User behavior insights - case study

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1 Data structure

Each row in the dataset represents one pageview for a user (identified by the `user_id`). The whole customer journey can be traced through the timestamps, the session number as well as the `page_id`, which is a consecutive number per user/session for the pages they visited. The `pagepath` reveals the actual page type the user was on. If the page type identifies a hotel (e.g., offerlist, hotel/media etc.) we also provide the respective `hotel_uuid` identifier.

A booking is indicated by the `transaction` pagepath. The given `hotel_uuid` identifies the booked hotel then.

2 Task

The solution should include at least 2-3 insights that we can talk about in the technical interview. It doesn't need to be comprehensive, we're more interested in your approach and how you would derive business insights than in the actual results.

3 Setup

[1]:
```
# load libraries
import numpy as np
import pandas as pd
import sys, time

# determine the path to the source folder
pth_to_src = 'C:/DEV/Case_study_HolidayCheck/'
```

4 Define utility functions

[2]:
```
# Define utility functions (i.e., additional auxillary python functions) for␣
↪later usage:

# Alternatively: store utility functions in separate script and load them
# sys.path.append(pth_to_src+'utils/')
# from utility import plot_rel_freq, plot_rel_freq_by_group, get_description,␣
↪plot_distribution
```

```
def plot_rel_freq(df, var_name,  title = 'Relative frequency', top_x = None):
    """
    Plot relative frequencies of a variable
    :param df: (dataframe) containing data to be used for ploting.
    :param var_name: (string) name of variable to compute relative frequencies␣
 ↪of.
    :param title: (string) title to be printed on the plot.
    :param top_x: (integer) if not None: Number of most common variable values␣
 ↪to be considered in plot.
    :output: (None)
    """
    # get the number of cases for each distict value of var_name in the␣
 ↪dataframe df:
    dfg = pd.DataFrame(df.groupby([ var_name ]).size(), columns = [ var_name ]);␣
 ↪dfg.index.name ='Index'
    # compute the relative frequencies:
    dfg /=dfg.sum()
    if not top_x is None:
        # order the grouped table by ascending order of the var_name variable:
        dfg = dfg.sort_values(dfg.columns[0],ascending=False)
        # select the top_x entries:
        dfg = dfg.loc[dfg.index[0:(top_x-1)],:]
    # plot the result
    dfg.plot(kind='bar',title=title, ylabel='Relative frequency')


def plot_rel_freq_by_group(df, var_name, group_var_name, title = 'Relative␣
 ↪frequency', top_x = None, custom_order = None):
    """
    Plot relative frequencies of a variable per group
    :param df: (dataframe) containing data to be used for ploting.
    :param var_name: (string) name of variable to compute relative frequencies␣
 ↪of.
    :param group_var_name: (string) name of variable to group by.
    :param title: (string) title to be printed on the plot.
    :param top_x: (integer) if not None: Number of most common variable values␣
 ↪to be considered in plot.
    :custom_order: (list) if not None: a user-defined list to order the grouped␣
 ↪outcome.
    :output: (None)
    """
    # get the number of cases for each distict value of a var_name and␣
 ↪group_name combination in the dataframe df:
    dfg = df.groupby([ var_name, group_var_name ]).size().unstack()
    # compute the relative frequencies:
```

```python
    dfg /=dfg.sum()
    # use a user-defined list to order the grouped table
    if not custom_order is None:
        dfg = dfg.reindex(custom_order)
    if not top_x is None:
        # order the grouped table by ascending order of the var_name variable
        dfg = dfg.sort_values(dfg.columns[0],ascending=False)
        # select the top_x entries:
        dfg = dfg.loc[dfg.index[0:(top_x-1)],:]
    # plot the result
    dfg.plot(kind='bar',title=title, ylabel='Relative frequency')


def get_description(df, var_name):
    """
    Get the statistical description of a variable for booking and non-booking␣
↪users.
    :param df: (dataframe) containing data to be analysed.
    :param var_name: (string) name of variable to be described.
    :output df1: (dataframe) containing the statistical description of the␣
↪variable var_name for booking and non-booking users.
    """
    # remove duplicate observations per user:
    df1 = df[['user_id',var_name,'is_buyer']].drop_duplicates()
    # create the output data frame:
    df1 = pd.DataFrame({'Booking users':df1.loc[df1.is_buyer==1,var_name].
↪describe(), 'Non-booking users': df1.loc[df1.is_buyer==0,var_name].describe()})
    return df1


def plot_distribution(df, var_name, group_var_name = None, title = ''):
    """
    Create distribution plots of a variable
    :param df: (dataframe) containing data to be used for ploting.
    :param var_name: (string) name of variable to compute relative frequencies␣
↪of.
    :param group_var_name: (string) if not None: name of variable to group by.
    :param title: (string) title to be printed on the plot.
    :output: (None)
    """
    import matplotlib.pyplot as plt
    import seaborn as sns
    fig = plt.figure(figsize=(12, 6))
    plt.title(title)
    if not group_var_name is None:
        df.groupby(df.index.get_level_values(group_var_name))[var_name].apply(
            lambda x: sns.kdeplot(x, label=x.name))
```

```
        plt.legend(loc='best')
    else:
        ax = sns.displot(df[var_name],kde=True,rug=True)
    plt.xlabel(var_name)
    plt.ylabel('kernel density estimation')
    plt.show()
```

5 Read the data

[3]:
```
# Read the dataframe:
df = pd.read_csv(pth_to_src+'data/userbehavior.csv',  parse_dates=['timestamp'],␣
 ↪infer_datetime_format=True)
```

[4]:
```
# sort dataframe according to 'user_id','session_id','timestamp','page_id' in␣
 ↪ascending order.
# Doing so (re)ensures that the dataframe is the expected order and lines are in␣
 ↪a sequential order.
df = df.sort_values(['user_id','session_id','timestamp','page_id'])
# reset the index:
df = df.reset_index()
```

6 Add additional variables

[5]:
```
# Add a variable to indicate a booking action:
df['booked']= 1*(df.page_name=='transaction')
```

[6]:
```
# Add a variable to indicate the day of the week:
df['weekday'] = df['timestamp'].dt.day_name()
```

[7]:
```
# Add a variable to indicate the hour of the day:
df['hour'] = df['timestamp'].dt.hour
```

7 Describe the data overall briefly

[8]:
```
# describe the dataframe briefly
print('The dataframe has %d rows and %d columns.'% df.shape)
print('First rows of the dataframe:')
print(df.head())
print('\nColumns of dataframe:')
print(df.columns)
```

```
The dataframe has 3297196 rows and 11 columns.
First rows of the dataframe:
     index                       user_id  session_id           timestamp  \
0  3239084  ++3HPCLueAkaMjet8R9BNe3D90g=           1 2022-02-02 11:35:19
1  3239085  ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:52:27
```

```
2  3239086  ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:52:39
3  3239087  ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:53:11
4  3239090  ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:53:44

    device  page_id     page_name                             hotel_uuid  \
0  desktop        1  /forum/topic                                    NaN
1   mobile        1         /home                                    NaN
2   mobile        1         /home                                    NaN
3   mobile        2     /hotellist                                   NaN
4   mobile        3     /offerlist  66562c02-f746-37b3-acce-1702beb8fe5d

   booked    weekday  hour
0       0  Wednesday    11
1       0     Sunday    20
2       0     Sunday    20
3       0     Sunday    20
4       0     Sunday    20

Columns of dataframe:
Index(['index', 'user_id', 'session_id', 'timestamp', 'device', 'page_id',
       'page_name', 'hotel_uuid', 'booked', 'weekday', 'hour'],
      dtype='object')
```

[9]:

```python
# dataframe description:
print('Number of users:            %d'% len(df.user_id.unique()))
print('Number of session_ids:      %d'% len(df.session_id.unique()))
print('Number of devices:          %d'% len(df.device.unique()))
print('Number of page_ids:         %d'% len(df.page_id.unique()))
print('Number of page_names:       %d'% len(df.page_name.unique()))
print('Number of hotel_uuid:       %d'% len(df.hotel_uuid.unique()))
print('First timestemp:            %s'% df.timestamp.min())
print('Last timestemp:             %s'% df.timestamp.max())
print('Considered time period:     %s'% str(df.timestamp.max() - df.timestamp.
 ↪min()))
print('Number of bookings:         %d'% sum(df.booked))
print('Number of users who booked: %d'% len(df[df.booked==1].user_id.unique()))
print('\n')
```

```
Number of users:            20380
Number of session_ids:      896
Number of devices:          3
Number of page_ids:         1456
Number of page_names:       443
Number of hotel_uuid:       16198
First timestemp:            2022-02-01 00:00:00
Last timestemp:             2022-02-28 23:59:59
Considered time period:     27 days 23:59:59
Number of bookings:         9497
```

```
Number of users who booked: 8744
```

8 Understand the data structure more deeply

8.1 Is the data set unique per user, session, timestamp and page id combination?

Analysis

[10]:
```
# get unique data set  per user, session, timestamp and page id combination
df1 = pd.DataFrame(df.groupby(['user_id','session_id','timestamp','page_id']
).agg('size'))
df1.reset_index(inplace=True)
```

[11]:
```
print('Number of rows in the full data set:   %d. \nNumber of rows in unique␣
↪data set:     %d.  \nAre both data sets of the same length: %s.'%(len(df),␣
↪len(df1), len(df1)==len(df)))
```

```
Number of rows in the full data set:   3297196.
Number of rows in unique data set:     2740823.
Are both data sets of the same length: False.
```

Conclusion No, the data set is not unique per user, session, timestamp and page id combination.

8.2 Why is the data set not unique per user, session, timestamp and page id combination?

Analysis

[12]:
```
print('Number of non-unique rows: %d (per user, session, timestamp and page id␣
↪combination).'%sum(df1[0]>1))
```

```
Number of non-unique rows: 273282 (per user, session, timestamp and page id
combination).
```

[13]:
```
print('Examples of non-unique rows (per user, session, timestamp and page id␣
↪combination):')
df1.loc[df1.index[df1[0]>1],:]
```

```
Examples of non-unique rows (per user, session, timestamp and page id
combination):
```

[13]:
```
                              user_id  session_id           timestamp  \
7        ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:53:49
10       ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:54:36
13       ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:54:44
17       ++6W7NF0RJB5aoqbpgjbFi+Tk2U=           1 2022-02-27 20:55:26
34       ++aQdeHnI6Sj71QMj8vsqzV5LUU=           3 2022-02-27 19:05:45
...                               ...         ...                 ...
```

```
2740785  zytuflFuJXiO5TFPSLoBFLwxWJ0=           2 2022-02-18 17:45:37
2740786  zytuflFuJXiO5TFPSLoBFLwxWJ0=           2 2022-02-18 17:45:38
2740787  zytuflFuJXiO5TFPSLoBFLwxWJ0=           2 2022-02-18 17:45:39
2740794  zytuflFuJXiO5TFPSLoBFLwxWJ0=           2 2022-02-18 17:46:38
2740820  zzPB7rTNmMpTMHiyiop5fHe2Jkk=           1 2022-02-11 14:53:18

         page_id  0
7              3  2
10             4  2
13             5  5
17             7  2
34             6  2
...          ... ..
2740785       38  4
2740786       38  2
2740787       38  4
2740794       41  4
2740820        4  2

[273282 rows x 5 columns]
```

[14]:
```
# clean workspace
del df1
```

[15]:
```
# pick an example of non-unique rows to review it further in detail
print('Data of example of non-unique rows (per user, session, timestamp and page␣
 ↪id combination):')
df[(df["user_id"]=='++i4iUzUtbf2GFsphbv1ZN81ieo=' )& (df["session_id"]==22) &␣
 ↪(df["timestamp"] == '2022-02-22 10:49:08')]
```

```
Data of example of non-unique rows (per user, session, timestamp and page id
combination):
```

[15]:
```
       index                       user_id  session_id           timestamp  \
695  3237418  ++i4iUzUtbf2GFsphbv1ZN81ieo=          22 2022-02-22 10:49:08
696  3237421  ++i4iUzUtbf2GFsphbv1ZN81ieo=          22 2022-02-22 10:49:08
697  3237422  ++i4iUzUtbf2GFsphbv1ZN81ieo=          22 2022-02-22 10:49:08
698  3237423  ++i4iUzUtbf2GFsphbv1ZN81ieo=          22 2022-02-22 10:49:08
699  3237426  ++i4iUzUtbf2GFsphbv1ZN81ieo=          22 2022-02-22 10:49:08
700  3237427  ++i4iUzUtbf2GFsphbv1ZN81ieo=          22 2022-02-22 10:49:08

      device  page_id  page_name                            hotel_uuid  \
695  desktop       14  /offerlist  d4f08d1f-22a6-3b66-bf74-f15a41c7a979
696  desktop       14  /offerlist  5fd59f56-87e6-4b57-acfc-0c27d7a23299
697  desktop       14  /offerlist  58a74c25-d55b-3886-a066-0578a985394a
698  desktop       14  /offerlist  58a74c25-d55b-3886-a066-0578a985394a
699  desktop       14  /offerlist  5fd59f56-87e6-4b57-acfc-0c27d7a23299
700  desktop       14  /offerlist  58a74c25-d55b-3886-a066-0578a985394a
```

```
     booked  weekday  hour
695       0  Tuesday    10
696       0  Tuesday    10
697       0  Tuesday    10
698       0  Tuesday    10
699       0  Tuesday    10
700       0  Tuesday    10
```

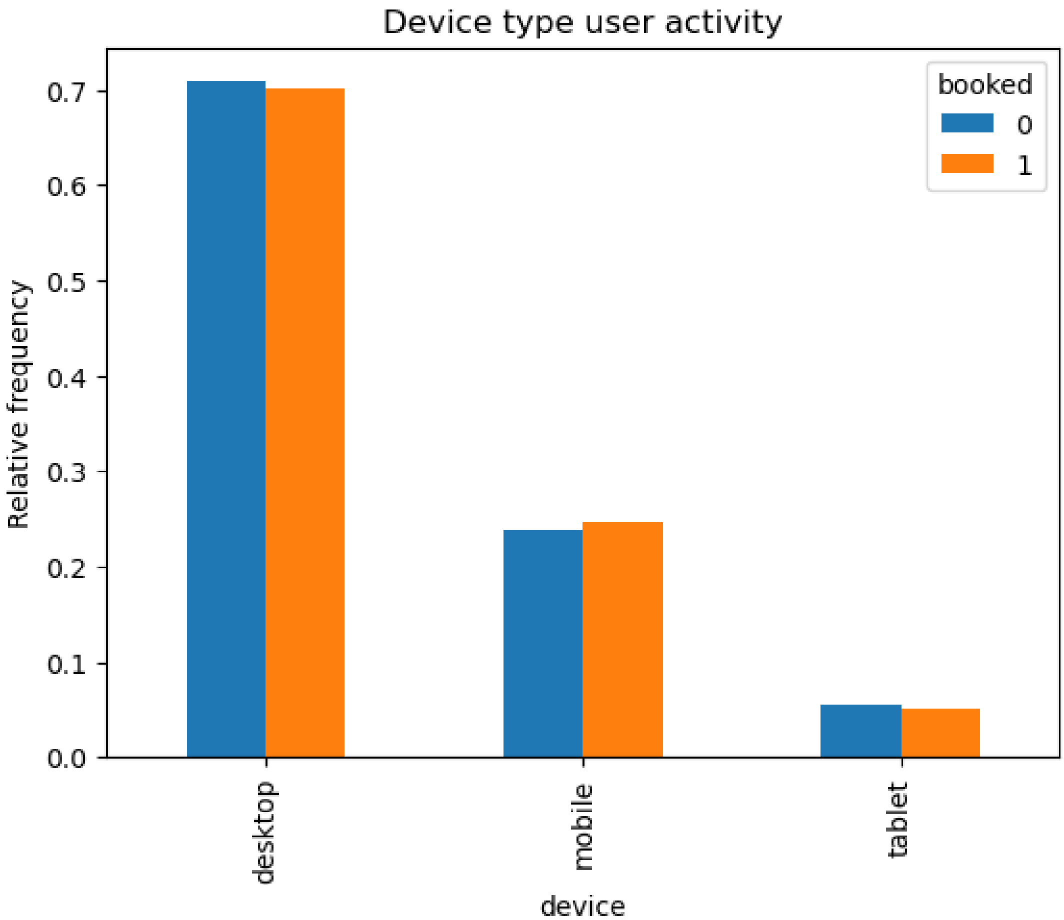
Conclusion There can be multiple rows in the data set per user, session, timestamp and page id combination. For example in the case different hotels or the same hotel are listed several times on the same offlist page.

9 User activity

9.1 User activity per device type

Analysis

[16]:
```
# Create frequency plot of user activity per device type and grouped by booking␣
↪user activity and non-booking user activity:
plot_rel_freq_by_group(df, 'device', 'booked', title='Device type user activity')
```



Assumption There are no structural technical differences of how clickstream data is produced per device type.

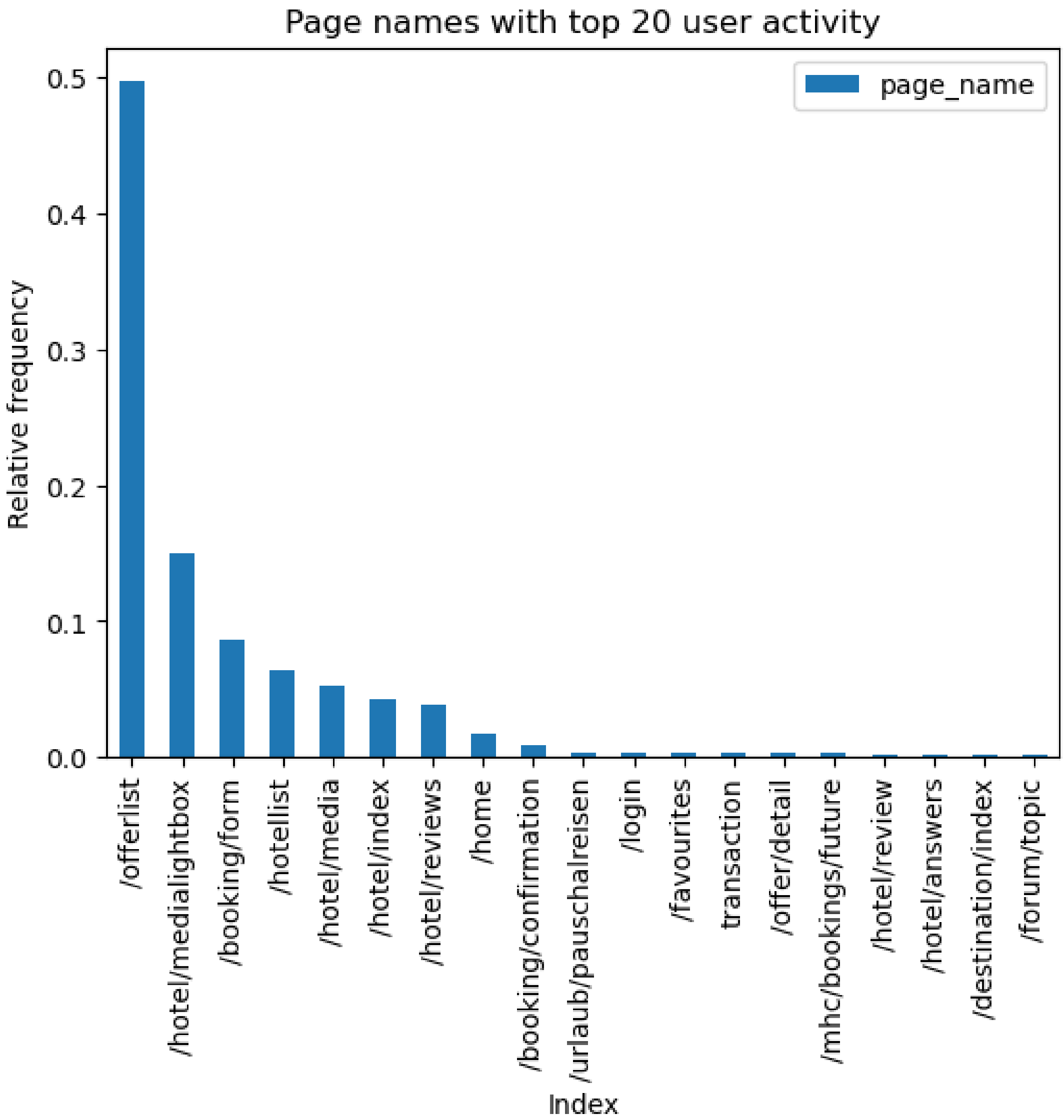
Conclusion

1. Desktop is by far the most common device type, mobile is also often used and tablet less often but still noticeably often.
2. There is no device type that is predominately used for booking or browsing behavior (without-booking).

9.2 User activity per page type

Analysis

[17]:
```
# Create frequency plot of user activity per pages types (page name).
# We consider here only the top 20 most used page types due to their relevance␣
↪and for a concise representation of the results.
plot_rel_freq(df, 'page_name', title='Page names with top 20 user activity',␣
↪top_x = 20)
```



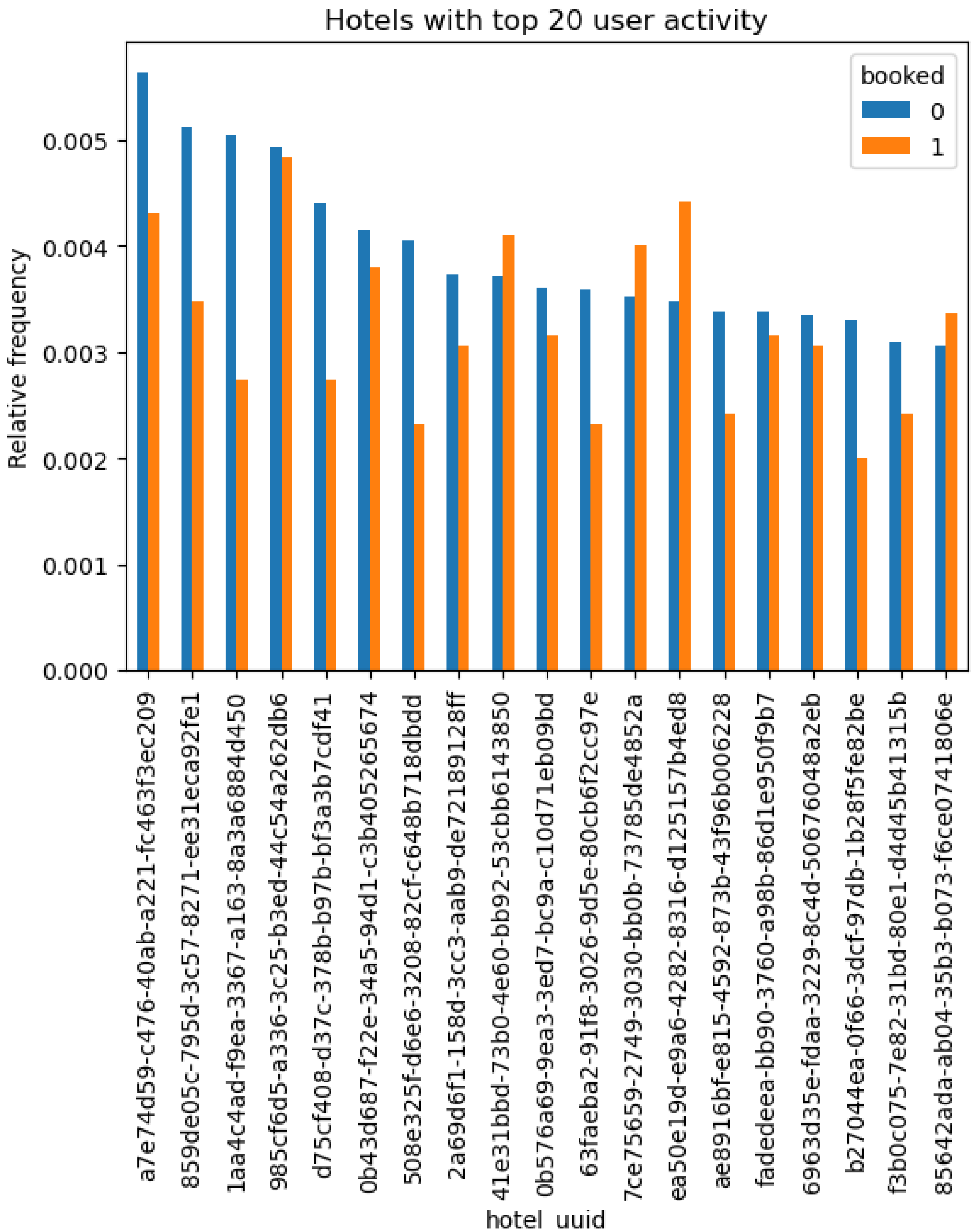
Conclusion Offerlist is with almost 50% the by far most common page type / page name. The top 8 page names represent roughly 90% of cumulative frequency of all page names. There is however a long tail of seldom appearing page names (400+).

9.3 User activity per hotel

Analysis

[18]:
```
# Create frequency plot of user activity per hotel (hotel uuid) and grouped by␣
↪booking user activity and non-booking user activity.
# We consider here only the top 20 most frequent hotels due to their relevance␣
↪and for a concise representation of the results.
```

```
plot_rel_freq_by_group(df, 'hotel_uuid', 'booked', title='Hotels with top 20␣
↪user activity', top_x = 20)
```



Conclusion

1. The most common hotels appear relatively similar often and their overall frequency is relatively low. **This indicates that there no domoninating hotels that are appearing all the time compared to others.**
2. We see that some hotels have a relatively higher (or lower) frequency of booking compared the browsing behavior (without-booking) of users on their pages. **This means that these hotels performe relatively well (worse) in converting users compared to other hotels.**

Possible further analysis Find the, e.g., top 20 hotels where the **gap between the relative frequency of browsing (without booking) and booking is the highest** or higher than a threshold. These hotel offering have a **high potential** and it is worthwhile to **indentify what is blocking** them to be better at converting users. Similarly, find the, e.g., top 20 hotels where the **gap between the relative frequency of booking and browsing (without booking) is the highest** or higher than a threshold. These hotel offering have are **overforming** and it is worthwhile to indentify what is makeing them excel at converting users.

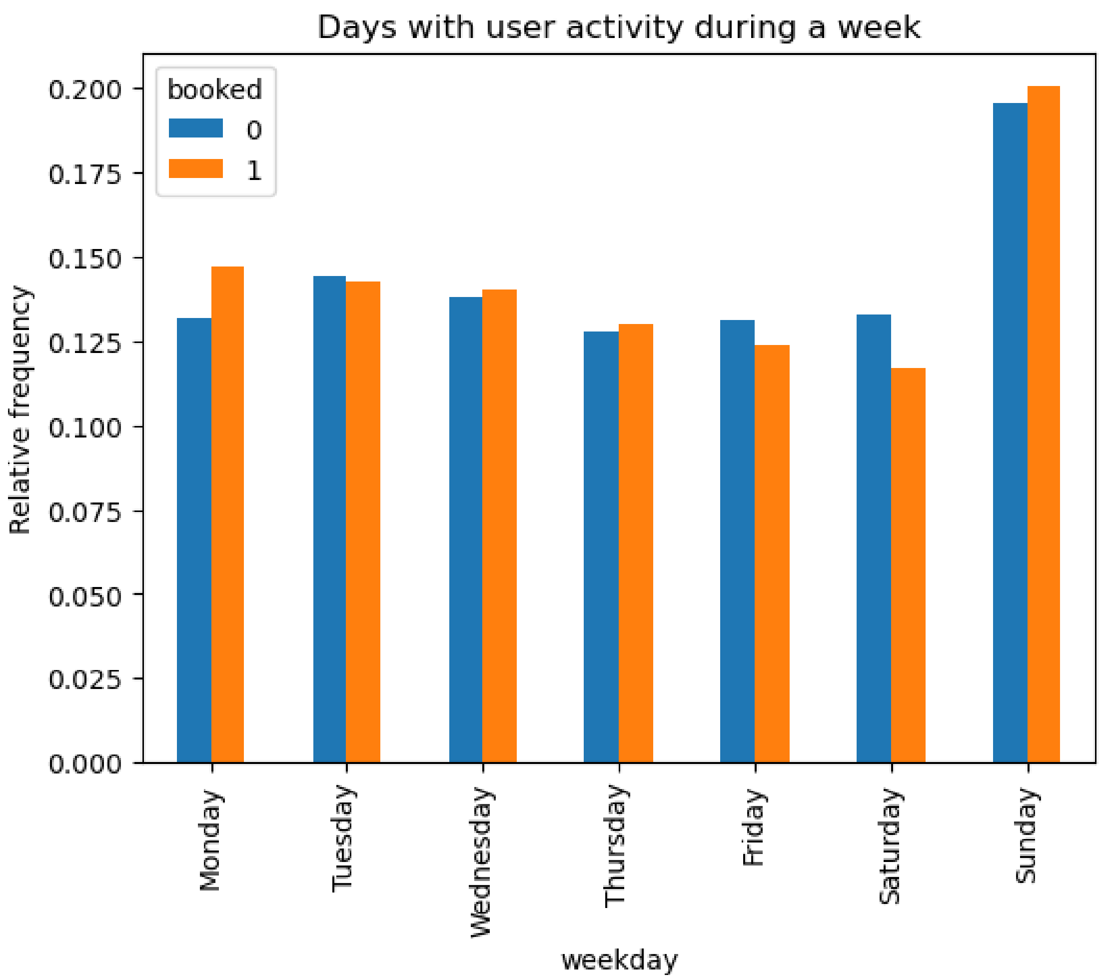
Possible business strategy implications

1. **Offer** the hotels with **high potential** (automatic) **recommendations** what to do to increase conversion.
2. **Support overforming** hotels to **incease their reach and attract more users** (e.g., increase there visibilty in the offerlist or grant them a special icon on the hotel detail page or on their offerlist representation)

9.4 User activity per day of the week

Analysis

[19]:
```
# Create frequency plot of user activity per day of the week and grouped by␣
↪booking user activity and non-booking user activity.
plot_rel_freq_by_group(df, 'weekday', 'booked', title='Days with user activity␣
↪during a week', custom_order=␣
↪['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday'])
```



Conclusion Sunday is the most important day in a week for both, booking and browsing (without-booking). The other days are relatively similar important for booking and browsing (without-booking). Whereas, Saturday is relatively more important for browsing (without-booking) and Monday for booking.__

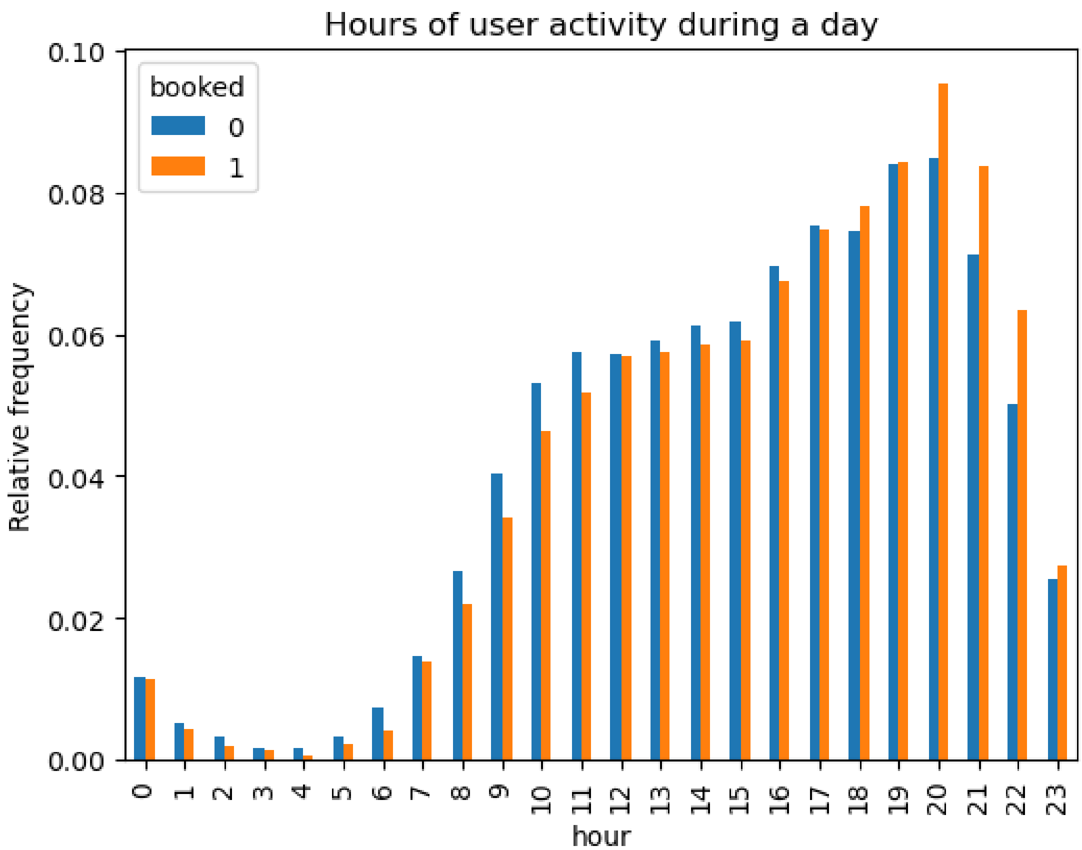
Possible business strategy implications

1. Support users to make booking decision on Friday and Saturday (e.g., relaxed cancellation policy, reservation).
2. Foster Sunday as peak browsing and booking day (e.g., with special offers, new deals, newsletter posts, external advertising).
3. Support Monday as booking day (e.g., with special last minute promotions or deals).

9.5 User activity per hour of the day

Analysis

[20]:
```
# Create frequency plot of user activity per hour of the day and grouped by␣
↪booking user activity and non-booking user activity.
plot_rel_freq_by_group(df, 'hour', 'booked', title='Hours of user activity␣
↪during a day')
```



Conclusion

1. **Booking and browsing (without-booking)** of users increase strongly from 6 am to 11 am, are constantly high from 11 am to 3 pm, and **peak from 4 pm to 9 pm, with the highest peak at 8pm.**
2. There is a tendency for relatively **more browsing (without-booking) during the earlier hours of a day** (until 5 pm) and a relatively **more booking during the later hours of a day (until 11 pm)**.

Possible business strategy implications

1. Support users to make booking decision earlier during the day (e.g., with short time offers and reservation with booking with same day cancellation).
2. Foster peak time and later hours booking (e.g., with late day special offers and deals until the end of day).

10 Customer journey

10.1 Add additional customer journey related metrics

[21]:
```
# Add indicator variable whether observation is before the first booking of a␣
↪user:
df['is_before_first_booking'] = (df.groupby(['user_id'])['booked'].cumsum() == 0␣
↪) * 1
```

[22]:
```
# Add indicator variable whether a user booked at least once:
df['is_buyer'] = df.groupby(['user_id'])['booked'].transform(max)
```

10.2 Consideration period

Definition The consideration period is defined here as the time from the first observed activity of a user until his first booking. For non-booking users, it is the time from first activity of the user until his last observed activity. The consideration period represents the window of opportunity in which a user form the purchase decision and in which the booking platform and hotel offerings have a chance to convert the use to book.

Assumptions

1. The user activity data is complete and there is relevant user activity outside the booking platform website and the dataset under consideration.
2. We ignore the fact that the dataset under consideration has a beginning and an end. Both can shorten the compute consideration period and we may find, e.g., that users who did not book in the time period of the dataset under consideration may book later, etc.
3. User activity can be tracked and also, e.g., across days and browsing activity sesssions.

In the case the assumptions from above are violated, the **measured consideration period** is **shorter than** the **actual one**.

Analysis

[23]:
```
# Add variable for the consideration period until first booking:
time0 = df['timestamp'][0]
# initialize the consideration_period variable
df['consideration_period'] = df['timestamp']
# set timestamps after the first booking to NaN to ignore them subsequently:
df.loc[(df['is_before_first_booking'] ==0) &␣
↪(df['is_buyer']==1),'consideration_period'] = np.NaN
# compute the consideration period until first booking
df['consideration_period'] = df.groupby(['user_id'])['consideration_period'].
↪transform(lambda x: x.max() - x.min()+time0)-time0
```

[24]:
```
# print the statistics:
get_description(df,'consideration_period')
```

```
[24]:                   Booking users          Non-booking users
count                            8744                      11636
mean   2 days 13:36:59.185269899  1 days 03:27:32.555345479
std    4 days 22:15:39.681867542  3 days 21:08:14.871832788
min               0 days 00:00:46            0 days 00:00:00
25%        0 days 00:25:17.500000            0 days 00:00:00
50%        0 days 01:40:57.500000            0 days 00:01:44
75%               2 days 19:22:34            0 days 00:19:52
max              27 days 04:29:22           27 days 11:46:16
```

```
[25]: # get rate of buyers from users with consideration period of 1 day or longer:
df1 = df[['user_id','consideration_period','is_buyer']].drop_duplicates()
df1.loc[df1.consideration_period >='1 days','is_buyer'].mean()
```

```
[25]: 0.667693661971831
```

```
[26]: # get rate of non-booking users with consideration period of 1 day or longer:
np.mean(df1[df1.is_buyer==0].consideration_period >='1 days')
```

```
[26]: 0.12976968030250946
```

Conclusion

1. We see that the **consideration period is highly skewed**: There many booking users who have a relatively short consideration period but others with a considerable long period. We find this when comparing the relatively large mean value and small median value (or the big difference between the 25% and the 75% quartile).
2. The **consideration period for non-booking** users is overall **very short**.
3. 67% of users with a consideration period of one day or longer are booking. 13% of the non-booking users have a consideration period of one day or more. This indicates a potential for converting these users.

Possible business strategy implication Use re-marketing, etc. to support users who did not convert on the first day but have an consideration period above a certain threshold (e.g., 1 day).

10.3 Dwell time on pages

Definition Dwell time on pages is defined as the time a user spends on website pages with a given page id. This is, it consists of the time a user is browsing, booking and collecting information about hotel offerings. Dwell time represents a measure of the information need a user has to complete the booking decision.

Assumptions

1. Analogous to the ones from above for the consideration period.
2. Multi-tab browsing does not influence the correctness of the data under consideration.
3. Differences of page rendering times are the same for all page types and/or can be ignored.

Analysis

[27]:
```
# Add variable for the dwell time until first booking:
time0 = df['timestamp'][0]
# initialize the dwell_time variable
df['dwell_time'] = df['timestamp']
# set timestamps after the first booking to NaN to ignore them subsequently:
df.loc[(df['is_before_first_booking'] ==0) & (df['is_buyer']==1),'dwell_time'] =
 ↪np.NaN
# compute the dwell time per session:
#df['dwell_time_session'] = df.groupby(['user_id','session_id'])['dwell_time'].
 ↪transform(lambda x: x.max() - x.min()+time0)-time0
dwell_time_session = df.groupby(['user_id','session_id'])['dwell_time'].
 ↪agg(lambda x: x.max() - x.min()+time0)-time0
```

[28]:
```
# compute the dwell time per user:
dwell_time_user = pd.DataFrame(dwell_time_session.groupby(['user_id']).sum());
 ↪dwell_time_user.columns = ['total_dwell_time']; dwell_time_user.
 ↪reset_index(inplace=True)
```

[29]:
```
# insert the dwell time per user into the dataframe df:
df = pd.merge(df,dwell_time_user, left_on=['user_id'], right_on=['user_id'],
 ↪how='inner')
```

[30]:
```
# print the statistics:
get_description(df,'total_dwell_time')
```

[30]:
```
                      Booking users          Non-booking users
count                          8744                      11636
mean   0 days 01:28:26.156107044  0 days 00:11:32.701701615
std    0 days 02:13:44.950759102  0 days 00:43:10.613271162
min              0 days 00:00:41            0 days 00:00:00
25%              0 days 00:20:34            0 days 00:00:00
50%              0 days 00:45:22            0 days 00:01:18
75%        0 days 01:39:32.250000      0 days 00:07:26.250000
max              2 days 00:29:02            1 days 01:44:56
```

Conclusion

1. We see that the **dwell time is somewhat skewed**: There some booking users who have a shorter dwell time period but others with longer dwell times. We find this when comparing the mean and median values (or the difference between the 25% and the 75% quartile).
2. The **dwell time for non-booking** users is overall **very short**. Even the 75% quartile of the dwell time of non-booking users is only 7 minutes, and therefore lower than the 25% quartile of the dwell time of booking users.

Possible business strategy implication Support (non-booking) users to stay longer on the website. 1. Investigate why these users spend only a short amount of time on the website via further analysis of the clickstream data (cf. section "Further analyses" below) or, e.g., via an online survey. 2. Remove blockers so that users spend more time browsing.

10.4 Viewed Hotels

Definition The number of viewed hotels is defined as the number of distinct hotel ids appearing in a user's clickstream data set from the first activity of the user until his first booking. For non-booking users, it is the number of distinct hotel ids appearing in a user's clickstream data set from the first activity of the user until his last observed activity. The number of viewed hotels represents the consideration set of hotels offerings a user considers to form his purchase decision to book or not to book.

Assumptions

1. Analogous to the ones from above for the consideration period.
2. The user noticed and considered each appearing hotel in his clickstream dataset.

Analysis

[31]:
```
# add distinct viewed hotels until first booking:
# initialize the viewed_hotels variable
df['viewed_hotels'] = df['hotel_uuid']
# set hotels after the first booking to NaN to ignore them subsequently:
df.loc[(df['is_before_first_booking'] ==0) &␣
↪(df['is_buyer']==1),'viewed_hotels'] = np.NaN
# compute the viewed_hotels until first booking
df['viewed_hotels'] = df.groupby(['user_id'])['viewed_hotels'].transform(lambda␣
↪x: len(x.unique()))
```

[32]:
```
# print the statistics:
get_description(df,'viewed_hotels')
```

[32]:

	Booking users	Non-booking users
count	8744.000000	11636.000000
mean	7.362420	2.417927
std	11.819627	5.655613
min	2.000000	1.000000
25%	2.000000	1.000000
50%	3.000000	1.000000
75%	8.000000	2.000000
max	201.000000	231.000000

Conclusion

1. We see that the **number of viewed hotels is somewhat skewed**: There some booking users who have a lower number of viewed hotels but others a higher number of viewed hotels. We find this when comparing the mean and median values (or the difference between the 25% and the 75% quartile).
2. The **number of viewed hotels for non-booking** users is overall **lower**. The 75% quartile of the number of viewed hotels of non-booking users is only 2.

Possible business strategy implication Support (non-booking) users to consider more hotel offerings. 1. Investigate why these users do not consider more hotel offerings via further analysis of the clickstream data (cf. section "Further analyses" below) or, e.g., via an online survey. 2. Remove blockers so that users increase the number of considered hotel offerings.

10.5 Further possible analyses

1. Plot the empirical distribution of the consideration period, dwell time and viewed hotels using, e.g., the function plot_distribution. Doing so will help to gain a deeper understanding of how frequent certain values of a variable are and therefore, e.g., how similar or different the activity behavior is across users.
2. Break the path information from the page_name variable down to possibly identify different page types and analyze the user activity on them, such as possibly the following: hotel detail pages, hotel review pages, hotel Q&A pages, image views, etc. Doing so would allow to add new aspects to the customer journey and better understand user behavior and needs.

11 Further possible analyses

11.1 Path analysis of customer Journey

Examples of questions to address: - Which are common paths of users on their way to booking? - Are there different paths for different users? - What are the transition probabilities for the different stages in the user paths and where are bottlenecks?

11.2 Analyze repeat bookers

Examples of questions to address: - Why do they book several hotels? - Do they spend overall more than one-time hotel bookers? - If so, what can we learn from them (e.g., from their hotel choices) to support one-time hotel bookers to book several hotels?