Airbnb Market Analysis

Project Objective

A city manager for Airbnb in Dublin and wants to better understand:

- what guests are searching for in Dublin,
- which inquiries hosts tend to accept.

Based on the findings the city manager will try to boost the number and quality of hosts in Dublin to fit the demands from guests. The goal of this project is to analyze, understand, visualize, and communicate the demand / supply in the market. For example, it may be useful to look at the breakdown of start date day of the week, or number of nights, or room type that is searched for, and how many hosts accepted the reservation. In particular, we are interested in:

- what the gaps are between guest demand and host supply that the new city manager could plug to increase the number of bookings in Dublin,
- what other data would be useful to have to deepen the analysis and understanding.

Table of Content

Data Import

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

In [2]:
```
os.getcwd()
```

Out[2]:
```
'C:\\Users\\najmi\\Downloads\\Data Analytics with Python Training\\Market Analysis\\datasets (3)\\datasets'
```

In [3]:
```
os.listdir()
```

Out[3]:
```
['.ipynb_checkpoints',
 'Airbnb Market Analysis.ipynb',
 'contacts.tsv',
 'searches.tsv']
```

In [4]:
```
# Import the datasets
def import_data(file_path):
    # Read the first few lines of the file to determine the separator
    with open(file_path, 'r') as file:
        first_line = file.readline()

    # Check for common separators
    if '\t' in first_line:
        sep = '\t'
    elif ',' in first_line:
        sep = ','
    elif ';' in first_line:
        sep = ';'
    else:
        raise ValueError("Unknown separator in file")
```

```
    # Use determined separator to read the entire file
    data = pd.read_csv(file_path, sep=sep)
    return data

# Import dataset
searches = import_data('searches.tsv')

contacts = import_data('contacts.tsv')
```

Data Profiling

searches Dataset

In [5]:
```
def profile_data(df):
    print('First 5 rows of dataset:')
    display(df.head())
    print('Last 5 rows of dataset:')
    display(df.tail())
    print('Percentage of NaN values in dataset:\n', df.isna().sum()/len(df), '\n')
    print('Number of duplicated rows:', df.duplicated().sum())

profile_data(searches)
```

```
First 5 rows of dataset:
```

	ds	id_user	ds_checkin	ds_checkout	n_searches	n_nights	n_guests_min	n_guests_max	origin_country	filter_price_
0	2014-10-01	0000af0a-6f26-4233-9832-27efbfb36148	2014-10-09	2014-10-12	16	3.0	2	2	IE	
1	2014-10-01	0000af0a-6f26-4233-9832-27efbfb36148	2014-10-09	2014-10-19	3	10.0	1	2	IE	
2	2014-10-01	000cd9d3-e05b-4016-9e09-34a6f8ba2fc5	NaN	NaN	1	NaN	1	1	GB	
3	2014-10-01	000cd9d3-e05b-4016-9e09-34a6f8ba2fc5	2014-11-08	2014-11-10	11	2.0	1	2	GB	
4	2014-10-01	001c04f0-5a94-4ee0-bf5d-3591265256de	NaN	NaN	1	NaN	1	1	IE	

```
Last 5 rows of dataset:
```

	ds	id_user	ds_checkin	ds_checkout	n_searches	n_nights	n_guests_min	n_guests_max	origin_country	filter_
35732	2014-10-14	ff3c92ed-ebea-4691-a808-cc6fb73f2f55	NaN	NaN	3	NaN	2	2	US	
35733	2014-10-14	ff61875b-1d27-4ee4-bd4e-36671d3bfed4	NaN	NaN	2	NaN	1	1	US	
35734	2014-10-14	ff946a14-777b-4597-91b2-3277921214cd	2014-11-03	2014-11-06	10	3.0	1	3	IL	
35735	2014-10-14	ffc681d4-3668-4448-af38-6f73bc9fb89d	NaN	NaN	5	NaN	1	1	IE	
35736	2014-10-14	ffe0f0c3-f8e3-418e-82e5-3a29fdd183bd	NaN	NaN	3	NaN	1	1	US	

```
Percentage of NaN values in dataset:
 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 neighbourhood column in searches has 96.23% of null values. This could lead to innacurate 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.

contacts Dataset

In [6]:
```
profile_data(contacts)
```

```
First 5 rows of dataset:
```

	id_guest	id_host	id_listing	ts_contact_at	ts_reply_at	ts_accepted_at	ts_booking_at	ds_checkin	ds_checkout
0	000dfad9-459b-4f0b-8310-3d6ab34e4f57	13bb24b8-d432-43a2-9755-5ea11b43bb69	21d2b1a2-fdc3-4b4c-a1f0-0eaf0cc02370	2014-10-04 16:26:28.0	2014-10-04 16:26:28.0	2014-10-04 16:26:28.0	2014-10-04 16:26:28.0	2014-10-13	2014-10-15
1	00197051-c6cb-4c3a-99e9-86615b819874	46aa3897-9c00-4d76-ac66-a307593d0675	fb5ed09a-9848-4f2c-b2ef-34deb62164fb	2014-11-04 09:10:03.0	2014-11-04 09:45:50.0	2014-11-04 09:45:50.0	2014-11-04 12:20:46.0	2014-11-27	2014-11-30
2	0027538e-aa9e-4a02-8979-b8397e5d4cba	6bbb88ca-db66-48c5-9c4b-862f7706284a	d3871da6-8012-4dc4-b508-c91f2c10c297	2014-10-10 12:02:50.0	2014-10-10 15:07:01.0	NaN	NaN	2014-10-17	2014-10-19
3	0027538e-aa9e-4a02-8979-b8397e5d4cba	8772bc85-a9b7-4d85-a52d-41f3620c2912	0d9b5583-8053-4b67-adfe-8c29eb12efed	2014-10-10 15:23:53.0	NaN	NaN	NaN	2014-10-17	2014-10-19
4	0027538e-aa9e-4a02-8979-b8397e5d4cba	ac162061-55e2-4072-ac91-2e080f9581f2	ec68e0af-b0f2-42c7-b6f8-d41061c083ff	2014-10-10 15:22:26.0	2014-10-10 15:24:26.0	2014-10-10 15:24:26.0	2014-10-10 15:52:42.0	2014-10-17	2014-10-19

```
Last 5 rows of dataset:
```

	id_guest	id_host	id_listing	ts_contact_at	ts_reply_at	ts_accepted_at	ts_booking_at	ds_checkin	ds_check
7818	ffe366f0-6ab6-4e94-818a-c69c125fed3c	8be6bf94-aeb3-4a51-8ac4-db60baedfea1	7732bad8-e800-49f3-8751-e7604e3fb5a3	2014-10-07 21:43:00.0	2014-10-08 08:19:33.0	2014-10-08 08:19:33.0	NaN	2014-10-17	2014-10
7819	ffe366f0-6ab6-4e94-818a-c69c125fed3c	b92639c1-a5a8-48f6-8484-4fe6f62d1c6d	cc3a6bd4-d64f-4cbe-b947-c36c3851b487	2014-10-13 15:38:28.0	2014-10-13 15:44:56.0	NaN	NaN	2014-10-17	2014-10
7820	ffe366f0-6ab6-4e94-818a-c69c125fed3c	d0b6d89a-4379-43f2-9560-4943df5b8f4f	6e5b4380-66d2-4f2a-8f89-d2794598997d	2014-10-13 15:40:49.0	2014-10-13 15:42:46.0	NaN	NaN	2014-10-17	2014-10
7821	ffe366f0-6ab6-4e94-818a-c69c125fed3c	f86bc9ab-e199-4254-8609-fd67d6aaed42	28caf371-6d1d-4e06-aaf1-e660966ac7a1	2014-10-07 21:30:31.0	2014-10-08 19:04:43.0	NaN	NaN	2014-10-17	2014-10
7822	fffea166-9432-43a7-8b1b-09d6f30c1c07	6d656267-642e-4972-bdec-a35d82b84ebb	90dddef6-23ef-4df3-b454-8fd3d0e8cade	2014-10-08 00:05:05.0	2014-10-12 20:58:12.0	NaN	NaN	2014-11-11	2014-11

```
Percentage of NaN values in dataset:
 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
```

Exploratory Data Analysis

searches Dataset Analysis

In [7]:
```
# Drop filter_neighborhoods column
searches = searches.drop(columns=['filter_neighborhoods'])
```

In [8]:
```
print('Shape of dataset:', searches.shape)
```

```
Shape of dataset: (35737, 12)
```

In [9]:
```
searches.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35737 entries, 0 to 35736
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   ds                 35737 non-null  object 
 1   id_user            35737 non-null  object 
 2   ds_checkin         23888 non-null  object 
 3   ds_checkout        23888 non-null  object 
 4   n_searches         35737 non-null  int64  
 5   n_nights           23888 non-null  float64
 6   n_guests_min       35737 non-null  int64  
 7   n_guests_max       35737 non-null  int64  
 8   origin_country     35737 non-null  object 
 9   filter_price_min   13322 non-null  float64
 10  filter_price_max   13322 non-null  float64
 11  filter_room_types  16191 non-null  object 
dtypes: float64(3), int64(3), object(6)
memory usage: 3.3+ MB
```

In [10]:
```
# 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_preparation'] = searches['ds_checkin'] - searches['ds']
```

In [11]:
```
# 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_preparation
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 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 25% is 1. Leads to believe that smaller accommodations are preferred.

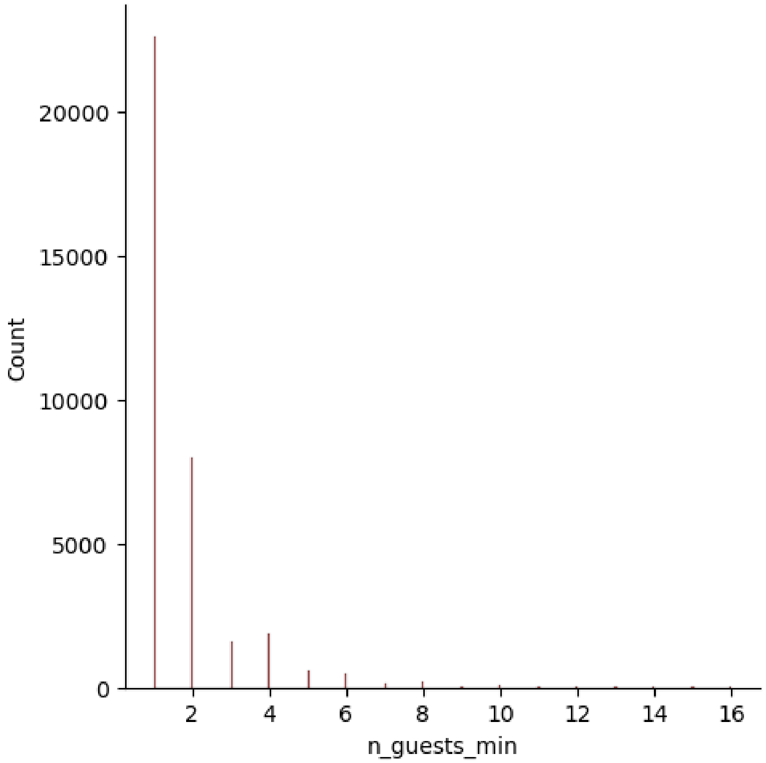
In [12]:
```
# Calculate skewness in searches dataset

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

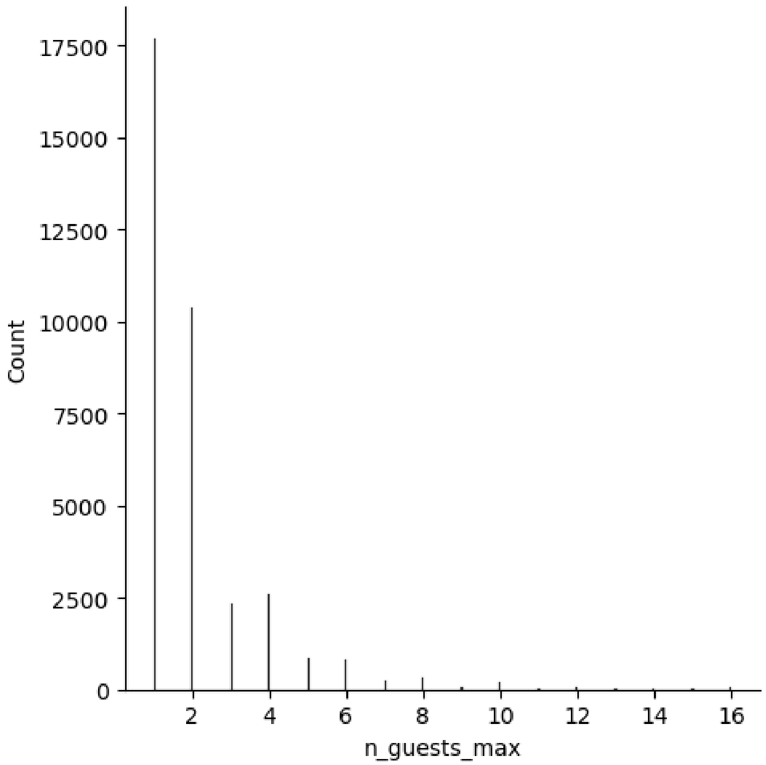
```
n_searches           7.509258
n_nights             9.942364
n_guests_min         3.583798
n_guests_max         3.148548
filter_price_min    11.087745
filter_price_max     2.999833
dtype: float64
```

All numeric columns have a coefficient value greater than 1. This results in a positive skewness. This suggests the present of outliers in these numerical columns which could heavily impact the descriptive statistics.

Distributions

In [13]:
```
# 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()
```

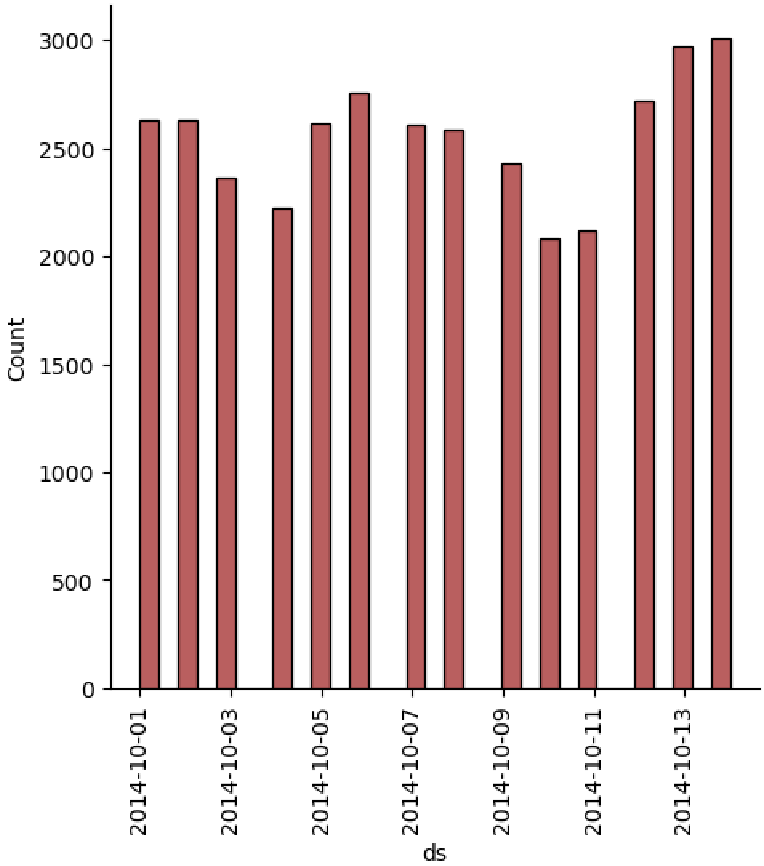




Both have similar distributions with 1 being the most popular option and 2 being the next popular option.

In [14]:
```
# When were searches conducted

ax = sns.displot(searches, x='ds', color='brown')
plt.xticks(rotation=90)
```

Out[14]:
```
(array([16344., 16346., 16348., 16350., 16352., 16354., 16356.]),
 [Text(16344.0, 0, '2014-10-01'),
  Text(16346.0, 0, '2014-10-03'),
  Text(16348.0, 0, '2014-10-05'),
  Text(16350.0, 0, '2014-10-07'),
  Text(16352.0, 0, '2014-10-09'),
  Text(16354.0, 0, '2014-10-11'),
  Text(16356.0, 0, '2014-10-13')])
```

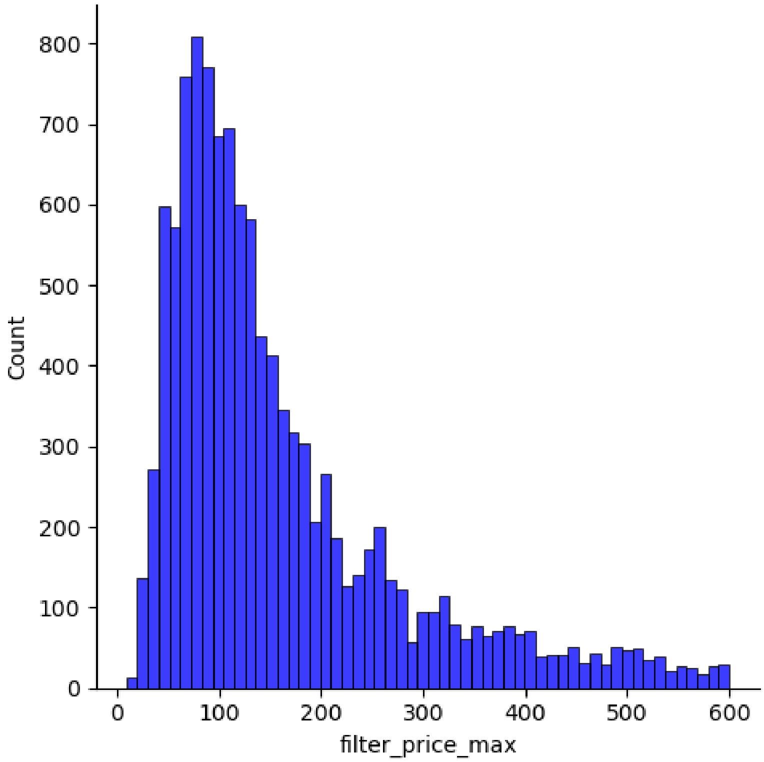


Noticed all date searches were between 1st of October 2014 to 14th of October 2014. No major variation in when search was conducted between these dates.

In [15]:
```
# Percentage of dataset with a filter_price_max above 600

print('Percentage of dataset with max price above 600:', len(searches[searches['filter_price_max'] > 600]) /
```

```
Percentage of dataset with max price above 600: 5.311022189887232 %
```

In [16]:
```
# 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()
```



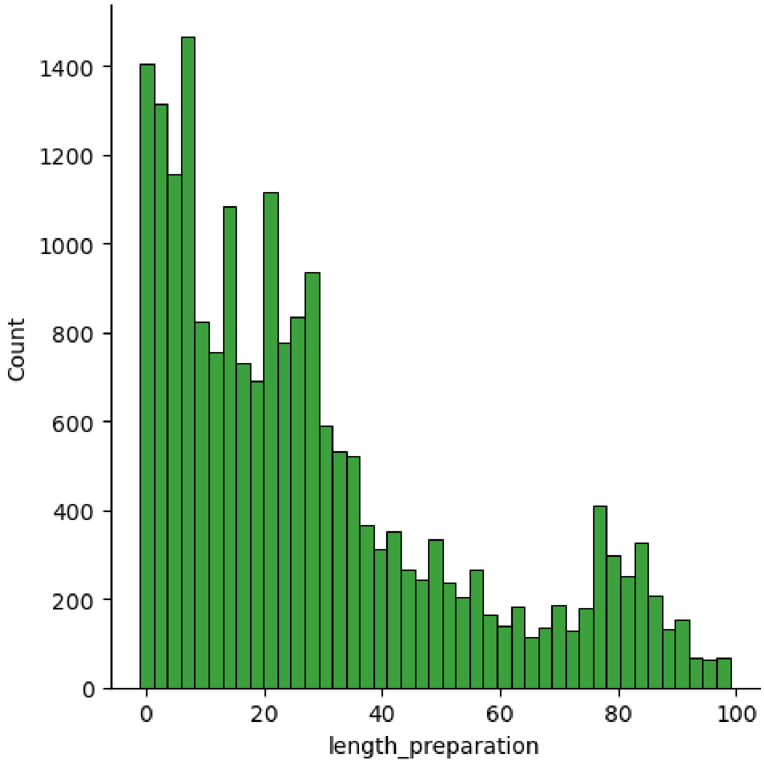
`filter_price_max` was chosen instead of `filter_price_min` due to the min usually being set at $0.

To futher 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 5.31\% of the dataset has values greater than 600.

It can be seen that the price filter distribution peaks at around 80 which shows that most people has a budget within that value.

In [17]:
```
# Distribution of length_preparation of searches

# Percentage of dataset beyond 100 days
distribution = searches['length_preparation'] / np.timedelta64(1, 'D') # converts to numerical format
print('Percentage of dataset beyond 100 days:', len(distribution[distribution > 100]) / len(distribution) *

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

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

```
Percentage of dataset beyond 100 days: 9.396423874415872 %
```



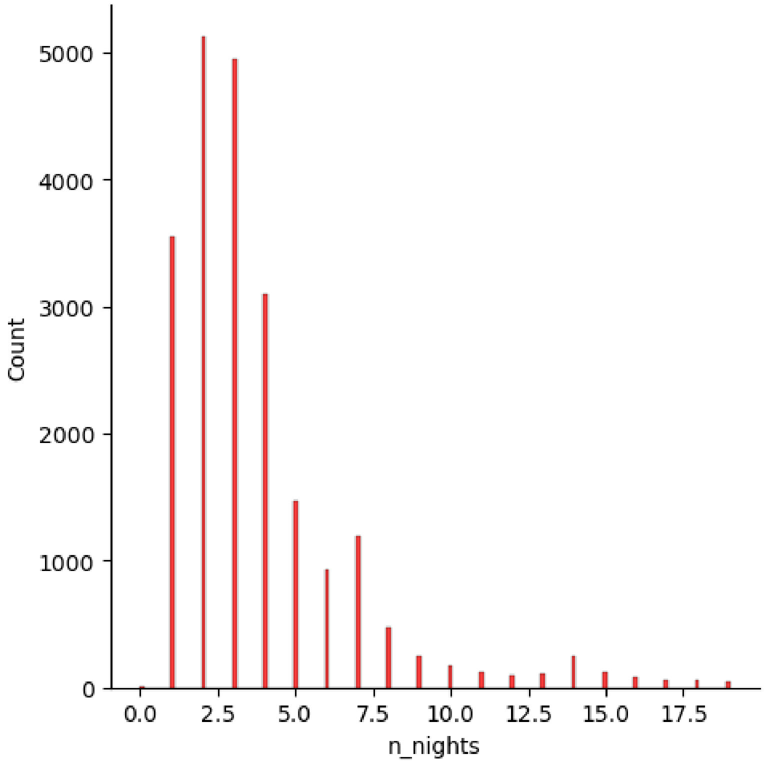
100 days was chosen as the limit since only 9.40% of the dataset exists beyond that.

Most people appear to make very brief preparation prior to check in as `length_preparation` seems to largely concentrate within the `0 - 20 days` range. This may also imply that people likes to make impromptu visits.

In [18]:

```
# Distribution of n_nights of searches

# Percentage of dataset beyond 20 nights
print('Percentage of dataset beyond 20 nights:', len(searches[searches['n_nights'] > 20]) / len(searches['n_

# Remove n_nights beyond 20 days
searches_within_twenty = searches[searches['n_nights'] < 20]
print('Mean n_nights:', (searches.loc[searches['n_nights'] < 20, 'n_nights']).mean())

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

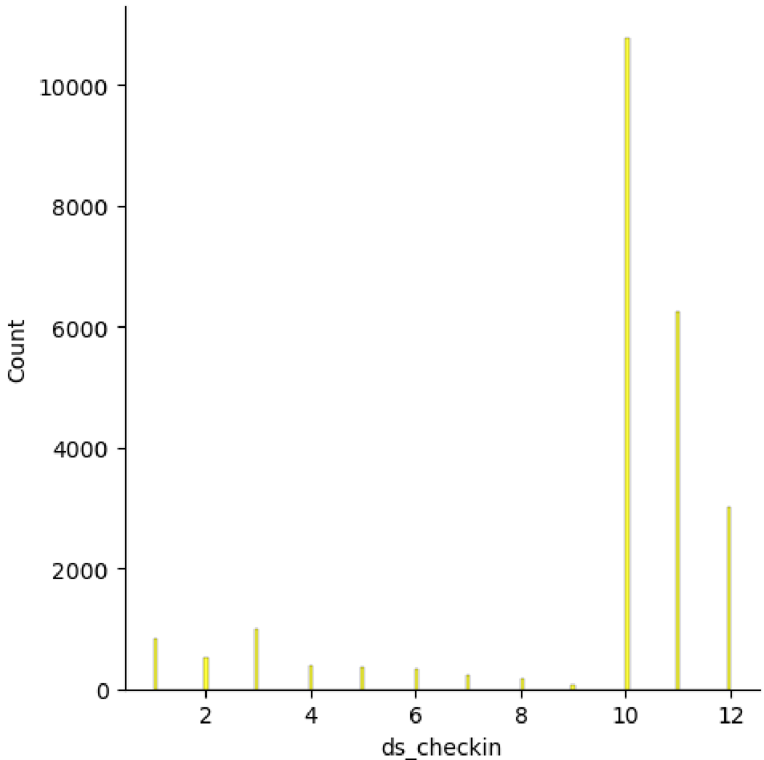
```
Percentage of dataset beyond 20 nights: 4.737387021854101 %

Mean n_nights: 3.766924084360746
```



Removing `n_nights` beyond 20 days since only 4.73% of the dataset exists beyond 20 days.

Based on the distribution, most people tend to spend `3 - 4 nights` on their visits.

In [19]:
```
# Distribution of months of ds_checkin of searches

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

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



Used only the check-in month, as check-out is usually within 3/4 days. The mean `n_nights` after removing the upper outlier limit is 3.7, so assumed 3 or 4 days after check-in date people usually check-out.

In [20]:
```
# Types of rooms searched for

searches['filter_room_types'].value_counts().sort_values(ascending=False).head(10)
```

Out[20]:
```
,Entire home/apt                                                6331
Entire home/apt                                                 3667
,Private room                                                   1693
Private room                                                    1147
,Entire home/apt,Entire home/apt,Private room                    415
Entire home/apt,Private room                                     379
,Entire home/apt,Entire home/apt,Private room,Private room       370
,Entire home/apt,Private room                                    365
,Entire home/apt,Private room,Private room                       230
,Private room,Entire home/apt                                    137
Name: filter_room_types, dtype: int64
```

Most of the room types requested were entire home/apt and private rooms sometimes shared rooms. This column should be cleaned 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

In [21]:
```
# Clean and transform the filter_room_types column to remove repeated values within the same cell and standa
valid_room_types = {'Entire home/apt':'Entire Place', 'Private room':'Private Room',
                    'Hotel room':'Hotel Room', 'Shared room':'Shared Room'}

def clean_room_types(room_types):
    if pd.isna(room_types):
        return ''
    # Split by comma and strip whitespace and leading comma
    types = [rt.strip().lstrip(',') for rt in room_types.split(',')]
    # Keep only unique, valid types and map to standardized names via set comprehension
    cleaned_types = {valid_room_types.get(rt) for rt in types if rt in valid_room_types}
    # Return a standardized string with unique types
    return ', '.join(cleaned_types)

# Apply the function to the filter_room_types column, also replacing any blanks with np.nan,
# followed by replacing the np.nan with its original values if it's not part of the valid_room_types diction
searches['filter_room_types_cleaned'] = (searches['filter_room_types']
                                         .apply(clean_room_types)
                                         .replace('', np.nan)
                                         .fillna(searches['filter_room_types'])
                                        )
```

In [22]:
```
searches['filter_room_types_cleaned'].value_counts().sort_values(ascending=False)
```

Out[22]:
```
Entire Place                            9998
Private Room                            2840
Entire Place, Private Room              2404
Entire Place, Private Room, Shared Room  460
Private Room, Shared Room                260
Shared Room                              128
Entire Place, Shared Room                101
Name: filter_room_types_cleaned, dtype: int64
```

The above output still gives similar result as the previous where most search filter is set to `Entire Place`, followed by `Private Room`.

In [23]:
```
# 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)
search_origin.nlargest(15, 'count')
```

Out[23]:

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

Most of the searches originate from `Ireland`, followed by `United States` and `Great Britain`. This makes sense as people who lives local to the area tend to have more knowledge and awareness to inquire on a trip to the area.

contacts Dataset Analysis

In [24]:

```
# 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) # If ts_accepted_at is no

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

# Review dataset
display(contacts.dtypes)
display(contacts.describe())
print('Shape of dataset:', contacts.shape)
```

```
id_guest                    object
id_host                     object
id_listing                  object
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

```
Shape of dataset: (7823, 13)
```

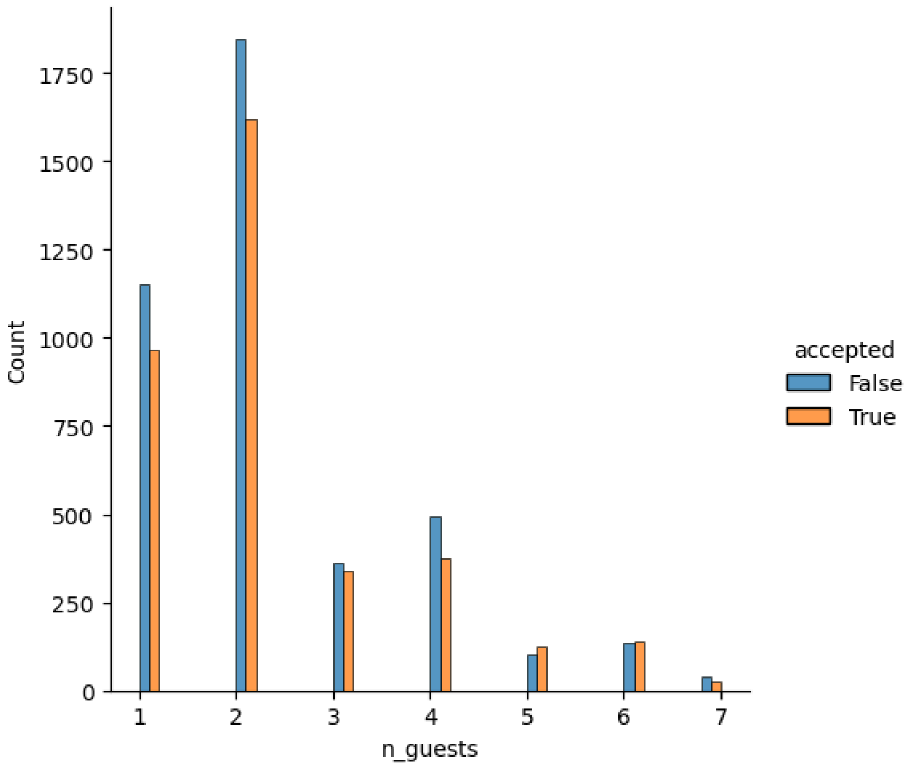
In [25]:
```
# Calculate skewness in contacts dataset

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 coefficient value greater than 1 except for `accepted` which could be due to it being derived from existing columns.

In [26]:
```
# Number of guests stayed

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

Out[26]:
```
<seaborn.axisgrid.FacetGrid at 0x20d2dccd2d0>
```



Choosing less than 8 guests, since only 0.75% of the contacts dataset has 8 or more guests. To better visualize the majority distribution we removed rows with 8 or more guests.

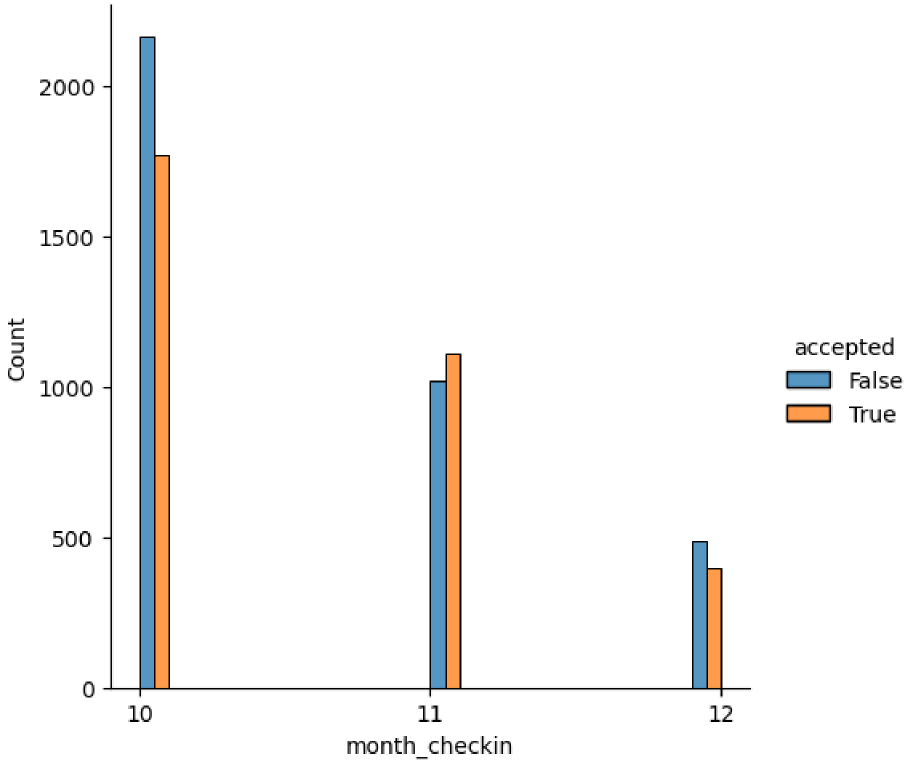
2 guests is the most popular option to book, but 1 guest is the most popularly searched option. This leads me to believe there is a lack of supply of viable single guest rooms.

In [27]:
```
# Conversion rate from accepting to booking

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

Out[27]:
```
0.5993934381031155
```

The conversion rate is about `60%` which suggests that it is not definite for a booking to happen even when the host accepts an inquiry.

In [28]:
```
# Timeframe of when guests checkin segmented by accepted vs rejected
contacts['month_checkin'] = contacts['ds_checkin'].dt.month
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()
```



`October` seems to have the most number of inquiry with **accepted being more than rejected**. The highest number of inquiry made among the other months is possibly due to it being the holiday month of the year.

Merged Datasets Analysis

In [29]:
```
# Merge datasets for further analysis

merged_datasets = contacts.merge(searches, left_on='id_guest', right_on='id_user')
print('Shape of dataset:', merged_datasets.shape)
merged_datasets.head()
```

```
Shape of dataset: (28536, 28)
```

Out[29]:

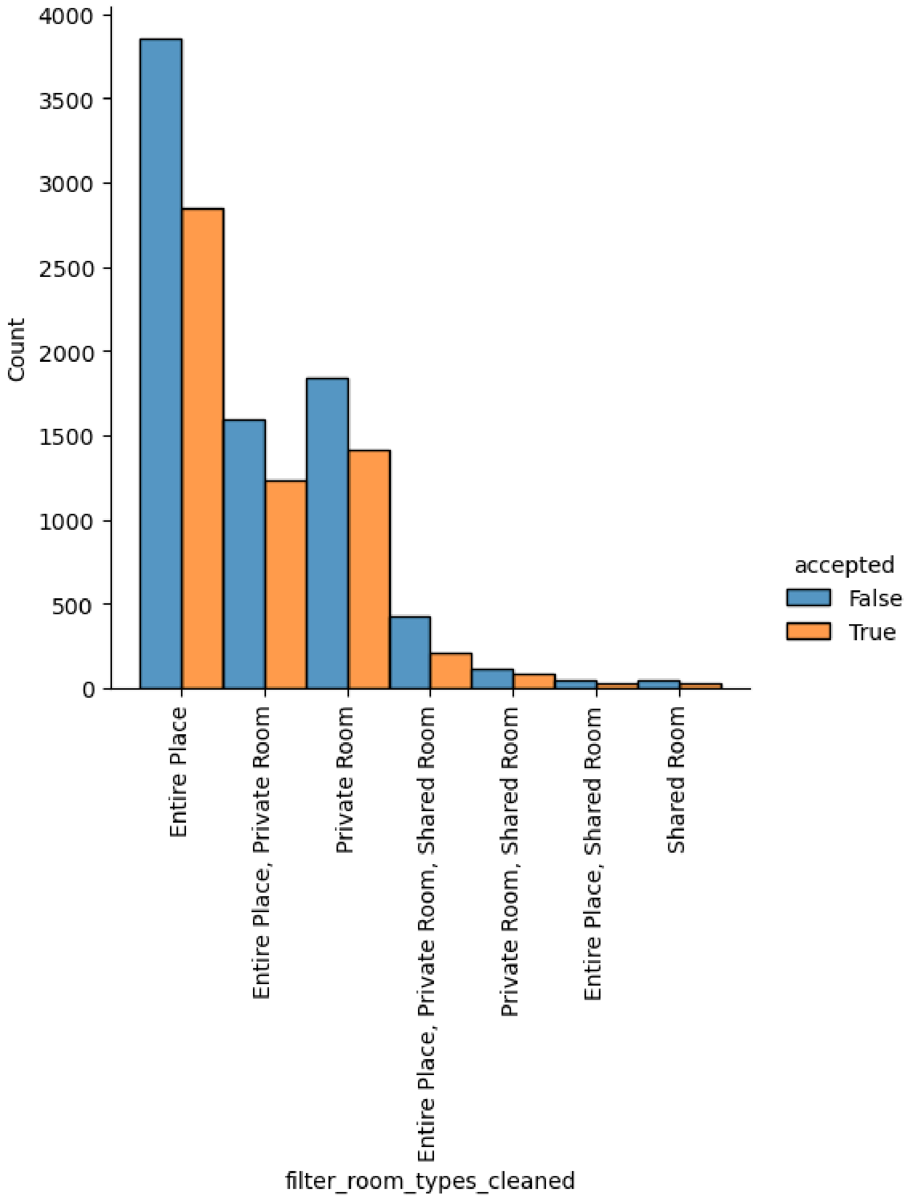
	id_guest	id_host	id_listing	ts_contact_at	ts_reply_at	ts_accepted_at	ts_booking_at	ds_checkin_x	ds_checko
0	000dfad9-459b-4f0b-8310-3d6ab34e4f57	13bb24b8-d432-43a2-9755-5ea11b43bb69	21d2b1a2-fdc3-4b4c-a1f0-0eaf0cc02370	2014-10-04 16:26:28	2014-10-04 16:26:28	2014-10-04 16:26:28	2014-10-04 16:26:28	2014-10-13	2014-1
1	00197051-c6cb-4c3a-99e9-86615b819874	46aa3897-9c00-4d76-ac66-a307593d0675	fb5ed09a-9848-4f2c-b2ef-34deb62164fb	2014-11-04 09:10:03	2014-11-04 09:45:50	2014-11-04 09:45:50	2014-11-04 12:20:46	2014-11-27	2014-1
2	0027538e-aa9e-4a02-8979-b8397e5d4cba	6bbb88ca-db66-48c5-9c4b-862f7706284a	d3871da6-8012-4dc4-b508-c91f2c10c297	2014-10-10 12:02:50	2014-10-10 15:07:01	NaT	NaT	2014-10-17	2014-1
3	0027538e-aa9e-4a02-8979-b8397e5d4cba	6bbb88ca-db66-48c5-9c4b-862f7706284a	d3871da6-8012-4dc4-b508-c91f2c10c297	2014-10-10 12:02:50	2014-10-10 15:07:01	NaT	NaT	2014-10-17	2014-1
4	0027538e-aa9e-4a02-8979-b8397e5d4cba	8772bc85-a9b7-4d85-a52d-41f3620c2912	0d9b5583-8053-4b67-adfe-8c29eb12efed	2014-10-10 15:23:53	NaT	NaT	NaT	2014-10-17	2014-1

5 rows × 28 columns

In [50]:

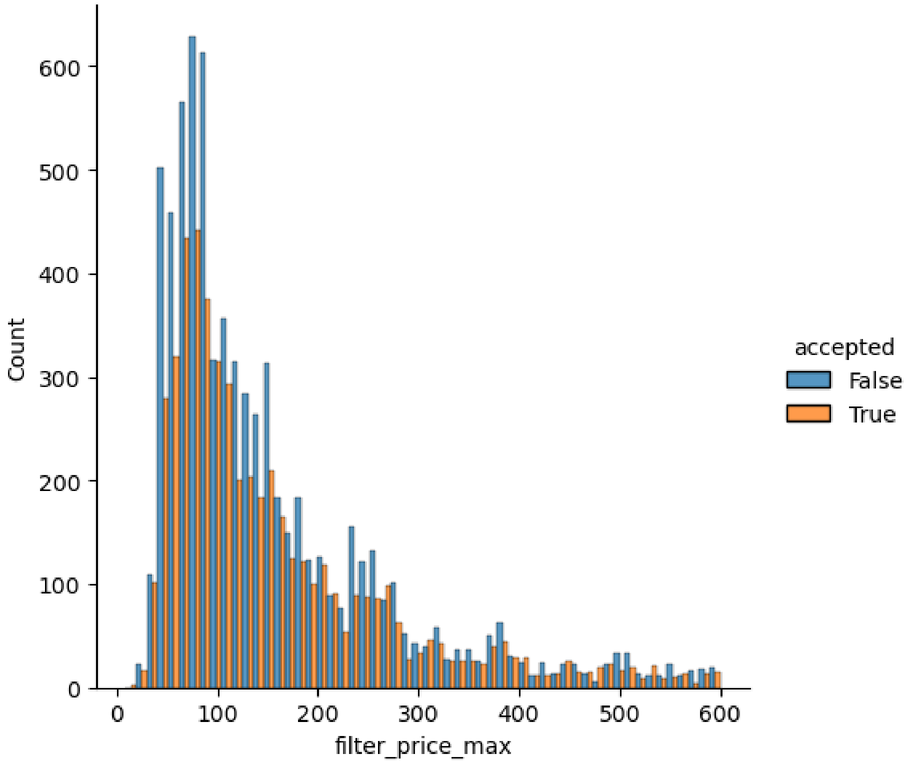
```python
# Check the acceptance rate based filter_room_types
display(merged_datasets.groupby('filter_room_types_cleaned').agg({'accepted':'mean'}))

sns.displot(merged_datasets, x='filter_room_types_cleaned', hue='accepted', multiple='dodge')
plt.xticks(rotation=90)
plt.show()
```

	accepted
filter_room_types_cleaned	
Entire Place	0.424903
Entire Place, Private Room	0.437257
Entire Place, Private Room, Shared Room	0.329705
Entire Place, Shared Room	0.362319
Private Room	0.434582
Private Room, Shared Room	0.430000
Shared Room	0.368421



It seems that the acceptance rate remains below 50% irrespective of room types, with **private room having the highest acceptance rate of 43.5%**.

In [30]:
```
# Check difference between prices searched segmented by 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 6.33% of the dataset has values greater than 600.

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

In [31]:
```
# 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[31]:

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 the table, it can be seen that regardless of `filter_price_max`, people are rejected at similar rates.

In [40]:
```
room_types_price = merged_datasets.groupby(['filter_room_types_cleaned', 'classification_max_price']).agg({'

def highlight_max(s):
    is_max = s == s.max()
    return ['background-color:green; color:white' if v else '' for v in is_max]

room_types_price.style.apply(highlight_max, axis=1)
```

Out[40]:

	accepted						
classification_max_price	0-100	100-200	200-300	300-400	400-500	500-600	600+
filter_room_types_cleaned							
Entire Place	0.323741	0.410194	0.445967	0.464539	0.484076	0.406780	0.434922
Entire Place, Private Room	0.426431	0.465870	0.437500	0.500000	0.450000	0.485714	0.422862
Entire Place, Private Room, Shared Room	0.351190	0.297297	0.303571	0.363636	0.466667	0.263158	0.325260
Entire Place, Shared Room	nan	0.375000	0.400000	0.416667	0.200000	nan	0.333333
Private Room	0.459400	0.417178	0.379032	0.375000	0.625000	0.529412	0.421099
Private Room, Shared Room	0.481481	0.480000	0.333333	0.400000	0.000000	1.000000	0.394231
Shared Room	0.272727	nan	0.125000	1.000000	0.500000	0.200000	0.441860

The table above shows that for `Private Room`, it is more likely that an inquiry will be accepted when price is set in the `400-600` range with an acceptance rate of `62.5%`.

In [33]:
```
# 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']
acceptance_country = acceptance_country.drop_duplicates()

acceptance_country = pd.merge(acceptance_country, country_count, how='left', on=['origin_country'])
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 i
acceptance_country = acceptance_country[acceptance_country['accepted'] == True]

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

Out[33]:

	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 has the lowest acceptance rate of 15% which is half of the acceptance rate of the second lowest acceptance rate country.

Let's visualize these data to gain more clarity and insights into Dublin Airbnb market by importing these datasets into Tableau.

In [51]:

```
# Load the datasets to Tableau for visualizations by converting to csv format
#searches.to_csv('searches_df.csv')
#contacts.to_csv('contacts_df.csv')
#merged_datasets.to_csv('merged_df.csv')
```

To further analyze the datasets for insights, trends, and correlations, the dataset `searches`, `contacts`, and `merged_datasets` will be **imported into SQL Server** to query for meaningful and actionable insights.

In [92]:

```
def data_to_sql(df, database_name, table_name, server):
    engine = sal.create_engine(f'mssql://{server}/master?driver=ODBC+DRIVER+17+FOR+SQL+SERVER', isolation_le
    conn = engine.connect()

    create_db_query = f"CREATE DATABASE {database_name}"
    conn.execute(create_db_query)

    verify_query = f"SELECT name FROM sys.databases WHERE name = '{database_name}'"
    result = conn.execute(verify_query)
    for row in result:
        print(f"Database created: {row[0]}")

    engine_new_db = sal.create_engine(f'mssql://{server}/{database_name}?driver=ODBC+DRIVER+17+FOR+SQL+SERVE
    conn_new_db = engine_new_db.connect()

    df.to_sql(table_name, con=conn_new_db, if_exists='replace', index=False)

    print("Table created and data loaded successfully.")

data_to_sql(df=searches, database_name='AirbnbMarket', table_name='searches_df', server='Najmi-XPS\SQLEXPRES
```

```
Database created: AirbnbMarket
C:\Users\najmi\AppData\Local\Temp\ipykernel_34920\4188778535.py:16: UserWarning: the 'timedelta' type is no
t supported, and will be written as integer values (ns frequency) to the database.
  df.to_sql(table_name, con=conn_new_db, if_exists='replace', index=False)
Table created and data loaded successfully.
```

In [99]:

```
def df_to_sql(df, database_name, table_name, server, action):
    engine = sal.create_engine(f'mssql://{server}/{database_name}?driver=ODBC+DRIVER+17+FOR+SQL+SERVER', isc

    conn = engine.connect()
    df.to_sql(table_name, con=conn, if_exists=action, index=False)

    print(f"Table created and {table_name} loaded successfully.")

df_to_sql(df=contacts, database_name='AirbnbMarket', table_name='contacts_df', server='Najmi-XPS\SQLEXPRESS'
```

```
C:\Users\najmi\AppData\Local\Temp\ipykernel_34920\3737874543.py:5: UserWarning: the 'timedelta' type is not
supported, and will be written as integer values (ns frequency) to the database.
  df.to_sql(table_name, con=conn, if_exists=action, index=False)
Table created and contacts_df loaded successfully.
```

In [100…

```
def df_to_sql(df, database_name, table_name, server, action):
    engine = sal.create_engine(f'mssql://{server}/{database_name}?driver=ODBC+DRIVER+17+FOR+SQL+SERVER', isc

    conn = engine.connect()
    df.to_sql(table_name, con=conn, if_exists=action, index=False)

    print(f"Table created and {table_name} loaded successfully.")

df_to_sql(df=merged_datasets, database_name='AirbnbMarket', table_name='merged_df', server='Najmi-XPS\SQLEXF
```

```
C:\Users\najmi\AppData\Local\Temp\ipykernel_34920\3486187542.py:5: UserWarning: the 'timedelta' type is not
supported, and will be written as integer values (ns frequency) to the database.
  df.to_sql(table_name, con=conn, if_exists=action, index=False)
Table created and merged_df loaded successfully.
```

In [105…

```
searches['ds_checkin'].max()
```

Out[105]:

```
Timestamp('2016-06-02 00:00:00')
```

In [106…

```
contacts['ds_checkout'].max()
```

Out[106]:

```
Timestamp('2015-12-01 00:00:00')
```

In [ ]: