Mounting GDrive directory

In [1]:
```
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 [2]:
```
%pip install basemap dill --quiet
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 860.7/860.7 kB 9.2 MB/s eta 0:
00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 115.3/115.3 kB 9.8 MB/s eta 0:
00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 30.5/30.5 MB 41.4 MB/s eta 0:0
0:00
```

In [3]:
```
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
from mpl_toolkits.basemap import Basemap
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

from sklearn.cluster import DBSCAN
```

Reading data

The datasets below are already downloaded from previous notebook:

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

In [4]:
```
# 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.

# Features from feature engineering section
feature_average_daily_events = pd.read_csv('data/feature_average_daily_event
```

Subtask 4: Advanced visualization and clustering

1. Geospatial visualization

a) Plot the visualization plot for a sample of 100'000 data points

In [5]:
```
# Map plot function

def map_plot(data, color=None, region_config=None):
  plt.figure(figsize=(16,6))

  if not region_config:
    m = Basemap()
  else:
    m = Basemap(
        projection='merc',
        llcrnrlat=region_config['lat_min'],
        urcrnrlat=region_config['lat_max'],
        llcrnrlon=region_config['lon_min'],
        urcrnrlon=region_config['lon_max'],
        lat_ts=35,
        resolution='c'
    )
  m.shadedrelief()
  m.drawcoastlines(linewidth=.1)
  m.drawcountries(linewidth=.1)

  m.scatter(
      *m(data.longitude, data.latitude),
      marker='o',
      s=3,
      color= color or 'r',
  )

  plt.show()
```

```
    plt.clf()
    plt.close("all")
```

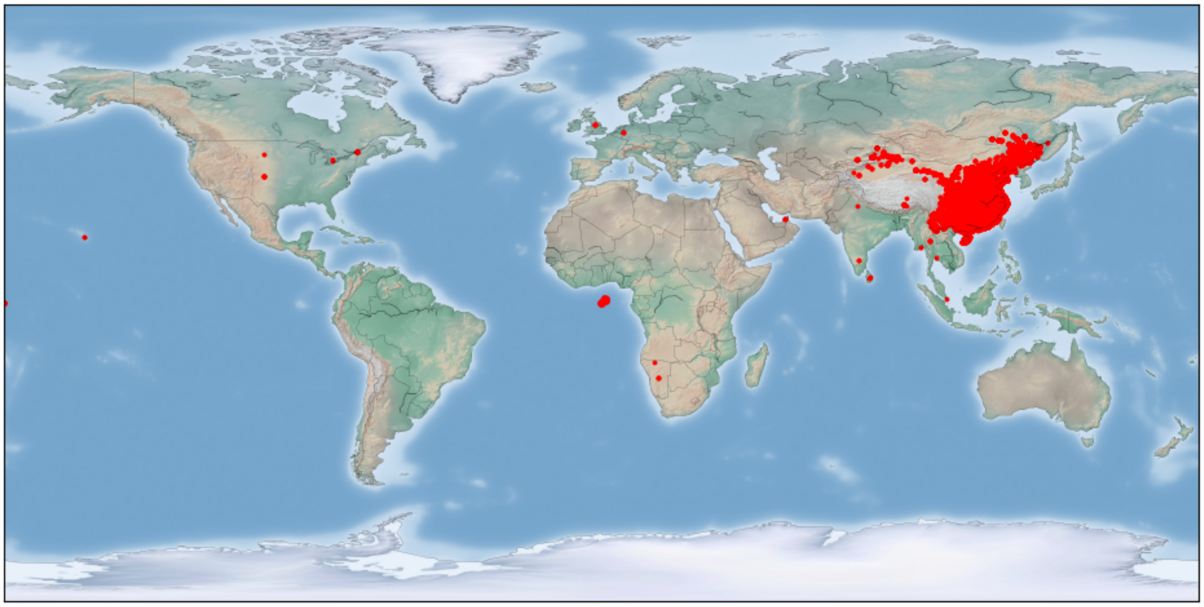
In [6]:
```
# Get 100'000 sample points
sample_locations = train_event_data[~(train_event_data.latitude.isna() | tra
sample_locations
```

Out[6]:

	device_id	gender	age	group_train	event_id	datetimestam
505392	1059108490518970000	M	29	M25-32	2711276.0	2016-05-(23:27:
870788	-1002733576670970000	M	47	M32+	210973.0	2016-05-(21:38:(
65851	118276158630381000	M	18	M0-24	2013506.0	2016-05-(03:40::
832193	-8241952332260660000	M	19	M0-24	253577.0	2016-05-(14:35:!
800736	5371847614880380000	M	26	M25-32	13511.0	2016-05-(13:12:4
...	...	...	...	...	...	
272192	-3845046065455220000	M	27	M25-32	3191238.0	2016-05-(09:51:2
1079938	9163721051841010000	M	31	M25-32	687525.0	2016-05-(19:28:(
1160273	-1319995297521480000	M	31	M25-32	2221899.0	2016-05-(21:38:2
756893	-9122745692722600000	M	36	M32+	497795.0	2016-05-(07:12:3
28309	-1131132926846460000	M	46	M32+	1597167.0	2016-05-(06:16:(

100000 rows × 8 columns

In [7]:
```
map_plot(sample_locations)
```



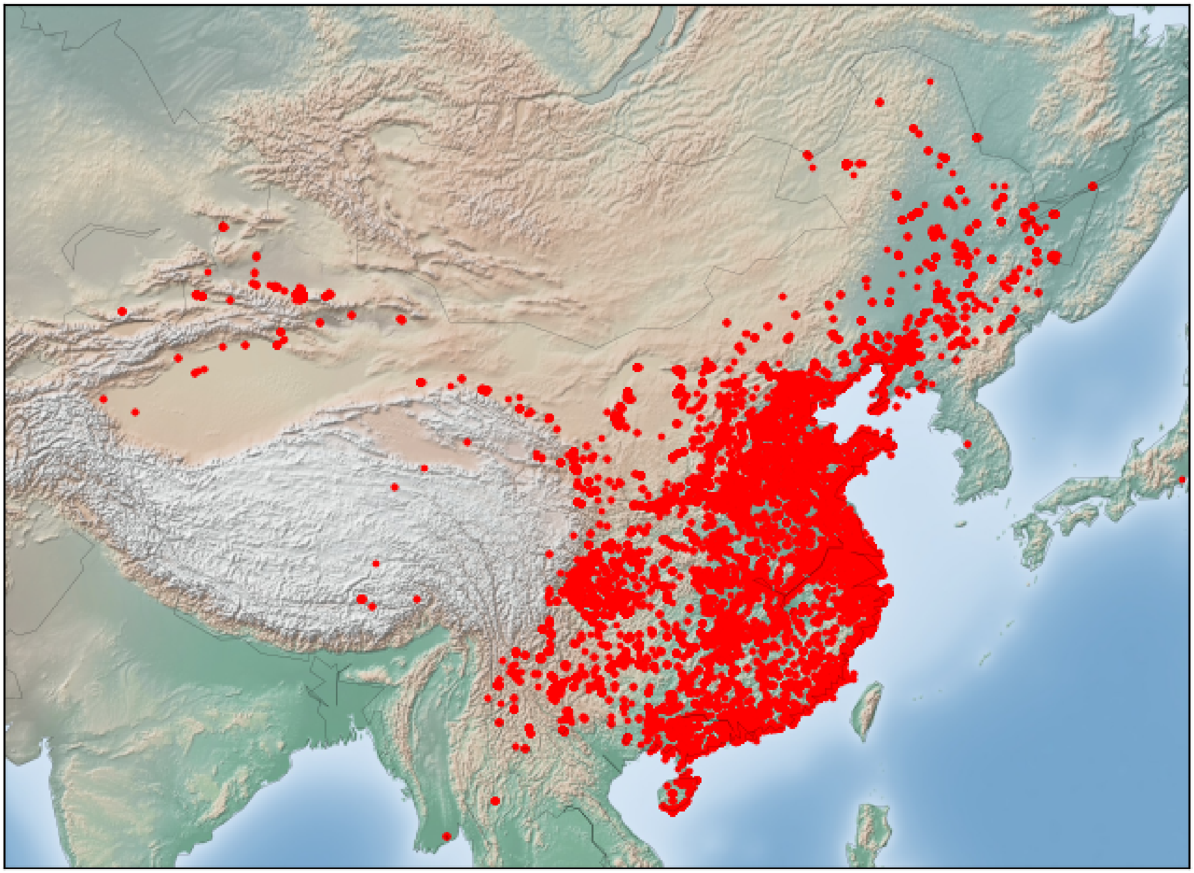
Most of the events are from East Asia. Let's narrow down to the region with most events.

In [8]:
```
lat_min, lat_max = 15, 55
lon_min, lon_max = 70, 140
region_config = dict(lat_min=lat_min, lat_max=lat_max, lon_min=lon_min, lon_

idx = (
    (~(train_event_data['latitude'].isna() | train_event_data['longitude'].i
    (train_event_data['latitude'] > lat_min) &
    (train_event_data['latitude'] < lat_max) &
    (train_event_data['longitude'] > lon_min) &
    (train_event_data['longitude'] < lon_max)
)
regional_locations = train_event_data[idx]
sample_regional_locations = regional_locations.sample(int(1e5))
```

In [9]:
```
map_plot(sample_regional_locations, region_config=region_config)
```

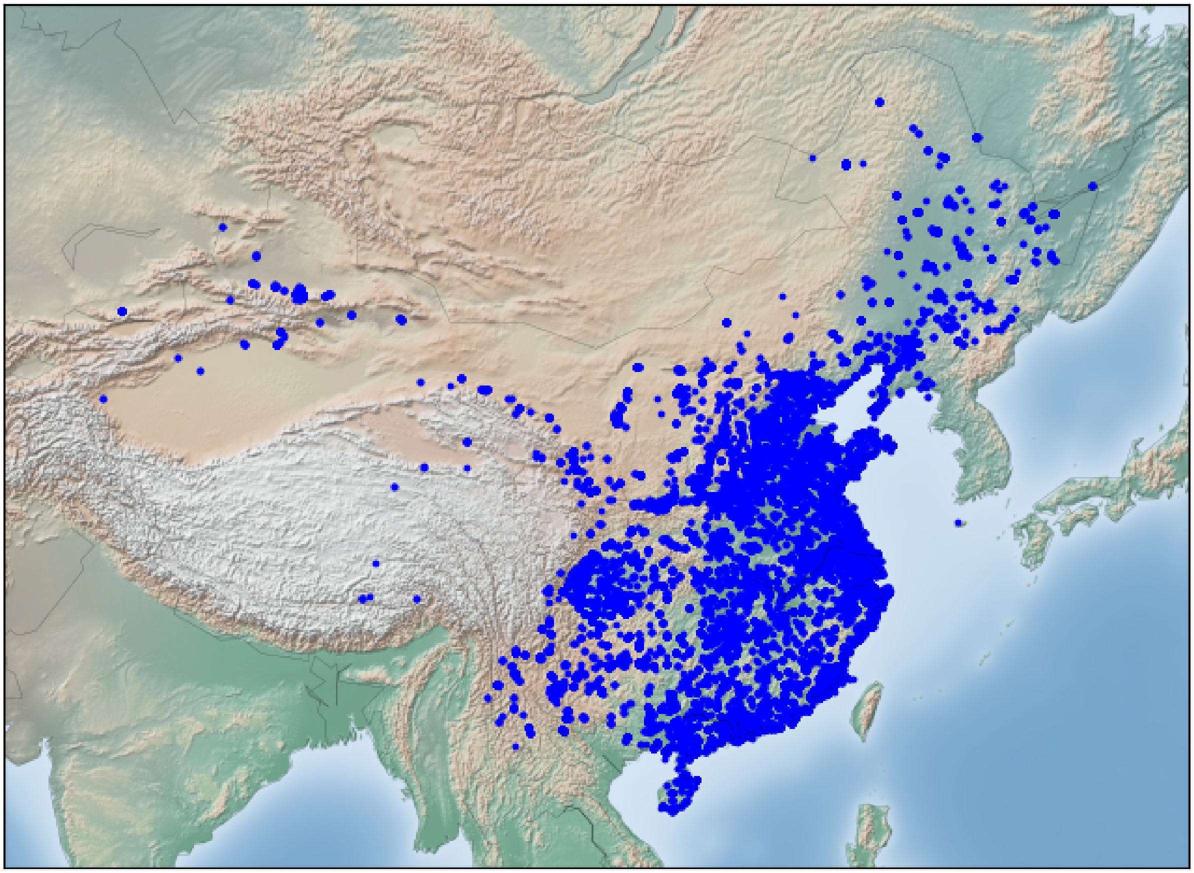
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

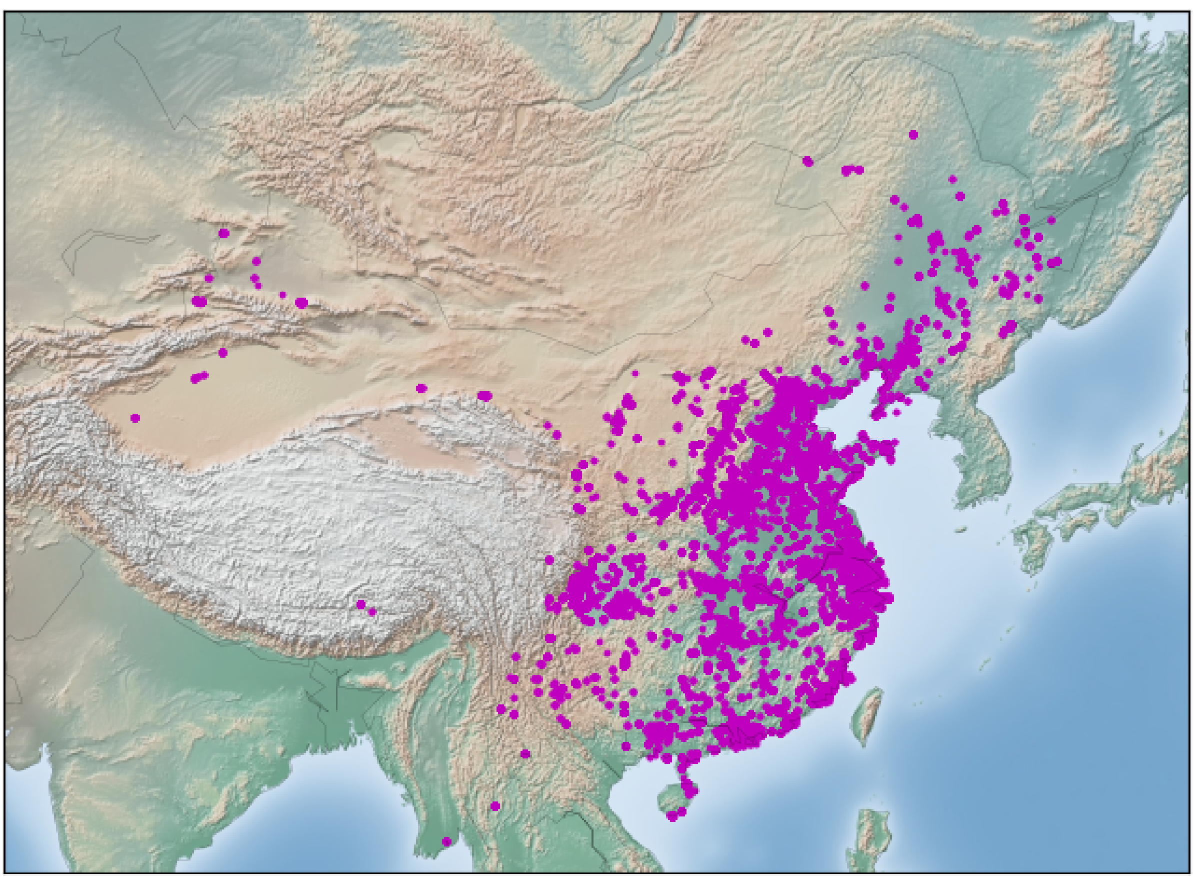


b) Compare the event visualization plots based on the users' gender information

In [10]:
```
sample_male_locations = regional_locations[regional_locations['gender'] == '
sample_female_locations = regional_locations[regional_locations['gender'] ==

map_plot(sample_male_locations, color='b', region_config=region_config)
map_plot(sample_female_locations, color='m', region_config=region_config)
```





There are more male users East Asia than female users.

c) Compare the event visualization plots based on the following age groups: 0-24, 25-32, 32+

In [11]:
```
sample_young_age_locations = regional_locations[regional_locations['age'] <
sample_middle_age_locations = regional_locations[(regional_locations['age']
sample_old_age_locations = regional_locations[regional_locations['age'] >= 3
```

In [12]:
```
for sample, color in zip(
    [sample_young_age_locations, sample_middle_age_locations, sample_old_age
    ['r', 'm', 'b'],
):
  map_plot(sample, color=color, region_config=region_config)
```

```
Output hidden; open in https://colab.research.google.com to view.
```

The distribution by age group is not much difference between groups and with the overall distribution.

2. DBSCAN clustering as a preprocessing technique

In [13]:
```
# Clustering based on average location for each device id
regional_locations_by_device = regional_locations.groupby('device_id')[['lat
# Clustering the region of interest, others locations will be treated as a c
regional_locations_coord = regional_locations_by_device[['latitude', 'longit
regional_locations_coord
```

Out[13]:
```
array([[ 23.19      , 113.24      ],
       [ 30.87151515, 114.36234848],
       [ 46.61897436, 124.88846154],
       ...,
       [ 30.25874693, 120.16542998],
       [ 26.555     , 101.7525    ],
       [ 32.64333333, 118.97333333]])
```

In [14]:
```
kms_per_radian = 6371.0088
epsilon = 2.0 / kms_per_radian  # Grouping people within 2 km
db = DBSCAN(
    # cluster_method='dbscan',
    eps=epsilon,
    min_samples=5, # Need 5 neighbors in order to consider a core point
    algorithm = 'ball_tree',
    metric = 'haversine',
    n_jobs=-1, # Use all processors
).fit(np.radians(regional_locations_coord))

location_clusters = pd.Series(db.labels_)
print('Number of clusters:', location_clusters.nunique())
location_clusters
```

```
Number of clusters: 224
```

Out[14]:
```
0        26
1        -1
2        -1
3        -1
4         0
         ..
11552    75
11553    -1
11554    53
11555    -1
11556    -1
Length: 11557, dtype: int64
```

In [15]:
```
# Assign cluster labels to train data
regional_locations_by_device['location_cluster'] = location_clusters

# Save core points to another dataframe
dbscan_core_points = regional_locations_by_device[
    regional_locations_by_device['location_cluster'] != -1
][
    ['latitude', 'longitude', 'location_cluster']
]
display(dbscan_core_points.info())
dbscan_core_points
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3066 entries, 0 to 11554
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   latitude          3066 non-null   float64
 1   longitude         3066 non-null   float64
 2   location_cluster  3066 non-null   int64  
dtypes: float64(2), int64(1)
memory usage: 95.8 KB
None
```

Out[15]:

	latitude	longitude	location_cluster
0	23.190000	113.240000	26
4	22.660000	114.020000	0
7	22.730000	113.800000	1
9	39.854583	116.300139	2
14	39.110000	117.220000	3
...	...	...	...
11533	22.617500	114.101250	6
11540	31.148548	121.407581	10
11547	30.670000	104.110000	23
11552	41.810000	123.460000	75
11554	30.258747	120.165430	53

3066 rows × 3 columns

In [16]:

```
# Create feature from location cluster
feature_location_cluster = train_event_data['device_id'].drop_duplicates()
# Merge by device id
feature_location_cluster = pd.merge(
    feature_location_cluster,
    regional_locations_by_device[['device_id', 'location_cluster']],
    on='device_id',
    how='left'
)
feature_location_cluster.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 74645 entries, 0 to 74644
Data columns (total 2 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   device_id         74645 non-null  int64  
 1   location_cluster  11557 non-null  float64
dtypes: float64(1), int64(1)
memory usage: 1.7 MB
```

In [17]:

```
# Fill all other points with label -1
feature_location_cluster['location_cluster'] = feature_location_cluster['loc
feature_location_cluster.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 74645 entries, 0 to 74644
Data columns (total 2 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   device_id         74645 non-null  int64
 1   location_cluster  74645 non-null  int64
dtypes: int64(2)
memory usage: 1.7 MB
```

In [18]:
```python
# Save cluster labels
feature_location_cluster.to_csv('data/feature_location_cluster.csv')
os.listdir('data')
```

Out[18]:
```
['train_mobile_brand.csv',
 'app_events_meta_data.csv',
 'train_event_data.csv',
 'app_events.csv',
 'feature_average_daily_events.csv',
 'train',
 'test',
 'feature_location_cluster.csv']
```

3. Final data preparation and train-test split

a) Check the datasets and features again to see what columns to include in train/test data

In [19]:
```python
for df, label in zip(
    [
        app_events,
        train_event_data,
        app_events_meta_data,
        train_mobile_brand,
        feature_average_daily_events,
        feature_location_cluster,
    ],
    [
        'app_events',
        'train_event_data',
        'app_events_meta_data',
        'train_mobile_brand',
        'feature_average_daily_events',
        'feature_location_cluster',
    ],
):
  display(HTML(f'<h2>{label} columns:</h2>'))
  display(df.columns.values)
  display(HTML('<hr/>'))
```

app_events columns:

```
, 'is_installed', 'is_active'], dtype=object)
```

---

train_event_data columns:

```
array(['device_id', 'gender', 'age', 'group_train', 'event_id',
       'datetimestamp', 'latitude', 'longitude'], dtype=object)
```

---

app_events_meta_data columns:

```
array(['app_id', 'label_id', 'category'], dtype=object)
```

---

train_mobile_brand columns:

```
array(['device_id', 'gender', 'age', 'group_train', 'phone_brand',
       'device_model'], dtype=object)
```

---

feature_average_daily_events columns:

```
array(['device_id', 'average_daily_events'], dtype=object)
```

---

feature_location_cluster columns:

```
array(['device_id', 'location_cluster'], dtype=object)
```

---

b) Choose features and labels from each data

- `train_event_data`:
  - `device_id`
  - `gender`
  - `age`
  - `event_id` (to split by scenarios: devices with and without events)
- `app_events`: This is the transitive data, so we don't use this
- `app_events_meta_data` (we only use the categories of apps on the device):
  - `device_id` (mapping by `app_id` ↔ `event_id` ↔ `device_id`)
  - `category`
- `train_mobile_brand`:
  - `device_id`
  - `phone_brand`
  - `device_model`
- `feature_average_daily_events`:
  - `device_id`
  - `average_daily_events`
- `feature_location_cluster`:

- `device_id`
- `location_cluster`

In [20]:
```
# Starter records
input_data = train_event_data[['device_id', 'gender', 'age', 'event_id']]

# Show some records
print('number of unique devices:', input_data['device_id'].nunique())
display(input_data.head())
```

```
number of unique devices: 74645
```

	device_id	gender	age	event_id
0	-7548291590301750000	M	33	2369465.0
1	-7548291590301750000	M	33	1080869.0
2	-7548291590301750000	M	33	1079338.0
3	-7548291590301750000	M	33	1078881.0
4	-7548291590301750000	M	33	1068711.0

In [21]:
```
# Merge with app_events to get the app_id (an event is from a single app)
input_data_with_categories = pd.merge(
    input_data,
    app_events[['app_id', 'event_id']],
    on='event_id',
    how='left',
)
# Merge with app_events_meta_data to get the categories
input_data_with_categories = pd.merge(
    input_data_with_categories,
    # Filter out apps without category before merging
    app_events_meta_data[
        ~app_events_meta_data['category'].isna()
    ][['app_id', 'category']].groupby('app_id').agg(list),
    on='app_id',
    how='left',
).drop(columns=['app_id'])
# Rename category column
input_data_with_categories = input_data_with_categories.rename(
    columns={'category': 'app_categories'},
)
# Merge categories by device
input_data_with_categories = input_data_with_categories.groupby(
    [
        'device_id',
        'gender',
        'age',
    ],
)['app_categories'].agg(
    lambda x: set(element
                  for lst in x[~x.isna()]
                  in lst
```

```
                )
).reset_index()
display(input_data_with_categories.info())
input_data_with_categories[input_data_with_categories['app_categories'].appl
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74645 entries, 0 to 74644
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   device_id       74645 non-null  int64
 1   gender          74645 non-null  object
 2   age             74645 non-null  int64
 3   app_categories  74645 non-null  object
dtypes: int64(2), object(2)
memory usage: 2.3+ MB
None
```

Out[21]:

	device_id	gender	age	app_categories
23	-9217193238265890000	M	33	{Technology Information}
44	-9212412905070440000	M	33	{Integrated Living}
80	-9201434269962940000	M	35	{video}
91	-9198513807097370000	M	22	{Contacts}
114	-9192503757087420000	M	41	{Technology Information}
...	...	...	...	...
74537	9198782493894550000	M	23	{Technology Information}
74578	9207229814361450000	F	29	{Taxi}
74580	9207308632673860000	F	24	{Contacts}
74621	9216925254504440000	M	41	{Technology Information}
74631	9219164468944550000	M	35	{P2P net loan, Wealth Management, Securities, ...

4039 rows × 4 columns

In [22]:

```
# Merge the phone_brand feature
input_data_with_categories_and_phone_brand = pd.merge(
    input_data_with_categories,
    train_mobile_brand[['device_id', 'phone_brand', 'device_model']],
    on='device_id',
    how='left',
)

display(input_data_with_categories_and_phone_brand.info())
input_data_with_categories_and_phone_brand
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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   app_categories  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: 4.0+ MB
None
```

Out[22]:

	device_id	gender	age	app_categories	phone_brand	device_m
0	-9223067244542180000	M	24	{}	vivo	
1	-9222956879900150000	M	36	{}	samsung	Galaxy N
2	-9222754701995930000	M	29	{}	Coolpad	8
3	-9222352239947200000	M	23	{}	Xiaomi	xn
4	-9222173362545970000	F	56	{}	samsung	Galaxy N
...	...	...	...	...	...	
74835	9220914901466450000	M	34	{}	Meizu	MX
74836	9221152396628730000	M	21	{}	Xiaomi	I
74837	9221608286127660000	F	43	{}	OPPO	
74838	9221843411551060000	M	17	{}	Gionee	
74839	9222849349208140000	M	23	{}	Xiaomi	

74840 rows × 6 columns

In [23]:

```python
# Merge the newly created features
input_data_with_full_details = pd.merge(
    input_data_with_categories_and_phone_brand,
    feature_average_daily_events,
    on='device_id',
    how='left',
)
input_data_with_full_details = pd.merge(
    input_data_with_full_details,
    feature_location_cluster,
    on='device_id',
    how='left',
)
input_data_with_full_details.set_index('device_id')
display(input_data_with_full_details.info())
input_data_with_full_details
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 74840 entries, 0 to 74839
Data columns (total 8 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   app_categories         74840 non-null  object
 4   phone_brand            74840 non-null  object
 5   device_model           74840 non-null  object
 6   average_daily_events   23402 non-null  float64
 7   location_cluster       74840 non-null  int64
dtypes: float64(1), int64(3), object(4)
memory usage: 5.1+ MB
None
```

Out[23]:

	device_id	gender	age	app_categories	phone_brand	device_n
0	-9223067244542180000	M	24	{}	vivo	
1	-9222956879900150000	M	36	{}	samsung	Galaxy N
2	-9222754701995930000	M	29	{}	Coolpad	8
3	-9222352239947200000	M	23	{}	Xiaomi	xn
4	-9222173362545970000	F	56	{}	samsung	Galaxy N
...	...	...	...	...	...	
74835	9220914901466450000	M	34	{}	Meizu	MX
74836	9221152396628730000	M	21	{}	Xiaomi	I
74837	9221608286127660000	F	43	{}	OPPO	
74838	9221843411551060000	M	17	{}	Gionee	
74839	9222849349208140000	M	23	{}	Xiaomi	

74840 rows × 8 columns

The data is ok and is ready for next step.

c) Tagging records by scenarios

- Scenario 1: All features are available
- Scenario 2: Only basic features about device are available

In [24]:

```python
segment_tag = (
    input_data_with_full_details['app_categories'].apply(lambda lst: len(lst
    (~input_data_with_full_details['average_daily_events'].isna())
).apply(lambda x: 1 if x else 2)
input_data_segment_tagged = input_data_with_full_details.copy()
input_data_segment_tagged['segment'] = segment_tag
```

```
input_data_segment_tagged = input_data_segment_tagged
display(input_data_segment_tagged.info())
input_data_segment_tagged
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 74840 entries, 0 to 74839
Data columns (total 9 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   app_categories         74840 non-null  object 
 4   phone_brand            74840 non-null  object 
 5   device_model           74840 non-null  object 
 6   average_daily_events   23402 non-null  float64
 7   location_cluster       74840 non-null  int64  
 8   segment                74840 non-null  int64  
dtypes: float64(1), int64(4), object(4)
memory usage: 5.7+ MB
None
```

Out[24]:

	device_id	gender	age	app_categories	phone_brand	device_m
0	-9223067244542180000	M	24	{}	vivo	
1	-9222956879900150000	M	36	{}	samsung	Galaxy N
2	-9222754701995930000	M	29	{}	Coolpad	8
3	-9222352239947200000	M	23	{}	Xiaomi	xn
4	-9222173362545970000	F	56	{}	samsung	Galaxy N
...	...	...	...	...	...	
74835	9220914901466450000	M	34	{}	Meizu	MX
74836	9221152396628730000	M	21	{}	Xiaomi	I
74837	9221608286127660000	F	43	{}	OPPO	
74838	9221843411551060000	M	17	{}	Gionee	
74839	9222849349208140000	M	23	{}	Xiaomi	

74840 rows × 9 columns

d) Preprocess feature columns

In [25]:

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import MultiLabelBinarizer, OneHotEncoder, Functi
```

In [26]:

```
# Reference: https://github.com/scikit-learn/scikit-learn/issues/11309#issue
from typing import Any, Callable, Sequence
from typing_extensions import Self
import numpy.typing as npt
```

```python
from sklearn.base import BaseEstimator, TransformerMixin

# Transform app categories
class MultiHotEncoder(BaseEstimator, TransformerMixin):
    """Wraps `MultiLabelBinarizer` in a form that can work with `ColumnTrans

    Note that the input `X` has to be a `pandas.DataFrame`.
    """

    def __init__(self, binarizer_creator: Callable[[], Any] | None = None, c
        # Import inside function to prevent issues with pickling
        from sklearn.preprocessing import MultiLabelBinarizer

        self.binarizer_creator = binarizer_creator or MultiLabelBinarizer
        self.dtype = dtype

        self.binarizers = []
        self.categories_ = self.classes_ = []
        self.columns = []

    def fit(self, X: pd.DataFrame, y: Any = None) -> Self:  # noqa
        self.columns = X.columns.to_list()

        for column_name in X:
            binarizer = self.binarizer_creator().fit(X[column_name])
            self.binarizers.append(binarizer)
            self.classes_.append(binarizer.classes_)  # noqa

        return self

    def transform(self, X: pd.DataFrame) -> np.ndarray:
        # Import inside function to prevent issues with pickling
        import numpy as np
        from sklearn.utils.validation import check_is_fitted

        check_is_fitted(self)

        if len(self.classes_) != X.shape[1]:
            raise ValueError(f"The fit transformer deals with {len(self.clas
                             f"while the input has {X.shape[1]}.")

        return np.concatenate([binarizer.transform(X[c]).astype(self.dtype)
                               for c, binarizer in zip(X, self.binarizers)],

    def get_feature_names_out(self, input_features: Sequence[str] = None) ->
        # Import inside function to prevent issues with pickling
        import numpy as np
        from sklearn.utils.validation import check_is_fitted

        check_is_fitted(self)

        cats = self.categories_

        if input_features is None:
            input_features = self.columns
```

```
        elif len(input_features) != len(self.categories_):
            raise ValueError(f"input_features should have length equal to nu
                             f" got {len(input_features)}")

        return np.asarray([input_features[i] + "_" + str(t) for i in range(l
```

In [27]:

```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline

# Multi-label encode app categories
mlb_transform = ColumnTransformer(
    transformers=[
        ('mlb', MultiHotEncoder(), ['app_categories']),
    ],
    verbose_feature_names_out=False, # if True, "mlb_" will be prefixed to t
    remainder='passthrough' # this allows columns not being transformed to p
)
mlb_transform.set_output(transform='pandas')

# One-hot encode other category columns
ohe_transform = ColumnTransformer(
    transformers=[
        ('ohe', OneHotEncoder(sparse_output=False), ['location_cluster', 'ph
    ],
    verbose_feature_names_out=False, # if True, "ohe_" will be prefixed to t
    remainder='passthrough' # this allows columns not being transformed to p
)
ohe_transform.set_output(transform='pandas')

# Log transform average_daily_events
log_transform = ColumnTransformer(
    transformers=[
        ('log', FunctionTransformer(np.log1p), ['average_daily_events']),
    ],
    verbose_feature_names_out=False, # if True, "log_" will be prefixed to t
    remainder='passthrough' # this allows columns not being transformed to p
)
log_transform.set_output(transform='pandas')

# Scale transform average_daily_events
scale_transform = ColumnTransformer(
    transformers=[
        ('scale', StandardScaler(), ['average_daily_events']),
    ],
    verbose_feature_names_out=False, # if True, "scale_" will be prefixed to
    remainder='passthrough' # this allows columns not being transformed to p
)
scale_transform.set_output(transform='pandas')

# Preprocessing pipeline, need to save this for usage later in deployment
preprocessor = make_pipeline(
    mlb_transform,
    ohe_transform,
    log_transform,
    scale_transform,
```

```
preprocessed_data = preprocessor.fit_transform(
    input_data_segment_tagged[
        [col
         for col in input_data_segment_tagged
         if col not in ('device_id', 'gender', 'age', 'segment')
        ]
    ]
)
display(preprocessed_data.info())
preprocessed_data
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 74840 entries, 0 to 74839
Columns: 1856 entries, average_daily_events to app_categories_zombies game
dtypes: float64(1856)
memory usage: 1.0 GB
None
```

Out[27]:

	average_daily_events	location_cluster_-1	location_cluster_0	location_cluster_
0	NaN	1.0	0.0	0.(
1	1.488142	0.0	0.0	0.(
2	NaN	1.0	0.0	0.(
3	NaN	1.0	0.0	0.(
4	NaN	1.0	0.0	0.(
...	...	...	...	..
74835	0.124423	1.0	0.0	0.(
74836	NaN	1.0	0.0	0.(
74837	NaN	1.0	0.0	0.(
74838	NaN	1.0	0.0	0.(
74839	NaN	1.0	0.0	0.(

74840 rows × 1856 columns

e) Format labels

- For gender, we will use logistic regression.
- For age, since business problem is to make targeted ads to customers, it's better to group them into age groups and then select ads based on the group.

In [28]:

```
# Add device_id back
preprocessed_data['device_id'] = input_data_segment_tagged['device_id']

# Categorizing ages into groups
up'] = pd.cut(input_data_segment_tagged['age'], [0
```

```python
# Label-encoding gender and age columns
# Need to save the encoders into files for deployment later
gender_label_encoder = LabelEncoder()
age_label_encoder = LabelEncoder()

preprocessed_data['gender'] = gender_label_encoder.fit_transform(input_data_
preprocessed_data['age_group'] = age_label_encoder.fit_transform(preprocesse
preprocessed_data
```

Out[28]:

	average_daily_events	location_cluster_-1	location_cluster_0	location_cluster_
0	NaN	1.0	0.0	0.(
1	1.488142	0.0	0.0	0.(
2	NaN	1.0	0.0	0.(
3	NaN	1.0	0.0	0.(
4	NaN	1.0	0.0	0.(
...	...	...	...	..
74835	0.124423	1.0	0.0	0.(
74836	NaN	1.0	0.0	0.(
74837	NaN	1.0	0.0	0.(
74838	NaN	1.0	0.0	0.(
74839	NaN	1.0	0.0	0.(

74840 rows × 1859 columns

f) Train test split

In [29]:

```python
from sklearn.model_selection import train_test_split
```

In [30]:

```python
# Segment by scenarios before splitting to ensure the percentage of splits
segment_1 = preprocessed_data[input_data_segment_tagged['segment'] == 1]
segment_1 = segment_1.reset_index(drop=True)
segment_2 = preprocessed_data[input_data_segment_tagged['segment'] == 2]
segment_2 = segment_2[['device_id', 'gender', 'age_group', *[col for col in
segment_2 = segment_2.reset_index(drop=True)

for df, label in zip(
    [
        segment_1,
        segment_2,
    ],
    [
        'segment_1',
        'segment_2'
```

```
    ],
):
    display(HTML(f'<h2>{label}</h2>'))
    display(df)
```

segment_1

	average_daily_events	location_cluster_-1	location_cluster_0	location_cluster_1
0	-2.113998	1.0	0.0	0.0
1	-0.045799	1.0	0.0	0.0
2	-1.301406	1.0	0.0	0.0
3	-0.474263	1.0	0.0	0.0
4	-0.474263	1.0	0.0	0.0
...	...	...	...	...
4054	-0.613401	1.0	0.0	0.0
4055	-0.514947	1.0	0.0	0.0
4056	-0.714326	1.0	0.0	0.0
4057	1.153500	1.0	0.0	0.0
4058	2.595918	0.0	0.0	0.0

4059 rows × 1859 columns

segment_2

	device_id	gender	age_group	phone_brand_AUX	phone_brand_B
0	-9223067244542180000	1	0	0.0	
1	-9222956879900150000	1	2	0.0	
2	-9222754701995930000	1	1	0.0	
3	-9222352239947200000	1	0	0.0	
4	-9222173362545970000	0	3	0.0	
...	...	...	...	...	
70776	9220914901466450000	1	2	0.0	
70777	9221152396628730000	1	0	0.0	
70778	9221608286127660000	0	2	0.0	
70779	9221843411551060000	1	0	0.0	
70780	9222849349208140000	1	0	0.0	

70781 rows × 100 columns

In [31]:

```
# Train/test split
(
    segment_1_train,
    segment_1_test,
) = train_test_split(
    segment_1,
    test_size=.3,
    random_state=0,
)
(
    segment_2_train,
    segment_2_test,
) = train_test_split(
    segment_2,
    test_size=.3,
    random_state=0,
)

for df, label in zip(
    [
        segment_1_train,
        segment_1_test,
        segment_2_train,
        segment_2_test,
    ],
    [
        'segment_1_train',
        'segment_1_test',
        'segment_2_train',
        'segment_2_test',
    ]
```

```
):
    df = df.reset_index(drop=True)
    display(HTML(f'<h2>{label}</h2>'))
    print('shape:', df.shape)
    display(df)
```

segment_1_train

```
shape: (2841, 1859)
```

	average_daily_events	location_cluster_-1	location_cluster_0	location_cluster_1
0	0.380427	1.0	0.0	0.0
1	-0.621224	1.0	0.0	0.0
2	-2.669088	1.0	0.0	0.0
3	1.157734	1.0	0.0	0.0
4	-0.123856	1.0	0.0	0.0
...	...	...	...	...
2836	-0.623716	1.0	0.0	0.0
2837	1.288079	0.0	0.0	0.0
2838	-0.705781	1.0	0.0	0.0
2839	-0.026953	1.0	0.0	0.0
2840	1.041286	0.0	1.0	0.0

2841 rows × 1859 columns

segment_1_test

```
shape: (1218, 1859)
```

	average_daily_events	location_cluster_-1	location_cluster_0	location_cluster_1	l
0	2.356397	0.0	0.0	0.0	
1	-0.523348	1.0	0.0	0.0	
2	0.073159	1.0	0.0	0.0	
3	1.744514	0.0	0.0	0.0	
4	1.057478	1.0	0.0	0.0	
...	...	...	...	...	
1213	0.480375	1.0	0.0	0.0	
1214	-0.893056	1.0	0.0	0.0	
1215	0.478324	1.0	0.0	0.0	
1216	-0.013296	0.0	0.0	0.0	
1217	0.272121	1.0	0.0	0.0	

1218 rows × 1859 columns

segment_2_train

```
shape: (49546, 100)
```

	device_id	gender	age_group	phone_brand_AUX	phone_brand_
0	5563127744213600000	1	1	0.0	
1	-8049553530811300000	1	0	0.0	
2	4042086948304470000	1	1	0.0	
3	-679142927640773000	1	1	0.0	
4	8085592460854130000	1	1	0.0	
...	...	...	...	...	
49541	-3695505048429830000	0	2	0.0	
49542	2733856391065410000	1	0	0.0	
49543	1885626787384140000	1	0	0.0	
49544	2130080773515700000	1	1	0.0	
49545	8565664770426470000	0	2	0.0	

49546 rows × 100 columns

segment_2_test

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	device_id	gender	age_group	phone_brand_AUX	phone_brand_B
0	-19169847070955000	0	3	0.0	
1	2403589567148540000	1	2	0.0	
2	4604662545429270000	0	1	0.0	
3	4019394794123470000	0	2	0.0	
4	-1021613832219450000	1	2	0.0	
...	...	...	...	...	
21230	3557324664602540000	1	1	0.0	
21231	-931978254629029000	0	1	0.0	
21232	-2171067714073140000	0	0	0.0	
21233	-7956453462733460000	1	0	0.0	
21234	5294464040764260000	1	0	0.0	

21235 rows × 100 columns

g) Test case to make sure the encoders can be used in deployment

In [32]:
```
# Test data to use in deployment
deploy_data = input_data_segment_tagged.loc[input_data_segment_tagged['devic
deploy_data = pd.merge(
    deploy_data,
    train_event_data[['device_id', 'latitude', 'longitude']],
    on='device_id',
    how='left',
)
```

In [33]:
```
test_input_data = deploy_data.loc[0]
test_input_data = test_input_data.to_json()
test_input_data
```

Out[33]:

'{"device_id":-9212412905070440000,"gender":"M","age":33,"app_categories":["Integrated Living"],"phone_brand":"Meizu","device_model":"\\u00e9\\u00ad\\u2026\\u00e8\\u201c\\u009d2","average_daily_events":6635879.4285714282,"location_cluster":-1,"segment":1,"latitude":0.0,"longitude":0.0}'

In [34]:
```
class InputProcessor:
    '''
    Copy this class definition to
    '''
    def __init__(self, preprocessor, dbscan_core_points):
        self.epsilon = 2.0 / 6371.0088  # Grouping people within 2 km
        self.preprocessor = preprocessor
        self.dbscan_core_points = dbscan_core_points
```

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```python
    def find_location_cluster(self, coord):
        '''
        Find cluster labels for new points.
        If the point is within epsilon distance to a core point then we give
        the core point's label to that point.
        '''
        # Import inside function to prevent issues with pickling
        import numpy as np
        from sklearn.metrics.pairwise import haversine_distances

        distances = haversine_distances(
            np.radians(self.dbscan_core_points[['latitude', 'longitude']]),
            np.radians(coord),
        )
        location_clusters = self.dbscan_core_points[distances < self.epsilon
        label = location_clusters[0] if location_clusters.shape[0] else -1
        return label


    def process_input(self, json_str):
        '''
        Process json input string to the dataframe that model can consume.
        Example:
            {
                'app_categories': ['video', 'zombies game'],
                'phone_brand': 'Xiaomi',
                'device_model': 'MI 4',
                'average_daily_events': 45245644.5,
                'latitude': 22.660000,
                'longitude': 114.020000,
            }
        '''
        # Import inside function to prevent issues with pickling
        import pandas as pd

        df = pd.read_json(json_str, lines=True, nrows=1)
        df['location_cluster'] = self.find_location_cluster(df[['latitude',
        df = self.preprocessor.transform(df)
        return df

input_processor = InputProcessor(preprocessor, dbscan_core_points)
processed_test_data = input_processor.process_input(test_input_data)
display(processed_test_data.columns)
processed_test_data
```

```
Index(['average_daily_events', 'location_cluster_-1', 'location_cluster_0',
       'location_cluster_1', 'location_cluster_2', 'location_cluster_3',
       'location_cluster_4', 'location_cluster_5', 'location_cluster_6',
       'location_cluster_7',
       ...
       'app_categories_quality', 'app_categories_reading platform',
       'app_categories_realistic style comic', 'app_categories_service',
       'app_categories_show', 'app_categories_takeaway ordering',
       'app_categories_tourism product', 'app_categories_travel',
       'app_categories_video', 'app_categories_zombies game'],
      dtype='object', length=1856)
```

Out[34]:

	average_daily_events	location_cluster_-1	location_cluster_0	location_cluster_1	loc
0	-0.045799	1.0	0.0	0.0	

1 rows × 1856 columns

As we can see above, total number of columns (together with gender, age and average_daily_events) is 1858, which is correct.

h) Save transformer and train/test data for later and for deployment

In [35]:

```
import dill
```

In [36]:

```
# Save encoders for using later in deployment
os.makedirs('deploy', exist_ok=True)


with open('deploy/input_processor.pickle', 'wb') as f:
  dill.dump(input_processor, f)

with open('deploy/gender_label_encoder.pickle', 'wb') as f:
  dill.dump(gender_label_encoder, f)

with open('deploy/age_label_encoder.pickle', 'wb') as f:
  dill.dump(age_label_encoder, f)

# Save train/test data for model training
os.makedirs('data/train', exist_ok=True)
os.makedirs('data/test', exist_ok=True)

segment_1_train.to_csv('data/train/segment_1_train.csv', index=False)
segment_1_test.to_csv('data/test/segment_1_test.csv', index=False)
segment_2_train.to_csv('data/train/segment_2_train.csv', index=False)
segment_2_test.to_csv('data/test/segment_2_test.csv', index=False)

# Save the data that will be used in deployment
deploy_data.to_csv('deploy/deploy_data.csv', index=False)
```

In [37]:

```
for d in ('deploy', 'data/train', 'data/test'):
    print(d)
    display(os.listdir(d))
```

```
deploy
```

```
['gender_model_sc1_fit.pickle',
 'gender_model_sc2_fit.pickle',
 'age_model_sc1_fit.pickle',
 'age_model_sc2_fit.pickle',
 'input_processor.pickle',
 'age_label_encoder.pickle',
 'gender_label_encoder.pickle',
 'deploy_data.csv']
data/train
['segment_1_train.csv', 'segment_2_train.csv']
data/test
['segment_1_test.csv', 'segment_2_test.csv']
```