# Data Project from Airbnb - Solution

## Table of Contents



## Assignment

Airbnb wants to understand

- What guests are searching in Dublin
- Which inquiries do hosts tend to accept
- What gaps exist between guest demand and host supply
- Any other information that deepens the understanding of the data

The goal is to analyze, understand, visualize, and communicate the demand/supply of the market in Dublin

## Data Exploration

In [1]:
```
#Import libraries/dataset
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

contacts_file = ("contacts.tsv")
contacts = pd.read_csv(contacts_file, sep="\t")

searches_file = ("searches.tsv")
searches = pd.read_csv(searches_file, sep="\t")
```

In [2]:
```
#Find % of null values in datasets
print('Contacts')
print(contacts.isna().sum()/len(contacts), '\n')
print('Searches')
print(searches.isna().sum()/len(searches))
```

```
Contacts
id_guest          0.000000
id_host           0.000000
id_listing        0.000000
ts_contact_at     0.000000
ts_reply_at       0.077208
ts_accepted_at    0.536367
ts_booking_at     0.722101
ds_checkin        0.000000
ds_checkout       0.000000
n_guests          0.000000
n_messages        0.000000
dtype: float64

Searches
ds                      0.000000
id_user                 0.000000
ds_checkin              0.331561
ds_checkout             0.331561
n_searches              0.000000
n_nights                0.331561
n_guests_min            0.000000
n_guests_max            0.000000
origin_country          0.000000
filter_price_min        0.627221
filter_price_max        0.627221
filter_room_types       0.546940
filter_neighborhoods    0.962336
dtype: float64
```

The neighborhood column in searches has 96.2336% of null values. This could lead to inaccurate assumptions about the demand from people. When looking through the column, 'City Centre' was a common choice, so this should be investigated further with more data.

## *searches* Dataset

In [3]:
```
#Drop filter_neighborhoods column

searches = searches.drop(columns=['filter_neighborhoods'])
```

In [4]:
```
#Manipulation of searches dataset

#Convert date column to datetime data type for easier analysis
searches['ds'] = pd.to_datetime(searches['ds'])
searches['ds_checkin'] = pd.to_datetime(searches['ds_checkin'])
searches['ds_checkout'] = pd.to_datetime(searches['ds_checkout'])

#How soon they want the room
searches['length_preperation'] = searches['ds_checkin'] - searches['ds']
```

In [5]:
```
#Describe searches dataset

#Helps understand the dataset and its distribution of values within columns better
display(searches.describe())
```

n_searches n_nights n_guests_min n_guests_max filter_price_min filter_price_max length_preperation

| | n_searches | n_nights | n_guests_min | n_guests_max | filter_price_min | filter_price_max | length_preperation |
|---|---|---|---|---|---|---|---|
| **count** | 35737.000000 | 23888.000000 | 35737.000000 | 35737.000000 | 13322.000000 | 1.332200e+04 | 23888 |
| **mean** | 9.206565 | 7.672765 | 1.742955 | 2.105857 | 8.470200 | 9.019063e+07 | 51 days 08:11:53.730743469 |
| **std** | 17.348746 | 21.557614 | 1.460440 | 1.817358 | 53.987679 | 2.978482e+08 | 65 days 18:56:19.491940518 |
| **min** | 1.000000 | 0.000000 | 1.000000 | 1.000000 | 0.000000 | 9.000000e+00 | -1 days +00:00:00 |
| **25%** | 1.000000 | 2.000000 | 1.000000 | 1.000000 | 0.000000 | 8.600000e+01 | 10 days 00:00:00 |
| **50%** | 4.000000 | 3.000000 | 1.000000 | 2.000000 | 0.000000 | 1.390000e+02 | 26 days 00:00:00 |
| **75%** | 10.000000 | 5.000000 | 2.000000 | 2.000000 | 0.000000 | 3.010000e+02 | 67 days 00:00:00 |
| **max** | 448.000000 | 399.000000 | 16.000000 | 16.000000 | 1250.000000 | 1.073742e+09 | 604 days 00:00:00 |

This shows that the number of guests is usually 1 or 2. This can be understood since even at 75% the n_guests_min and n_guests_max are 2 and at 25% is 1. Leads to believe that smaller accommodations are preferred.

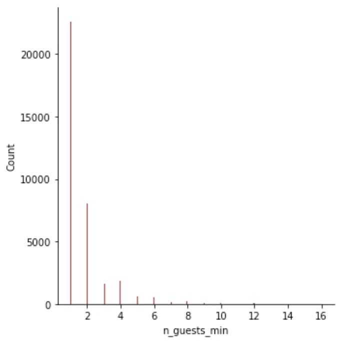
In [6]:
```
#Calculate skewness in searches dataset

display(searches.skew(axis = 0, numeric_only = True, skipna = True))
```

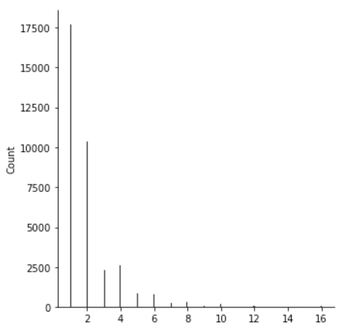
```
n_searches           7.509258
n_nights             9.942364
n_guests_min         3.583798
n_guests_max         3.148548
filter_price_min    11.087745
filter_price_max     2.999833
dtype: float64
```

All numeric columns have a Fisher-Pearson coefficient value greater than 1. This results in a positive skewness. With more time, I would have used a transformation method such as log transformation to reduce the skewness

## Distributions

In [7]:
```
#Distribution plot of n_guests_min and n_guests_max
sns.displot(searches, x = 'n_guests_min', color = 'brown')
sns.displot(searches, x = 'n_guests_max', color = 'black')
plt.show()
```

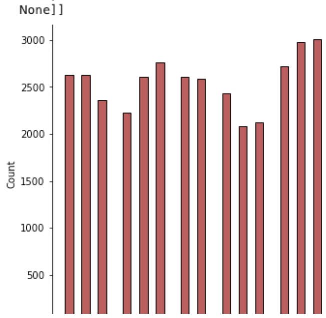


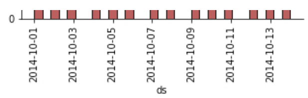




Both have similar distributions with 1 being the most popular option and 2 being the next popular option

In [8]:
```
#When were searches conducted

ax = sns.displot(searches, x = 'ds', color = 'brown')
[plt.setp(ax.get_xticklabels(), rotation=90) for ax in ax.axes.flat]
```

Out[8]:
```
[[None,
  None,
  None,
  None,
  None,
  None,
  None,
  None,
  None,
  None,
  None,
  None,
  None,
  None]]
```



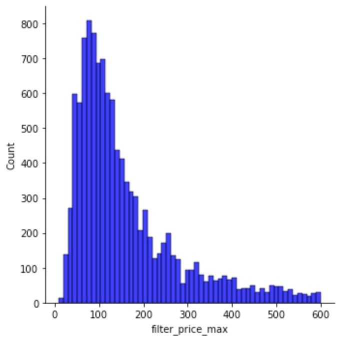



Noticed all date searches were between October 1st to October 14th. No major variation in when search was conducted between these dates

In [9]:
```
#Percentage of dataset with a filter_price_max above 600

print(len(searches[searches['filter_price_max'] > 600])/len(searches['filter_price_max'])*100, '%')
```

```
5.311022189887232 %
```

In [10]:
```
#Distribution of filter_price_max of searches

#Removing the set upper limit
searches_maxprice_removed = searches[searches['filter_price_max'] <= 600]

#Distribution plot of filter_price_max column
sns.displot(x=searches_maxprice_removed["filter_price_max"], color = 'blue')
plt.show()
```

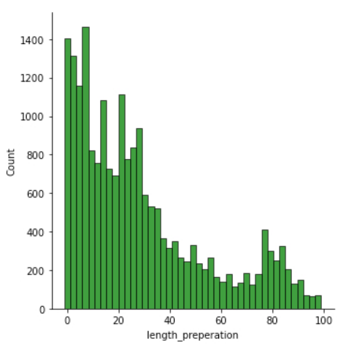



Filter_price_max was chosen instead of filter_price_min due to the min usually being set at $0

To further help better visualize the trend we set the filter price max as less or equal to 600. 600 was chosen as the limit since only 14.25% of the dataset has values greater than 600

In [11]:
```
#Distribution of length_preperation of searches

#Percentage of dataset beyond 100 days
distribution = searches["length_preperation"] / np.timedelta64(1, 'D')
print(len(distribution[distribution > 100])/len(distribution)*100, '% \n')

#Remove values beyond 100 days
distribution = distribution[distribution < 100]

#Distribution plot of length_preperation column
sns.displot(x=distribution, color = 'green')
plt.show()
```

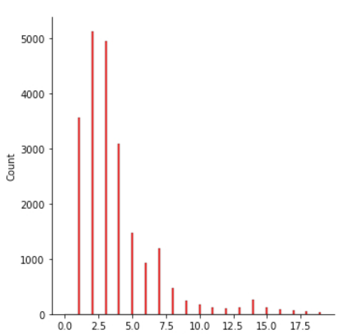
```
9.396423874415872 %
```




100 days was chosen as the limit since only 14.06% of the dataset exists beyond that

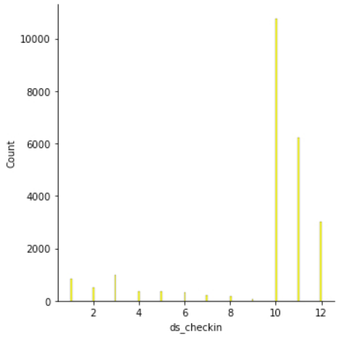
In [12]:
```
#Distribution of n_nights of searches

#Percentage of dataset beyond 20 nights
print(len(searches[searches['n_nights'] > 20])/len(searches['n_nights'])*100, '% \n')

#Remove n_nights beyond 20 days
searches_within_twenty = searches[searches['n_nights'] < 20]

#Distribution plot of length_preperation column
sns.displot(searches_within_twenty, x='n_nights', color = 'red')
plt.show()
```

```
4.737387021854101 %
```



Removing n_nights beyond 20 days since only 7.3% of the dataset exists beyond 20 days

In [13]:
```
#Distribution of months of ds_checkin of searches

checkin_month = pd.DatetimeIndex(searches['ds_checkin']).month

#Distribution plot of length_preperation column
sns.displot(checkin_month, color = 'yellow')
plt.show()
```




Used only the check-in month, cause checkout is usually within 5/6 days. The mean of n_nights after removing the upper outlier limit is 5.6, so assumed 5 or 6 days after the check-in date people usually checkout

In [14]:
```
#Types of rooms searched for

searches['filter_room_types'].unique()[0:15] #Display first 15 unique values
```

Out[14]:
```
array([',Entire home/apt,Entire home/apt,Private room,Private room', nan,
       ',Entire home/apt',
       'Entire home/apt,Entire home/apt,Private room,Private room',
       'Entire home/apt', ',Shared room,Private room',
       'Entire home/apt,Private room,Shared room,Private room,Shared room',
       'Private room', 'Entire home/apt,Private room', ',Private room',
       ',Entire home/apt,Private room',
       ',Entire home/apt,Private room,Private room',
       'Entire home/apt,Private room,Shared room',
       ',Entire home/apt,Entire home/apt,Private room',
       ',Entire home/apt,Entire home/apt,Shared room,Shared room'],
      dtype=object)
```

Most of the room types requested were entire home/apt and private rooms sometimes shared rooms. If given more time, I would have cleaned this column since most filter values are repeated within the same cell. On the Airbnb website, there are only 4 values in the type of place:

- Entire Place
- Private Room
- Hotel Room
- Shared Room

So searching how often these 4 strings occur would be how I go about it

In [15]:
```
#Find top 15 countries where searches originate from

#Group by origin country and finding the count of each country
search_origin = searches.groupby("origin_country").agg({'origin_country' : 'count'})
search_origin.columns = ['count']

search_origin = search_origin.sort_values('count', ascending = False) #Sort count in descending order
search_origin.nlargest(15, 'count') #Find the 15 largest values
```

Out[15]:

| origin_country | count |
|---|---|
| IE | 6608 |
| US | 5811 |
| GB | 4832 |
| FR | 3444 |
| IT | 2333 |
| DE | 2170 |
| ES | 1759 |
| CA | 1085 |
| AU | 962 |
| NL | 843 |
| BR | 636 |
| CH | 535 |
| BE | 386 |
| AT | 320 |
| RU | 274 |

## *contacts* Dataset

In [16]:
```
#Manipulation of contacts dataset

#Convert date columns to datetime data type
contacts['ts_contact_at'] = pd.to_datetime(contacts['ts_contact_at'])
contacts['ts_reply_at'] = pd.to_datetime(contacts['ts_reply_at'])
contacts['ts_accepted_at'] = pd.to_datetime(contacts['ts_accepted_at'])
contacts['ts_booking_at'] = pd.to_datetime(contacts['ts_booking_at'])
contacts['ds_checkin'] = pd.to_datetime(contacts['ds_checkin'])
contacts['ds_checkout'] = pd.to_datetime(contacts['ds_checkout'])
contacts['accepted'] = np.where(np.isnan(contacts['ts_accepted_at']), False, True)

contacts['length_stay'] = contacts['ds_checkout'] - contacts['ds_checkin']

#Understand dataset
display(contacts.dtypes)
display(contacts.describe())
```

```
id_guest                  object
id_host                   object
id_listing                object
ts_contact_at     datetime64[ns]
```

```
ts_contact_at       datetime64[ns]
ts_reply_at         datetime64[ns]
ts_accepted_at      datetime64[ns]
ts_booking_at       datetime64[ns]
ds_checkin          datetime64[ns]
ds_checkout         datetime64[ns]
n_guests                     int64
n_messages                   int64
accepted                      bool
length_stay        timedelta64[ns]
dtype: object
```

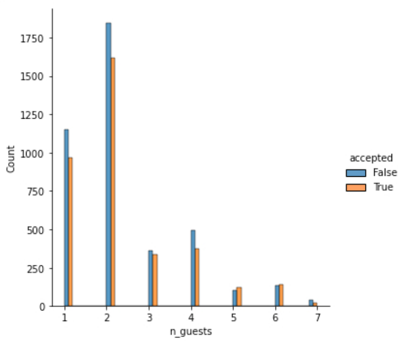
| | n_guests | n_messages | length_stay |
|---|---|---|---|
| **count** | 7823.000000 | 7823.000000 | 7823 |
| **mean** | 2.422600 | 6.319954 | 5 days 19:25:32.864629937 |
| **std** | 1.617347 | 6.472827 | 14 days 23:45:24.447710564 |
| **min** | 1.000000 | 1.000000 | 1 days 00:00:00 |
| **25%** | 1.000000 | 2.000000 | 2 days 00:00:00 |
| **50%** | 2.000000 | 4.000000 | 3 days 00:00:00 |
| **75%** | 3.000000 | 8.000000 | 5 days 00:00:00 |
| **max** | 16.000000 | 102.000000 | 334 days 00:00:00 |

In [17]:
```
#Calculate skewness in contacts dataset

display(contacts.skew(axis = 0, numeric_only = True, skipna = True))
```

```
n_guests      2.441468
n_messages    3.696440
accepted      0.145883
dtype: float64
```

All columns have a Fisher-Pearson coefficient value greater than 1. Except for accepted, which could be due to it being derived from an existing column. With more time, I would have used a transformation method such as box-cox to reduce the skewness.

In [18]:
```
#Number of guests stayed

contacts_less8 = contacts[contacts['n_guests'] < 8]
sns.displot(contacts_less8, x = 'n_guests', hue = 'accepted', multiple="dodge")
plt.show()
```



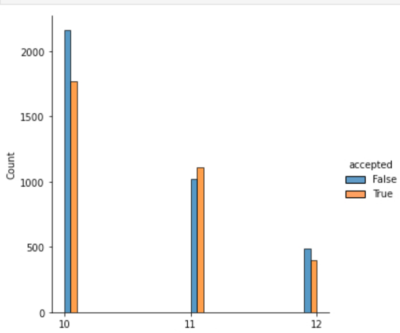

Choosing less than 8 guests, since only 1.46% (114 values) of the contacts dataset has 8 or more guests. To better visualize the majority distribution we removed rows with 8 or more guests.

2 guests is the most popular option to book, but 1 guest is the most popularly searched option. This leads me to believe there is a lack of supply of viable single guest rooms.

In [19]:
```
#Conversion rate from accepting to booking

contacts['ts_booking_at'].count()/contacts['ts_accepted_at'].count()
```

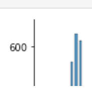
Out[19]:
```
0.5993934381031155
```

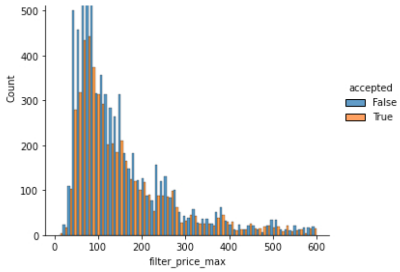
In [20]:
```
#Timeframe of when guests or accepted vs rejected

contacts['month_checkin'] = contacts['ds_checkin'].dt.month #Extract month from checkin date
contacts_checkin = contacts[contacts['month_checkin'] > 9] #Use only peak season months (Oct, Nov, Dec)

#Distribution of checkin among October, November, and December and split by acceptance
sns.displot(contacts_checkin, x='month_checkin', hue = 'accepted', multiple="dodge")
plt.xticks([10, 11, 12])
plt.show()
```




In [21]:
```
#Merge datasets for more analysis

merged_datasets = contacts.merge(searches, left_on='id_guest', right_on='id_user')
```

In [22]:
```
#Check difference between prices searched between accepted/rejected applicants

merged_pricemax_filter = merged_datasets.loc[(merged_datasets['filter_price_max'] <= 600)]

sns.displot(merged_pricemax_filter, x="filter_price_max", hue="accepted", multiple="dodge")
plt.show()
```






To further help better visualize the trend we set the filter price max as less or equal to 600. 600 was chosen as the limit since only 14.25% of the dataset has values greater than 600.

As seen, more people are rejected compared than accepted with an average acceptance rate of 43%

In [23]:
```
#Classify dataset based on filter_price_max

def label_price (row):
    if (row['filter_price_max'] >= 0) & (row['filter_price_max'] < 100):
        return '0-100'

    elif (row['filter_price_max'] >= 100) & (row['filter_price_max'] < 200):
        return '100-200'

    elif (row['filter_price_max'] >= 200) & (row['filter_price_max'] < 300):
        return '200-300'

    elif (row['filter_price_max'] >= 300) & (row['filter_price_max'] < 400):
        return '300-400'

    elif (row['filter_price_max'] >= 400) & (row['filter_price_max'] < 500):
        return '400-500'

    elif (row['filter_price_max'] >= 500) & (row['filter_price_max'] < 600):
        return '500-600'

    else:
        return '600+'

merged_datasets['classification_max_price'] = merged_datasets.apply(lambda row: label_price(row), axis=1)

merged_datasets.groupby('classification_max_price').agg({'accepted': 'mean'})
```

Out[23]:

| classification_max_price | accepted |
|---|---|
| 0-100 | 0.411160 |
| 100-200 | 0.430308 |
| 200-300 | 0.431149 |
| 300-400 | 0.450488 |
| 400-500 | 0.485549 |
| 500-600 | 0.422297 |
| 600+ | 0.433122 |

Based on this table, it can be seen that regardless of max_filter_price, people are rejected at similar rates

In [24]:
```
#Find the acceptance rate by country

dataset_country = merged_datasets[['origin_country', 'accepted']]

#Find acceptance count by country and accepted
accepted_count = dataset_country.groupby(['origin_country', 'accepted']).agg({'origin_country':'count'})
accepted_count.columns = ['count_accepted']

#Find acceptance count by country
country_count = dataset_country.groupby(['origin_country']).agg({'origin_country':'count'})
country_count.columns = ['count_country']

#Merge datasets for easier manipulation
acceptance_country = pd.merge(dataset_country, accepted_count,  how='left', on=['origin_country','accepted']) #Merge accepted count
acceptance_country = acceptance_country.drop_duplicates()

acceptance_country = pd.merge(acceptance_country, country_count, how='left', on=['origin_country']) #Merge total country count
acceptance_country = acceptance_country.sort_values(['count_country', 'accepted'], ascending = [False, True])
acceptance_country = acceptance_country[acceptance_country['count_country'] >= 100] #100 is used so there is a good amount of data to make assumptions
acceptance_country = acceptance_country[acceptance_country['accepted'] == True]

#Divide count_accepted column by count_country column to find acceptance rate by country
acceptance_country['acceptance_rate'] = acceptance_country['count_accepted']/acceptance_country['count_country']
acceptance_country.sort_values(['acceptance_rate'], ascending = True)
```

Out[24]:

| | origin_country | accepted | count_accepted | count_country | acceptance_rate |
|---|---|---|---|---|---|
| 73 | IN | True | 138 | 874 | 0.157895 |
| 55 | HR | True | 159 | 530 | 0.300000 |
| 72 | AT | True | 83 | 239 | 0.347280 |
| 54 | RU | True | 83 | 239 | 0.347280 |
| 11 | IT | True | 1183 | 3137 | 0.377112 |
| 100 | AE | True | 59 | 154 | 0.383117 |
| 0 | CA | True | 407 | 993 | 0.409869 |
| 13 | IE | True | 1217 | 2951 | 0.412403 |
| 24 | ES | True | 794 | 1914 | 0.414838 |
| 49 | RO | True | 50 | 118 | 0.423729 |
| 78 | CR | True | 82 | 188 | 0.436170 |
| 6 | GB | True | 1610 | 3667 | 0.439051 |
| 25 | BE | True | 134 | 304 | 0.440789 |
| 38 | BR | True | 215 | 482 | 0.446058 |
| 27 | AU | True | 268 | 590 | 0.454237 |
| 17 | FR | True | 1526 | 3232 | 0.472153 |
| 12 | CH | True | 279 | 585 | 0.476923 |
| 7 | US | True | 2050 | 4298 | 0.476966 |
| 14 | DE | True | 745 | 1535 | 0.485342 |

| | | | | | |
|---|---|---|---|---|---|
| **31** | NL | True | 212 | 433 | 0.489607 |
| **46** | SG | True | 115 | 232 | 0.495690 |
| **65** | PT | True | 101 | 203 | 0.497537 |
| **1** | DK | True | 86 | 125 | 0.688000 |

An interesting point is that India only has the lowest acceptance rate of 15%, which is half of the acceptance rate compared to the second lowest accepted country. Needs to be investigated further