_per_weekday.rename('event_count').reset_index()
events_per_weekday
```

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Out[ ]:

	Day of week	event_count
0	0	169381
1	1	180296
2	2	178371
3	3	180041
4	4	176657
5	5	166835
6	6	164017

In [ ]:

```
ax = sns.barplot(events_per_weekday, y='Day of week', x='event_count', orier
# Map day of week indexes to labels
ax.set_yticks(
    range(7),
    labels=[
        'Monday',
        'Tuesday',
        'Wednesday',
        'Thursday',
        'Friday',
        'Saturday',
        'Sunday',
    ]
)
plt.show()
```

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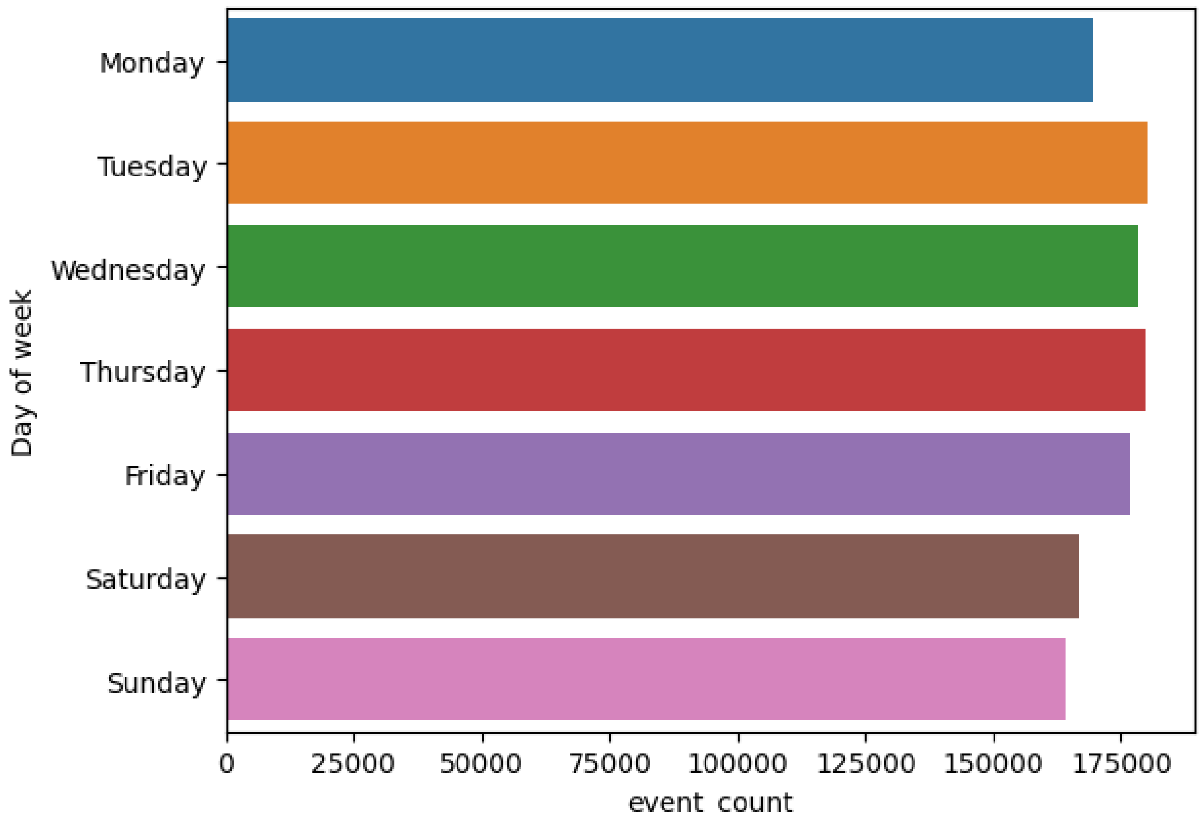

There events are distributed equally over days of week.

c) Distribution of events per hour for one week data

Let's see the distribution of events over entire dataset and pick one week to see hourly event frequency.

In [ ]:
```
# Filter out records with empty event_id
hourly_event_data = train_event_data[~train_event_data['event_id'].isna()]
# Normalize the timestamp to hour unit
hourly_event_data['datetimestamp'] = hourly_event_data['datetimestamp'].dt.t
# Count events for each hour in whole dataset
hourly_event_data = hourly_event_data.groupby('datetimestamp')['event_id'].c
hourly_event_data.to_frame()
```

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Out[ ]:

	event_id
datetimestamp	
2016-04-30 23:00	378
2016-05-01 00:00	6689
2016-05-01 01:00	3961
2016-05-01 02:00	3130
2016-05-01 03:00	2612
...	...
2016-05-07 20:00	8769
2016-05-07 21:00	9529
2016-05-07 22:00	8638
2016-05-07 23:00	6565
2016-05-08 00:00	1

170 rows × 1 columns

In [ ]:

```
hourly_event_data.plot.line()
plt.show()
```

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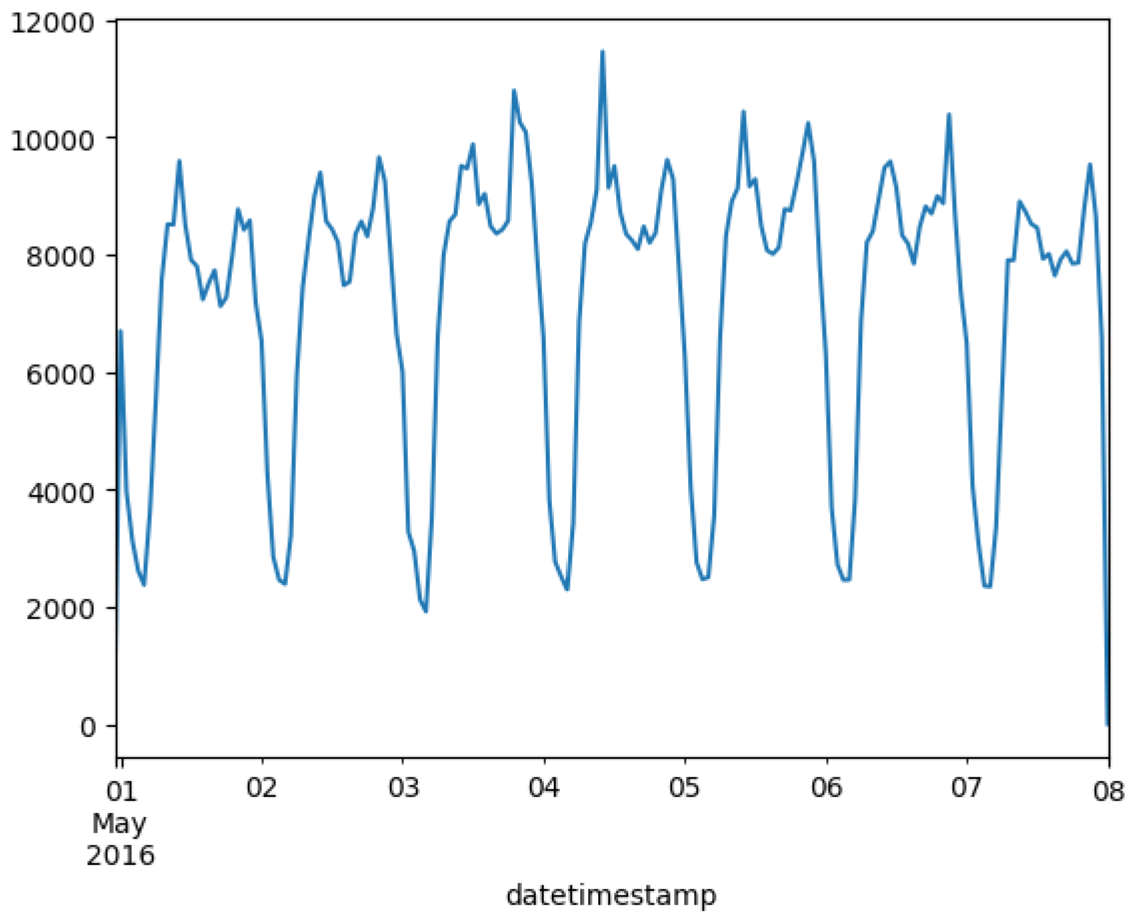

The dataset is already collected within 1 week time range. Let's see the distribution of events hourly for every day in a week.

In [ ]:

```
# Filter out records with empty event_id
one_week_hourly_event_data = train_event_data[~train_event_data['event_id'].
# Normalize the timestamp to hour unit
one_week_hourly_event_data['datetimestamp'] = (
    one_week_hourly_event_data['datetimestamp'].dt.to_period('H')
)
# Group by hour of the day and count events
one_week_hourly_event_data_by_hour = (
    one_week_hourly_event_data
      .groupby(one_week_hourly_event_data['datetimestamp'].dt.hour)['event_i
      .count()
      .reset_index()
      .rename(columns={'datetimestamp': 'Hour of day', 'event_id': 'event_cc
)
one_week_hourly_event_data_by_hour
```

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Out[ ]:

	Hour of day	event_count
0	0	44864
1	1	27090
2	2	20248
3	3	16991
4	4	16282
5	5	24536
6	6	43970
7	7	55583
8	8	59032
9	9	62226
10	10	68578
11	11	62920
12	12	62584
13	13	58304
14	14	56324
15	15	55224
16	16	57002
17	17	58200
18	18	57610
19	19	61947
20	20	65099
21	21	67498
22	22	61978
23	23	51508

In [ ]:

```
sns.lineplot(one_week_hourly_event_data_by_hour, x='Hour of day', y='event_c
plt.show()
```

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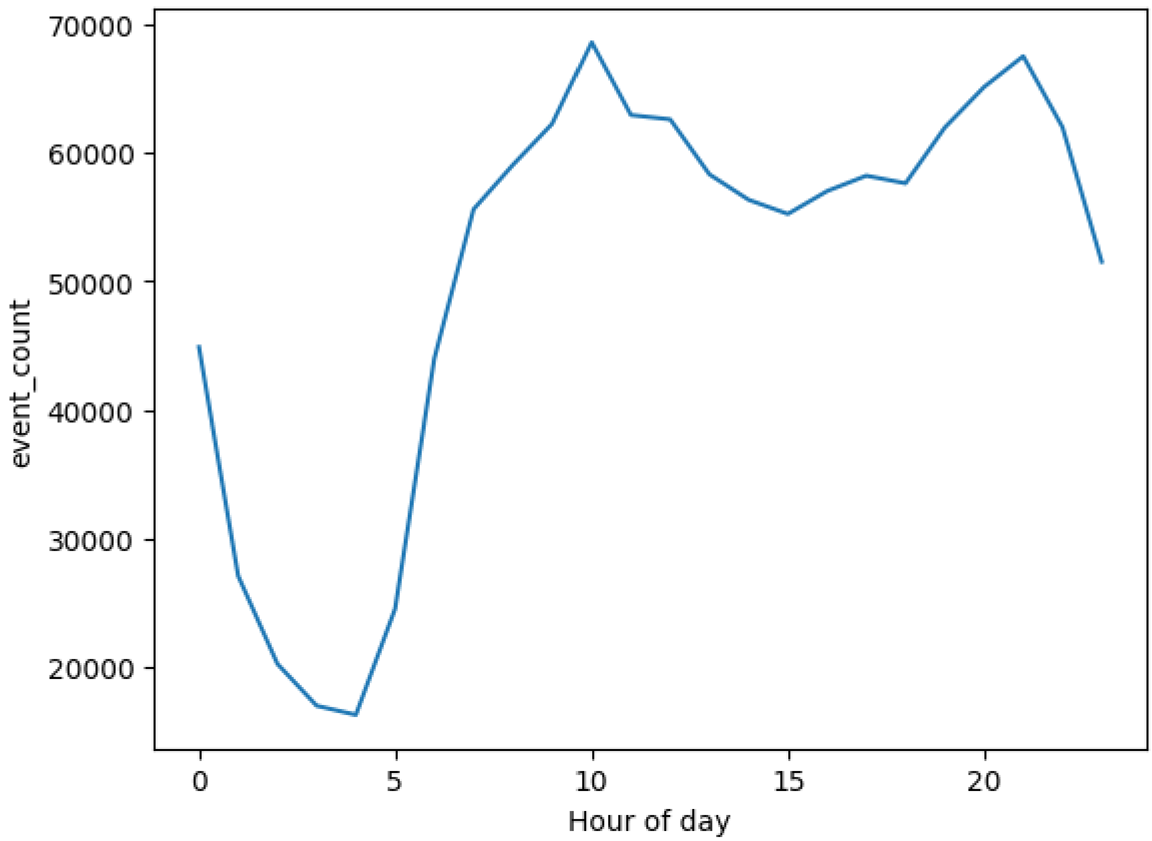

There is a period of low activity during 0h to 5h everyday.

d) Difference in the distribution of events per hour for males and females

In [ ]:
```
# From hourly event data, group by hour of day and gender
hourly_event_by_gender = one_week_hourly_event_data.groupby(
    [
        one_week_hourly_event_data['datetimestamp'].dt.hour,
        'gender',
    ]
)
# Count the events and then flatten columns
hourly_event_by_gender = hourly_event_by_gender['event_id'].count().reset_ir
hourly_event_by_gender = hourly_event_by_gender.rename(columns={
    'datetimestamp': 'Hour of day',
    'event_id': 'event_count',
})
hourly_event_by_gender
```

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Out[ ]:

	Hour of day	gender	event_count
0	0	F	11004
1	0	M	33860
2	1	F	6693
3	1	M	20397
4	2	F	5241
5	2	M	15007
6	3	F	4424
7	3	M	12567
8	4	F	4561
9	4	M	11721
10	5	F	7894
11	5	M	16642
12	6	F	14475
13	6	M	29495
14	7	F	17364
15	7	M	38219
16	8	F	17137
17	8	M	41895
18	9	F	17705
19	9	M	44521
20	10	F	19505
21	10	M	49073
22	11	F	17839
23	11	M	45081
24	12	F	17836
25	12	M	44748
26	13	F	16577
27	13	M	41727
28	14	F	16126
29	14	M	40198
30	15	F	16141
[illegible]	[illegible]	[illegible]	39083

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	Hour of day	gender	event_count
32	16	F	16288
33	16	M	40714
34	17	F	16550
35	17	M	41650
36	18	F	16486
37	18	M	41124
38	19	F	18314
39	19	M	43633
40	20	F	19670
41	20	M	45429
42	21	F	20934
43	21	M	46564
44	22	F	18242
45	22	M	43736
46	23	F	14286
47	23	M	37222

In [ ]:
```
sns.lineplot(hourly_event_by_gender, x='Hour of day', y='event_count', hue='
plt.show()
```

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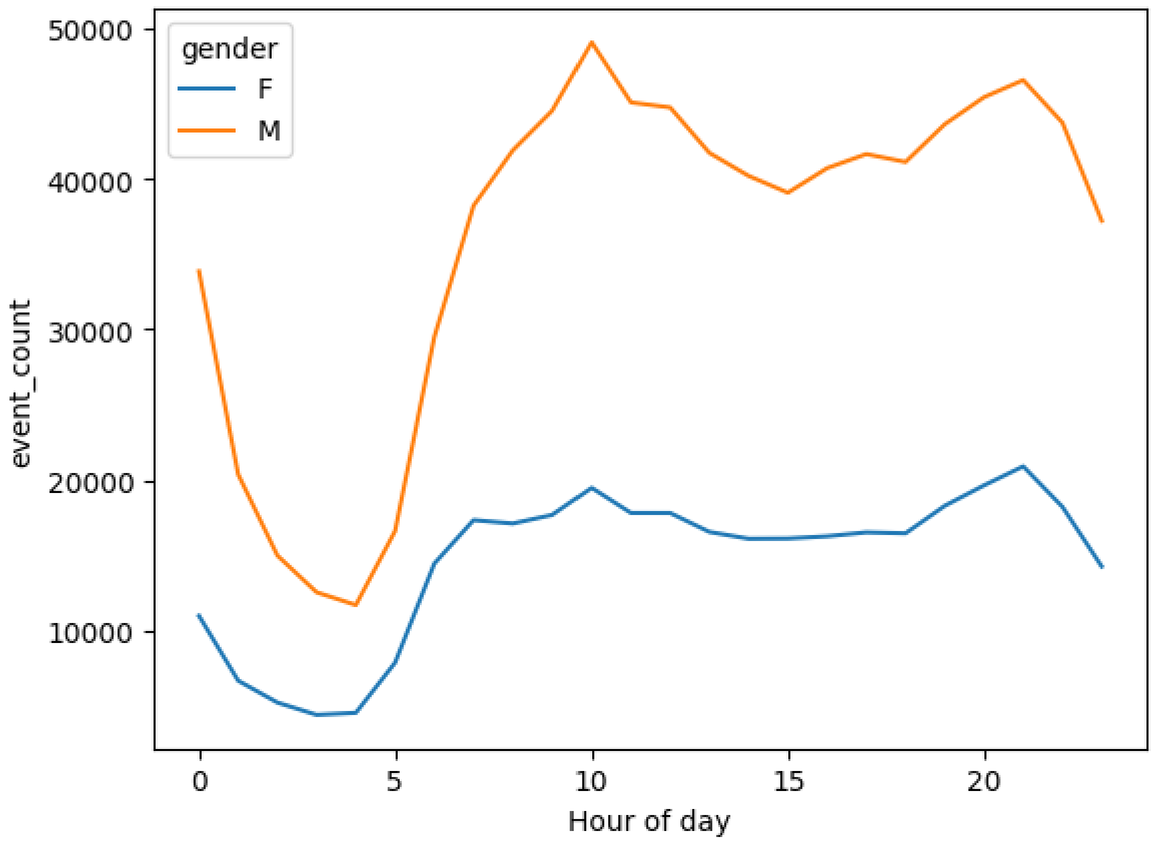

The event frequency of events generated from male user group is higher than female users.

Male users are very active at 10AM. Both male and female are active at around 9PM.

The frequency of events generated from female users are stable from morning to afternoon.

e) Difference in the distribution of events for different age groups over different days of week

In [ ]:

```
# Filter out records with empty event_id
age_group_events_per_weekday = train_event_data[~train_event_data['event_id'
# Get day of week from timestamp
age_group_events_per_weekday['Day of week'] = (
    age_group_events_per_weekday['datetimestamp'].apply(lambda d: d.dayofwee
)
# Create bins of age groups: 0–24, 25–32, 33–45, 46+
age_group_events_per_weekday['age_bin'] = pd.cut(
    age_group_events_per_weekday['age'],
    [0, 24, 32, 45, 100],
)
# Count events per day of week for each age bin
age_group_events_per_weekday = age_group_events_per_weekday.groupby(['Day of
age_group_events_per_weekday = age_group_events_per_weekday.reset_index().re
age_group_events_per_weekday
```

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Out[ ]:

	Day of week	age_bin	event_count
0	0	(0, 24]	27123
1	0	(24, 32]	65877
2	0	(32, 45]	55232
3	0	(45, 100]	21149
4	1	(0, 24]	26144
5	1	(24, 32]	71487
6	1	(32, 45]	59882
7	1	(45, 100]	22783
8	2	(0, 24]	27114
9	2	(24, 32]	69098
10	2	(32, 45]	58851
11	2	(45, 100]	23308
12	3	(0, 24]	26842
13	3	(24, 32]	72543
14	3	(32, 45]	57949
15	3	(45, 100]	22707
16	4	(0, 24]	26975
17	4	(24, 32]	70270
18	4	(32, 45]	57477
19	4	(45, 100]	21935
20	5	(0, 24]	26357
21	5	(24, 32]	65346
22	5	(32, 45]	53836
23	5	(45, 100]	21296
24	6	(0, 24]	24524
25	6	(24, 32]	64899
26	6	(32, 45]	54704
27	6	(45, 100]	19890

In [ ]:

```
ax = sns.barplot(age_group_events_per_weekday, y='Day of week', x='event_cou
# Map day of week indexes to labels
ax.set_yticks(
    range(7)
```

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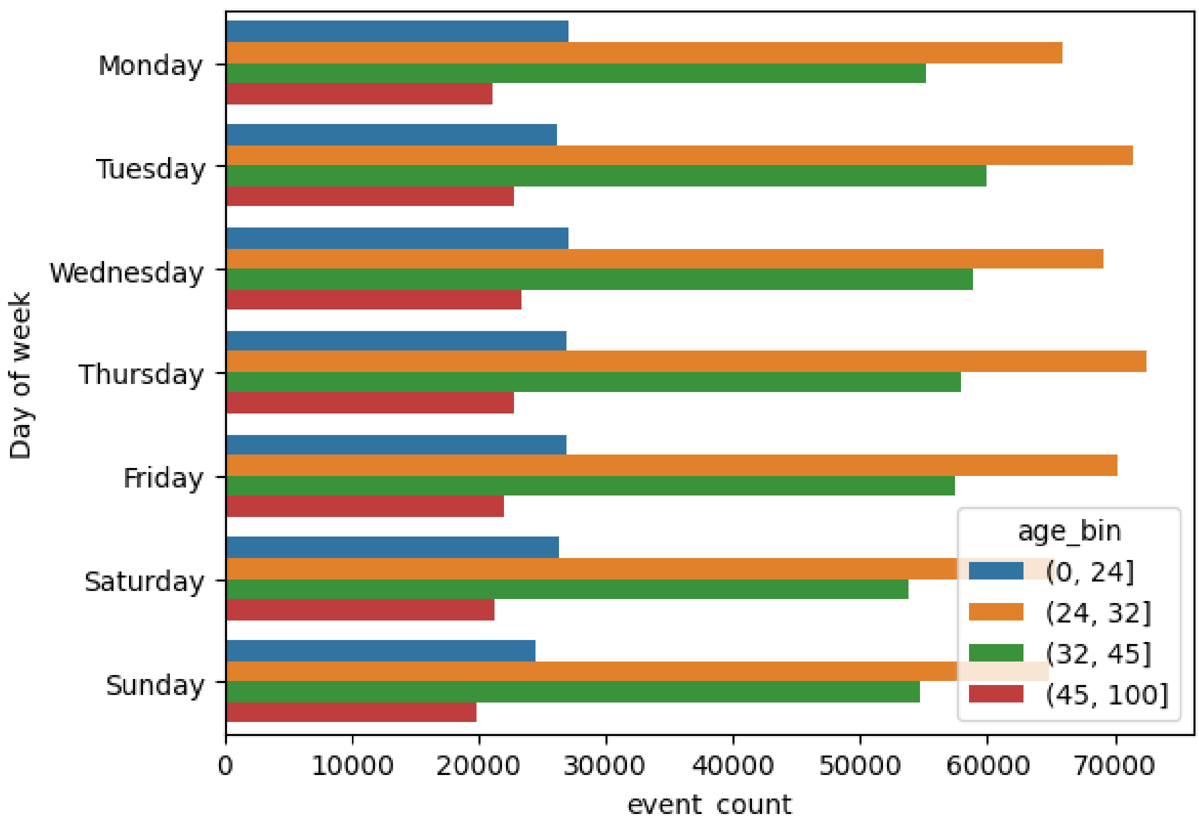
```
    labels=[
        'Monday',
        'Tuesday',
        'Wednesday',
        'Thursday',
        'Friday',
        'Saturday',
        'Sunday',
    ]
)
plt.show()
```



The general trends are not different much between age groups. But, looking at the frequency, the most active age group are persons of age from 25 to 32 years old and decreasing futher to both sides (younger and older).

3. Phone Brand and Application Preferences

a) Top 10 mobile brands across male and female consumers

In [ ]:
```
# Group devices by gender and phone brand then count them
phone_brand_count = train_mobile_brand.groupby(['gender', 'phone_brand'])['p
# Get top 10 brands per gender
top_brands_by_gender = phone_brand_count.groupby('gender').nlargest(10)
# We got duplicate index, so just drop one of them
top_brands_by_gender = top_brands_by_gender.droplevel(0)
# S...                              brand
```

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```
top_brands_by_gender = top_brands_by_gender.swaplevel(0,1)
# Sort descending in order to plot
top_brands_by_gender = top_brands_by_gender.unstack().sort_values(by=['F', '
top_brands_by_gender
```

Out[ ]:

gender	F	M
phone_brand		
Xiaomi	5930	11407
samsung	5443	8263
Huawei	4257	8744
vivo	2660	2998
OPPO	2581	3221
Meizu	1306	3404
Coolpad	1079	2270
lenovo	894	1801
Gionee	403	721
HTC	321	694

In [ ]:

```
top_brands_by_gender.plot.bar(stacked=True)
plt.show()
```

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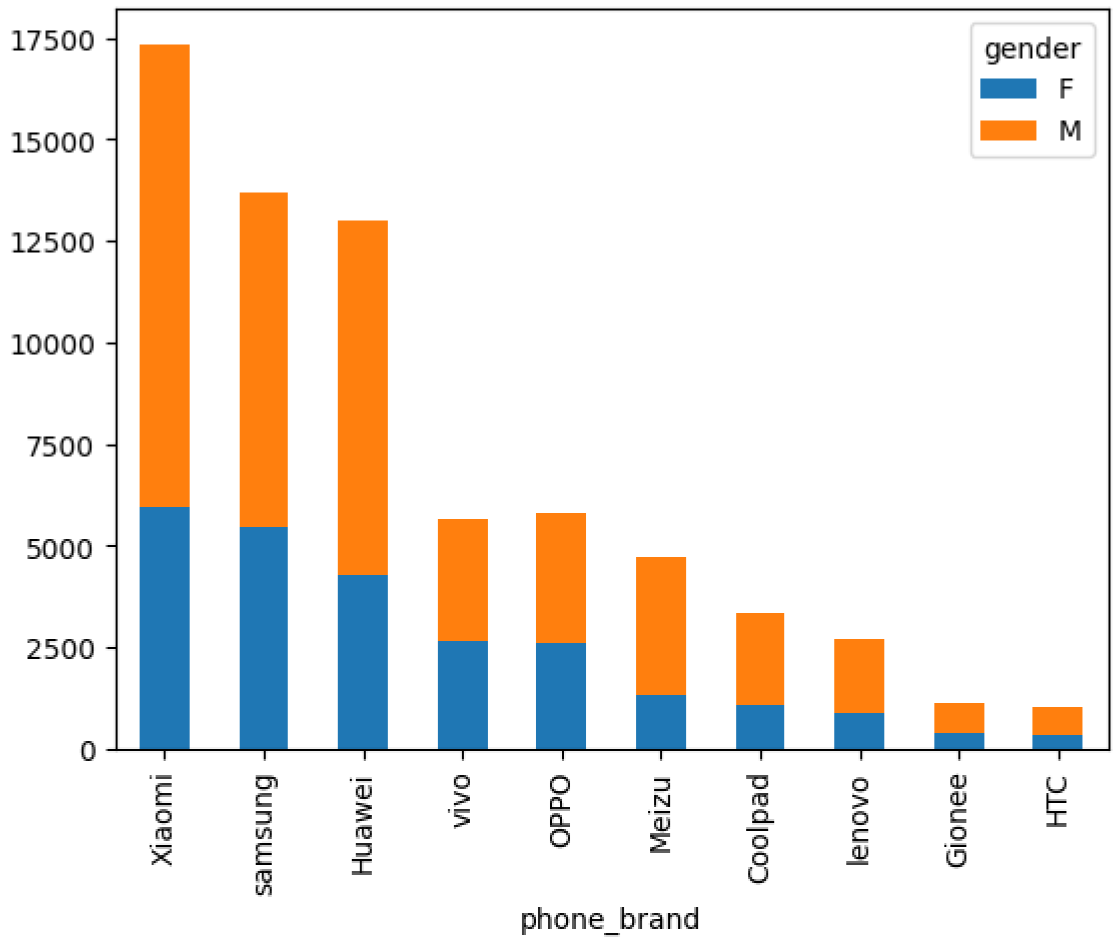

Xiaomi is the most popular brand for both male and female, followed by Samsung in the second place.

b) Top 10 frequent applications and the corresponding percentage of male and female consumers

In [ ]:

```
# Merge train_event_data and app_events to have app_id in dataframe
top_frequent_apps = pd.merge(
    # Filter out records with empty event_id
    train_event_data[~train_event_data['event_id'].isna()]['event_id'],
    app_events[['event_id', 'app_id']],
    on='event_id',
    how='inner',
)
# Just use 2 columns of interest
top_frequent_apps = top_frequent_apps[['event_id', 'app_id']]
# Group and count events per app and keep top 10 apps
top_frequent_apps = top_frequent_apps.groupby('app_id').count().nlargest(10,
# Reset index to flatten columns
top_frequent_apps = top_frequent_apps.reset_index().rename(columns={'event_i
# Mege with metadata to get the categories
top_frequent_apps = pd.merge(top_frequent_apps, app_events_meta_data[['app_i
# Only use 3 columns of interest
top_frequent_apps = top_frequent_apps[['app_id', 'event_count', 'category']]
                                    ing the categories
```

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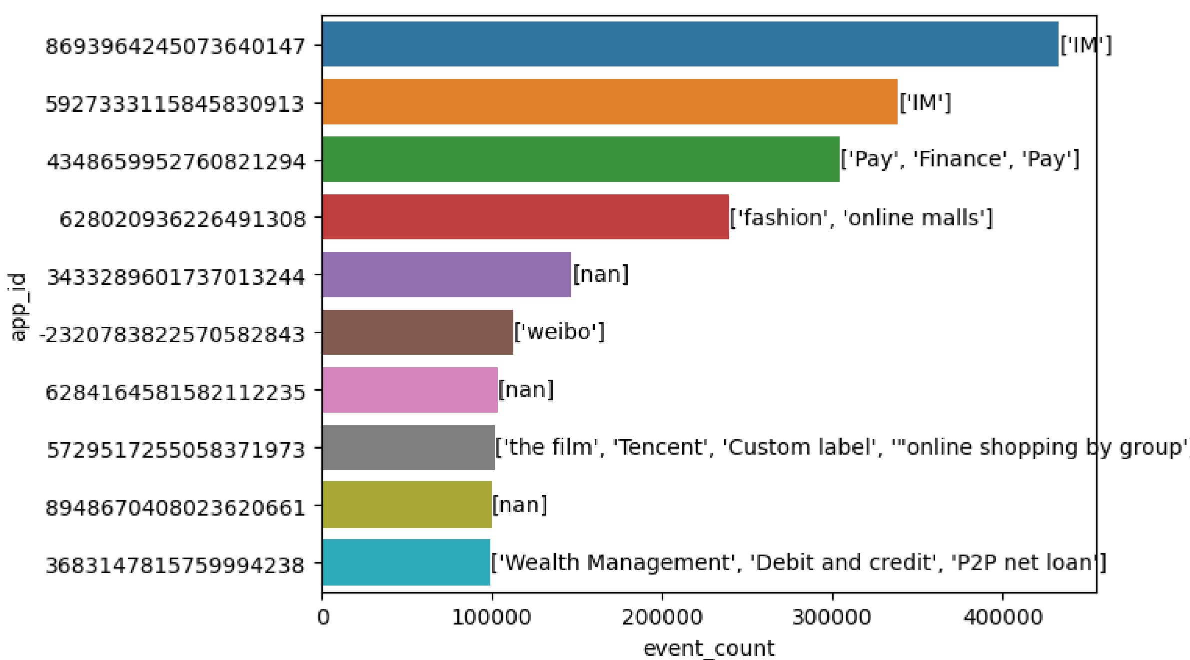
```
top_frequent_apps = top_frequent_apps.groupby(['app_id', 'event_count'])['ca
# Aggregate categories into lists and flatten columns again
top_frequent_apps = top_frequent_apps.apply(list).reset_index()
# Sort descending in order to plot
top_frequent_apps = top_frequent_apps.sort_values(by='event_count', ascendir
# Cast column app_id to string in order to keep ordering when plotting
top_frequent_apps['app_id'] = top_frequent_apps['app_id'].astype(str)
top_frequent_apps
```

Out[ ]:

	app_id	event_count	category
8	8693964245073640147	433106	[IM]
6	5927333115845830913	338681	[IM]
4	4348659952760821294	304722	[Pay, Finance, Pay]
1	628020936226491308	239018	[fashion, online malls]
2	3433289601737013244	147057	[nan]
0	-2320783822570582843	112841	[weibo]
7	6284164581582112235	103677	[nan]
5	5729517255058371973	101888	[the film, Tencent, Custom label, "online shop...
9	8948670408023620661	99963	[nan]
3	3683147815759994238	98647	[Wealth Management, Debit and credit, P2P net ...

In [ ]:

```
ax = sns.barplot(top_frequent_apps, y='app_id', x='event_count', orient='h')
ax.bar_label(ax.containers[0], labels=top_frequent_apps['category'], fmt='%g
plt.show()
```



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The most popular apps are social apps and apps related to shopping and online payments.

c) Top 10 mobile phone brands by age groups

In [ ]:
```
# Create age bins
phone_brand_count = train_mobile_brand[['age', 'phone_brand']]
phone_brand_count['age_bin'] = pd.cut(
    train_mobile_brand['age'],
    [0, 24, 32, 45, 100],
)
# Group devices by age_bin and phone brand then count them
phone_brand_count = phone_brand_count.groupby(['age_bin', 'phone_brand'])['p
# Get top 10 brands per age bin
top_brands_by_age_group = phone_brand_count.groupby('age_bin').nlargest(10)
# We got duplicate index, so just drop one of them
top_brands_by_age_group = top_brands_by_age_group.droplevel(0)
# Swap index age_bin↔phone_brand
top_brands_by_age_group = top_brands_by_age_group.swaplevel(0,1)
# Sort descending in order to plot
top_brands_by_age_group = top_brands_by_age_group.unstack()
top_brands_by_age_group = top_brands_by_age_group.loc[
    top_brands_by_age_group.sum(axis=1).sort_values(ascending=False).index
]
top_brands_by_age_group
```

Out[ ]:

age_bin	(0, 24]	(24, 32]	(32, 45]	(45, 100]
phone_brand				
Xiaomi	4235.0	7556.0	4005.0	1541.0
samsung	2370.0	5569.0	4183.0	1584.0
Huawei	2449.0	5122.0	3976.0	1454.0
OPPO	1861.0	2378.0	1185.0	378.0
vivo	1980.0	2329.0	1016.0	333.0
Meizu	1687.0	2057.0	690.0	276.0
Coolpad	811.0	1213.0	943.0	382.0
lenovo	614.0	1005.0	739.0	337.0
Gionee	328.0	400.0	279.0	117.0
HTC	237.0	436.0	251.0	NaN
ZTE	NaN	NaN	NaN	115.0

In [ ]:
```
top_brands_by_age_group.plot.bar(stacked=True)
plt.show()
```

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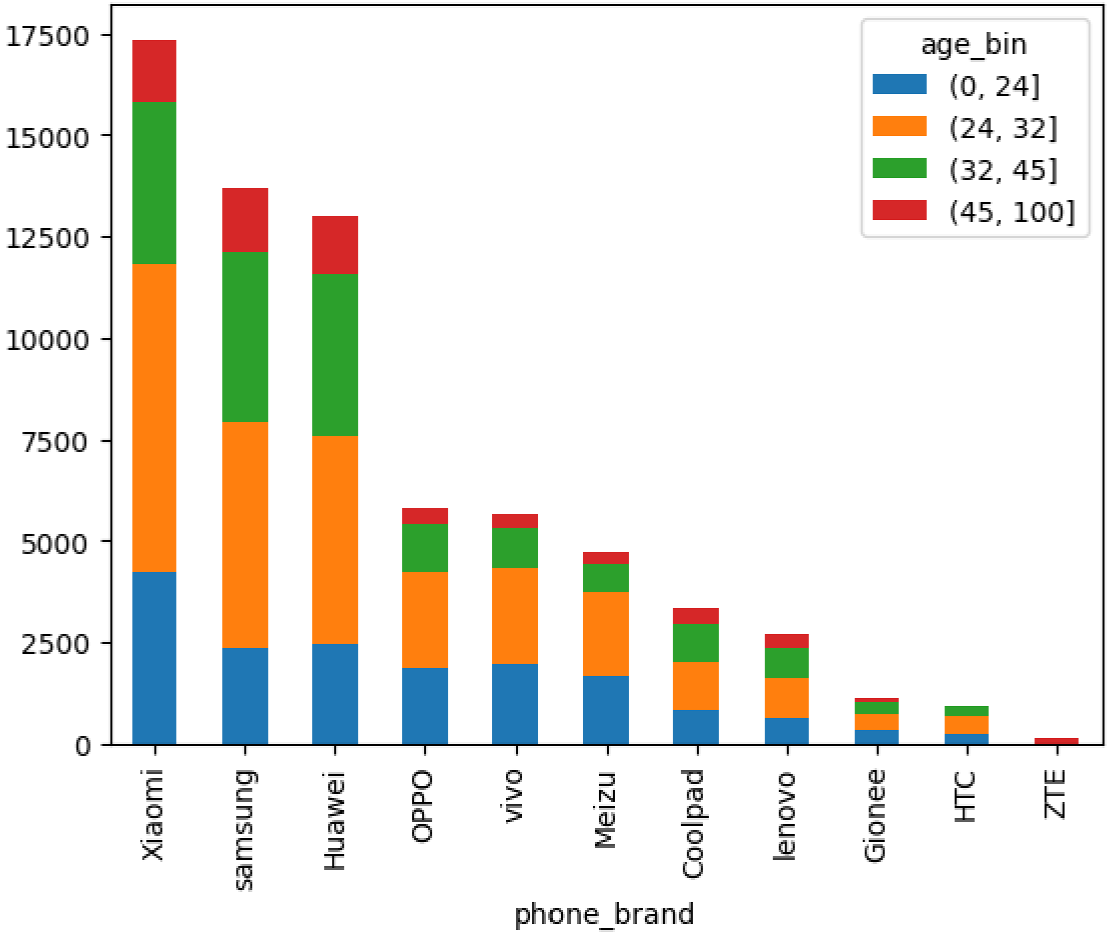

People from age group 25-32 are the majority in top brands. An interesting fact is that ZTE brand is only used by the elder people from age group 45-100 but no elder people uses HTC.

4. Feature engineering

a) Average daily events for each devices

There is a clear sign of relation between the time active on phone and gender/age as we can see while doing EDA above. So this maybe a good feature to have.

In [ ]:
```
events_per_day = train_event_data[~train_event_data['event_id'].isna()]
events_per_day['datetimestamp'] = (
    events_per_day['datetimestamp'].dt.to_period('d')
)
events_per_day = events_per_day.groupby(['device_id', 'datetimestamp'])['eve
feature_average_daily_events = events_per_day.reset_index().groupby('device_
feature_average_daily_events = feature_average_daily_events.rename('average_
feature_average_daily_events
```

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Out[ ]:
```
device_id
-9222956879900150000    4.524564e+07
-9221026417907250000    3.711151e+07
-9220830859283100000    4.175564e+06
-9220061629197650000    1.154161e+07
-9218960997324660000    1.588706e+06
                            ...
 9216925254504440000    2.976483e+07
 9217638755105360000    1.957215e+06
 9219164468944550000    1.809837e+08
 9219842210460030000    6.756232e+06
 9220914901466450000    8.211310e+06
Name: average_daily_events, Length: 23310, dtype: float64
```

In [ ]:
```
# Save for later
feature_average_daily_events.to_csv('data/feature_average_daily_events.csv')
os.listdir('data')
```

Out[ ]:
```
['app_events.csv',
 'train_event_data.csv',
 'app_events_meta_data.csv',
 'train_mobile_brand.csv',
 'feature_average_daily_events.csv']
```

We have created 1 feature into csv file at `data/feature_average_daily_events.csv`.

For other data columns, there is no sign that effective features can be generated from them after doing EDA:

- As location data is not reliable enough since location can be disabled and enabled anytime on user's devices, making new features from that will just add more noise to the train data so we don't do it.
- Patterns from app categories can be learned easily by the model so no need to put effort into engineering them.

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