In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegr
essor
import ml_insights as mli
%matplotlib inline
sns.set_style('whitegrid')
```

Reading the data

Visitors

This dataset contains a list of unique Thumbtack visitors who started request forms in either house cleaning or local moving categories within the last few months. Some of these users submitted a request. These customers then received between 0 and 5 quotes from pros (i.e., professionals providing services on Thumbtack). Customers who received quotes then had the option to hire one of the pros. date (string) the day the visitor came to Thumbtack

- device (string): whether the visitor is using a desktop or mobile device
- category (string): category for which the visitor needs a project done
- request_sent (integer): 1 if the user sent a request, 0 if not
- request_id (integer): unique identifier for a request, NA if the user did not submit a request
- how_far (string): for requests in the moving category, how far the customer estimates that they will move
- num_rooms (string): for requests in the cleaning category, how many rooms the customer has
- num_baths (string): for requests in the cleaning category, how many bathrooms the customer has

In [2]:
```
visitors = pd.read_csv('thumbtack/visitors.csv')
```

In [3]:
```
visitors.head()
```

Out[3]:

	session_date	device	category_name	sent_request	request_id	how_far	num_bedroo
0	8/1/16	desktop	House Cleaning (One Time)	1	9067.0	NaN	1 bedroom
1	8/1/16	desktop	Local Moving (under 50 miles)	1	12707.0	Less than 5 miles	NaN
2	8/1/16	desktop	Local Moving (under 50 miles)	1	19561.0	Less than 5 miles	NaN
3	8/1/16	mobile	Local Moving (under 50 miles)	1	31010.0	Less than 5 miles	NaN
4	8/1/16	mobile	Local Moving (under 50 miles)	1	6887.0	11 - 20 miles	NaN

In [4]:
```
visitors.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59996 entries, 0 to 59995
Data columns (total 8 columns):
session_date     59996 non-null object
device           59996 non-null object
category_name    59996 non-null object
sent_request     59996 non-null int64
request_id       34146 non-null float64
how_far          21451 non-null object
num_bedrooms     8638 non-null object
num_bathrooms    8638 non-null object
dtypes: float64(1), int64(1), object(6)
memory usage: 3.7+ MB
```

In [5]:
```
visitors.describe()
```

Out[5]:

	sent_request	request_id
count	59996.000000	34146.000000
mean	0.569138	17073.743396
std	0.495201	9857.564456
min	0.000000	1.000000
25%	0.000000	8537.250000
50%	1.000000	17073.500000
75%	1.000000	25609.750000
max	1.000000	34147.000000

Quotes

This dataset contains a list of quotes that pros sent in response to customer requests. Each quote is associated with a particular request and usually contains a price estimate.

- quote_id (integer): unique identifier for a quote
- request_id (integer): unique identifier for the request a quote is associated with
- quote_price (integer): estimated price in dollars for the project
- hired (boolean): 1 if the quote was marked as hired by the customer, 0 otherwise
- pro_id (integer): identifier for a pro

In [6]:
```
quotes = pd.read_csv('thumbtack/quotes.csv')
```

In [7]:
```
quotes.head()
```

Out[7]:

	request_id	quote_id	quote_price	hired	pro_id
0	1	38912310	NaN	0	851539
1	1	38912311	210.0	0	10113954
2	1	38913628	NaN	0	13498826
3	1	38914071	NaN	0	15921289
4	1	38912344	NaN	0	14506387

In [8]:
```
quotes.describe()
```

Out[8]:

	request_id	quote_id	quote_price	hired	pro_id
count	64330.000000	6.433000e+04	31554.000000	64330.000000	6.433000e+04
mean	16779.905301	3.873530e+07	242.516896	0.171724	9.368664e+06
std	9890.064189	5.822082e+05	273.232394	0.377143	5.156145e+06
min	1.000000	3.771956e+07	0.000000	0.000000	2.557000e+03
25%	8112.000000	3.822648e+07	120.000000	0.000000	5.328238e+06
50%	16673.500000	3.874019e+07	195.000000	0.000000	9.287742e+06
75%	25331.000000	3.924630e+07	350.000000	0.000000	1.428770e+07
max	34146.000000	3.965976e+07	25504.000000	1.000000	1.677167e+07

Question 1

Visitors and Conversion Rate

- How does the number of visitors change over time?
- What percent of visitors submit a project request?
- How do category and device influence these metrics?

In [9]:
```
#adding week number to identify trends
visitors['week_visited'] = pd.to_datetime(visitors.session_date).dt.week
```

Observing week over week growth of visits and conversion rate

In [10]:
```
weekly_activity = visitors.groupby(['week_visited'])['sent_request'].agg
(['sum','size']).reset_index()
weekly_activity.columns = ['week_visited','request_sent','total_visits']
```

Calculating conversion rate as the percentage of total visits that converted to requests sent for quotes

In [11]:
```
weekly_activity['conversion_rate'] = weekly_activity.request_sent/weekly
_activity.total_visits * 100
```

In [12]:
```
weekly_activity['%_change_in_visitors'] = weekly_activity.total_visits.p
ct_change() *100
```

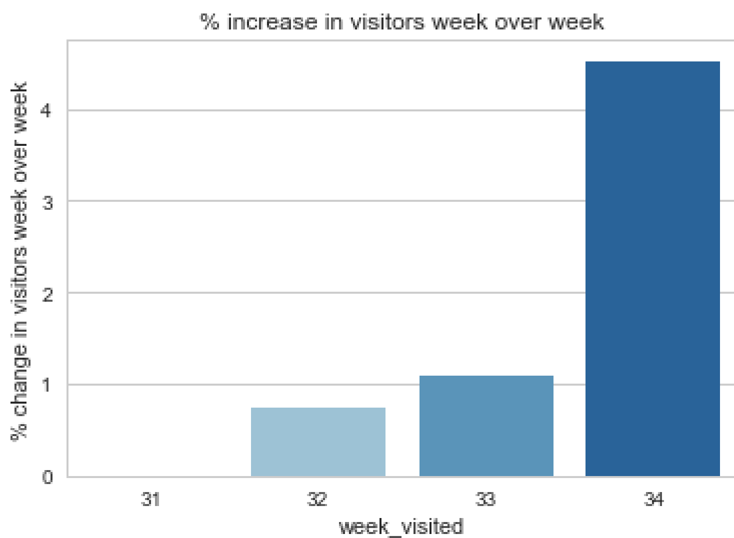
In [13]:
```
weekly_activity
```

Out[13]:

	week_visited	request_sent	total_visits	conversion_rate	%_change_in_visitors
0	31	8188	14668	55.822198	NaN
1	32	8416	14776	56.957228	0.736297
2	33	8603	14938	57.591378	1.096372
3	34	8939	15614	57.249904	4.525372

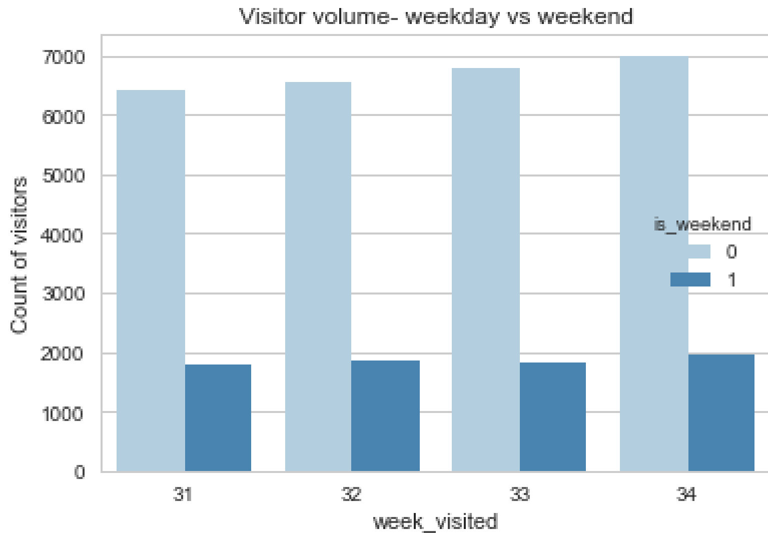
Here, we can observe that Thumbtack's visitors grew week over week- week 4 saw the highest increase in visitors

In [15]:
```
sns.barplot(x='week_visited',y='%_change_in_visitors',data=weekly_activi
ty,palette='Blues')
plt.title('% increase in visitors week over week')
plt.ylabel('% change in visitors week over week');
```



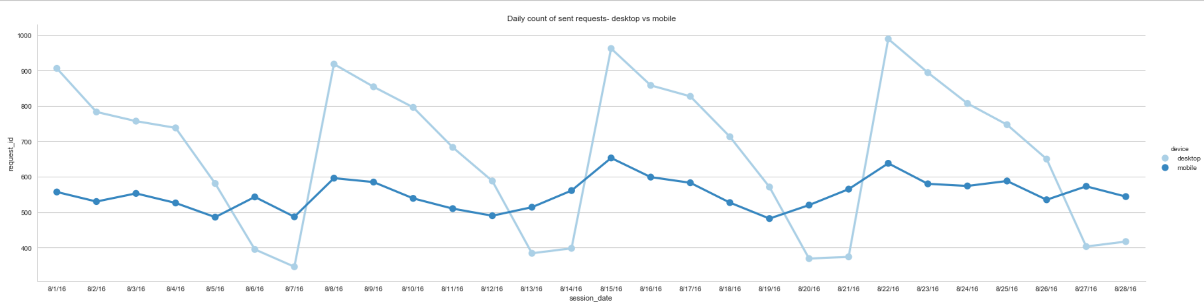
In [16]:
```
# creating a flag checking if a day is a weekend or a weekday
visitors['is_weekend'] = np.where(pd.to_datetime(visitors.session_date).
dt.weekday < 5, 0, 1)
```

In [18]:
```
sns.barplot(x='week_visited',y='request_id',hue='is_weekend',data=visito
rs, estimator=len,palette='Blues')
plt.title('Visitor volume- weekday vs weekend')
plt.ylabel('Count of visitors');
```



There are fewer visits during the weekend overall all

In [21]:
```
sns.factorplot(x='session_date',y='request_id',data=visitors,hue='devic
e',ci=None,size=6,aspect=4,estimator=len,palette='Blues')
plt.title('Daily count of sent requests- desktop vs mobile');
```



In [22]:
```
# % of visitors submitting a project request
visitors.sent_request.sum()/len(visitors) * 100
```

Out[22]:
```
56.9137942529502
```

In [23]:
```
#Percentage of sent requests per category
visitors.groupby('category_name')['sent_request'].sum() / visitors.sent_
request.sum() * 100
```

Out[23]:
```
category_name
House Cleaning (One Time)        32.115035
Local Moving (under 50 miles)    67.884965
Name: sent_request, dtype: float64
```

The largest contributors of sent requests are visitors from Local Moving (68%)

In [24]:
```
device_activity = visitors.groupby('device')['sent_request'].agg(['sum',
'size']).reset_index()
device_activity.columns = ['category_name','sent_requests','visits']
device_activity['conversion rate'] = device_activity['sent_requests'] /
device_activity['visits'] * 100
```

In [25]:
```
device_activity
```

Out[25]:

	category_name	sent_requests	visits	conversion rate
0	desktop	18708	32295	57.928472
1	mobile	15438	27701	55.730840

More than half the visitors access Thumbtack through desktop than Mobile, and the conversion rate for desktop is also better

In [26]:
```
category_activity = visitors.groupby('category_name')['sent_request'].ag
g(['sum','size']).reset_index()

category_activity.columns = ['category_name','sent_requests','visits']

category_activity['conversion rate'] = category_activity['sent_requests'
] / category_activity['visits'] * 100
```

In [27]:
```
category_activity
```

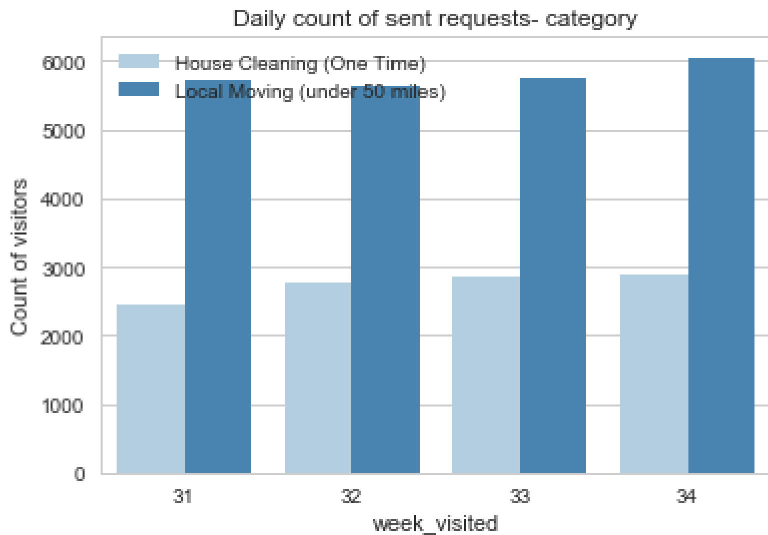
Out[27]:

	category_name	sent_requests	visits	conversion rate
0	House Cleaning (One Time)	10966	17347	63.215542
1	Local Moving (under 50 miles)	23180	42649	54.350630

Even though visitors send more Local Moving requests, the conversion rate for House Cleaning is better (63%)

In [28]:
```
sns.barplot(x='week_visited',y='sent_request',hue='category_name',data=v
isitors,estimator=sum,palette='Blues',ci=None)
plt.title('Daily count of sent requests- category')
plt.ylabel('Count of visitors')
plt.legend(loc='upper left')
```

Out[28]: <matplotlib.legend.Legend at 0x1271cf9b0>



Question 2

Quotes Per Request

- What is the distribution of number of quotes per request?
- What factors contribute to some requests getting more quotes than others?

In [29]:
```
#Extracting count of quotes for each request id from the quotes table
count_of_quotes = quotes.groupby('request_id')['quote_id'].count().reset
_index()
count_of_quotes.columns = ['request_id','count_of_quotes']
```

In [30]:
```
count_of_quotes.count_of_quotes.value_counts()
```

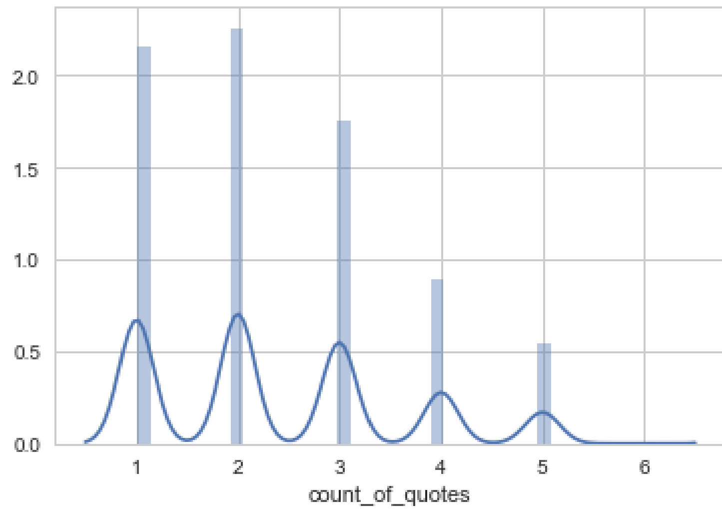
Out[30]:
```
2    7977
1    7630
3    6188
4    3139
5    1924
6       1
Name: count_of_quotes, dtype: int64
```

In [31]:
```
# finding out the % share of quote counts
count_of_quotes.count_of_quotes.value_counts() / len(count_of_quotes) *
100
```

Out[31]:
```
2    29.699542
1    28.407610
3    23.038832
4    11.686958
5     7.163334
6     0.003723
Name: count_of_quotes, dtype: float64
```

In [32]:
```
sns.distplot(count_of_quotes.count_of_quotes)
```

Out[32]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1271cf668>
```



In [33]:
```
visitors_request_counts = visitors.merge(count_of_quotes, on='request_i
d',how='left')
```

In [34]:
```
# filling missing values with 0 to aid in analysis
visitors_request_counts.fillna(0, inplace=True)
```

Identifying requests that have more than 3 quotes to understand the drivers of have more quotes

In [35]:
```
more_than_3_quotes = visitors_request_counts.loc[visitors_request_counts
.count_of_quotes > 3]
```

In [36]:
```
more_than_3_quotes.groupby('category_name')['request_id'].count()
```

Out[36]:
```
category_name
House Cleaning (One Time)        1165
Local Moving (under 50 miles)    3899
Name: request_id, dtype: int64
```

In [38]:
```
more_than_3_quotes.groupby(['category_name','how_far'])['request_id'].co
unt().reset_index()
```

Out[38]:

	category_name	how_far	request_id
0	House Cleaning (One Time)	0	1149
1	House Cleaning (One Time)	11 - 20 miles	6
2	House Cleaning (One Time)	21 - 30 miles	2
3	House Cleaning (One Time)	31 - 50 miles	4
4	House Cleaning (One Time)	5 - 10 miles	3
5	House Cleaning (One Time)	Less than 5 miles	1
6	Local Moving (under 50 miles)	0	38
7	Local Moving (under 50 miles)	11 - 20 miles	938
8	Local Moving (under 50 miles)	21 - 30 miles	635
9	Local Moving (under 50 miles)	31 - 50 miles	539
10	Local Moving (under 50 miles)	5 - 10 miles	753
11	Local Moving (under 50 miles)	Less than 5 miles	942
12	Local Moving (under 50 miles)	Within the same building	54

In [39]:
```
more_than_3_quotes.groupby(['category_name','num_bedrooms'])['request_i
d'].count().reset_index()
```

Out[39]:

	category_name	num_bedrooms	request_id
0	House Cleaning (One Time)	0	26
1	House Cleaning (One Time)	1 bedroom	101
2	House Cleaning (One Time)	2 bedrooms	255
3	House Cleaning (One Time)	3 bedrooms	462
4	House Cleaning (One Time)	4 bedrooms	234
5	House Cleaning (One Time)	5+ bedrooms	76
6	House Cleaning (One Time)	Studio	11
7	Local Moving (under 50 miles)	0	3884
8	Local Moving (under 50 miles)	1 bedroom	2
9	Local Moving (under 50 miles)	2 bedrooms	1
10	Local Moving (under 50 miles)	3 bedrooms	7
11	Local Moving (under 50 miles)	4 bedrooms	4
12	Local Moving (under 50 miles)	Studio	1

From the above tables, we observe that-

- Local Moving- a large number of requests for moves within 20 miles have 4 or 5 quotes
- House Cleaning- a large number of requests for cleaning are homes that have more than 2 bedrooms

Checking for each category what the drivers are

In [41]:
```
moving_data = visitors_request_counts.loc[visitors_request_counts.catego
ry_name== 'Local Moving (under 50 miles)']
```

In [42]:
```
more_than_3_moving = moving_data.loc[moving_data.count_of_quotes > 3]
```

In [43]:
```
more_than_3_moving.groupby('how_far')['request_id'].count().reset_index
()
```

Out[43]:

	how_far	request_id
0	0	38
1	11 - 20 miles	938
2	21 - 30 miles	635
3	31 - 50 miles	539
4	5 - 10 miles	753
5	Less than 5 miles	942
6	Within the same building	54

In [44]:
```
X_moving = moving_data[['device','how_far']]
y_moving = moving_data['count_of_quotes']
X_moving = pd.get_dummies(X_moving)
```

In [45]:
```
X_train, X_test, y_train, y_test = train_test_split(X_moving, y_moving,
test_size=0.20, random_state=42)
```

In [47]:
```
rf = RandomForestRegressor()
```

In [48]:
```
rf.fit(X_train,y_train)
```

Out[48]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_split=1e-07, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=10, n_jobs=1, oob_score=False, random_state=Non
e,
           verbose=0, warm_start=False)
```

In [49]:
```
y_pred_moving = rf.predict(X_test)
```

In [50]:
```
mean_squared_error(y_test,y_pred_moving)
```

Out[50]:
```
0.95301748611477599
```

In [51]:
```
sorted(list(zip(X_moving.columns,rf.feature_importances_)),key=lambda x:
 -1*x[1])
```

Out[51]:
```
[('how_far_0', 0.95072616548946942),
 ('how_far_31 - 50 miles', 0.018732910718452459),
 ('how_far_21 - 30 miles', 0.018548009881173548),
 ('how_far_11 - 20 miles', 0.0098785180582103768),
 ('how_far_Within the same building', 0.0010005796026057931),
 ('device_desktop', 0.00059492378494537814),
 ('device_mobile', 0.00041516556617451412),
 ('how_far_Less than 5 miles', 5.3017986804070712e-05),
 ('how_far_5 - 10 miles', 5.0708912164537191e-05)]
```

In [53]:
```
cleaning_data = visitors_request_counts.loc[visitors_request_counts.cate
gory_name== 'House Cleaning (One Time)'].copy()
```

In [54]:
```
X_cleaning = cleaning_data[['device','num_bedrooms','num_bathrooms']]
y_cleaning = cleaning_data['count_of_quotes']
X_cleaning = pd.get_dummies(X_cleaning)
```

In [55]:
```
X_train, X_test, y_train, y_test = train_test_split(X_cleaning, y_cleani
ng, test_size=0.20, random_state=42)
```

In [56]:
```
rf.fit(X_train,y_train)
```

Out[56]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_split=1e-07, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=10, n_jobs=1, oob_score=False, random_state=Non
e,
           verbose=0, warm_start=False)
```

In [57]:
```
y_pred_cleaning = rf.predict(X_test)
mean_squared_error(y_test,y_pred_cleaning)
```

Out[57]:
```
0.87554832296309748
```

In [59]:
```
sorted(list(zip(X_cleaning.columns,rf.feature_importances_)),key=lambda
x: -1*x[1])
```

Out[59]:
```
[('num_bathrooms_0', 0.58644187863436315),
 ('num_bedrooms_0', 0.39191799753172579),
 ('num_bathrooms_1 bathroom', 0.0052091651500576017),
 ('device_mobile', 0.0019985507141861976),
 ('num_bedrooms_2 bedrooms', 0.0019629283629425303),
 ('num_bathrooms_1.5 bathrooms', 0.0018955486450180446),
 ('num_bedrooms_4 bedrooms', 0.0016371034995435862),
 ('num_bedrooms_5+ bedrooms', 0.0016265417018670725),
 ('device_desktop', 0.0012385824780104312),
 ('num_bedrooms_3 bedrooms', 0.0012030099751987938),
 ('num_bedrooms_1 bedroom', 0.0011671437420 79386),
 ('num_bedrooms_Studio', 0.0011084012704055488),
 ('num_bathrooms_3 bathrooms', 0.0010557235718064199),
 ('num_bathrooms_4+ bathrooms', 0.00084239479609903858),
 ('num_bathrooms_2 bathrooms', 0.00069502992669654231)]
```

In [402]:
```
more_than_3_cleaning = cleaning_data.loc[cleaning_data.count_of_quotes >
 3]
```

In [419]:
```
more_than_3_cleaning.groupby('num_bedrooms')['request_id'].count().reset
_index()
```

Out[419]:

	num_bedrooms	request_id
0	0	26
1	1 bedroom	101
2	2 bedrooms	255
3	3 bedrooms	462
4	4 bedrooms	234
5	5+ bedrooms	76
6	Studio	11

In [60]:
```
def home_types(x):
    ''' A function to tag homes that have more than 2 bedrooms'''

    if x.num_bedrooms in ['3 bedrooms','4 bedrooms','5+ bedrooms']:
        return 'Homes with greater than 2 bedrooms'
    elif x.num_bedrooms == 0:
        return 'No bedroom count'
    else:
        return 'Homes with upto 2 bedrooms'
```

In [61]:
```
cleaning_data['home_type'] = cleaning_data.apply(lambda x: home_types(x
),axis=1)
```

In [62]:
```
cleaning_data.groupby('home_type')['count_of_quotes'].mean().reset_index
()
```

Out[62]:

	home_type	count_of_quotes
0	Homes with greater than 2 bedrooms	2.068908
1	Homes with upto 2 bedrooms	1.882726
2	No bedroom count	0.038248

As noticed above, homes with more than 2 bedrooms have a greater average quote count than homes with fewer than 2 bedrooms

Question 3

- By category, what is the distribution of quote prices for a project?
- By category, what price do you think Thumbtack should charge pros to quote? Why? Explain your reasoning for any assumptions that you make.

In [63]:
```
# merging visitor and quotes data
overall_data = quotes.merge(visitors,on='request_id',how='left')
```

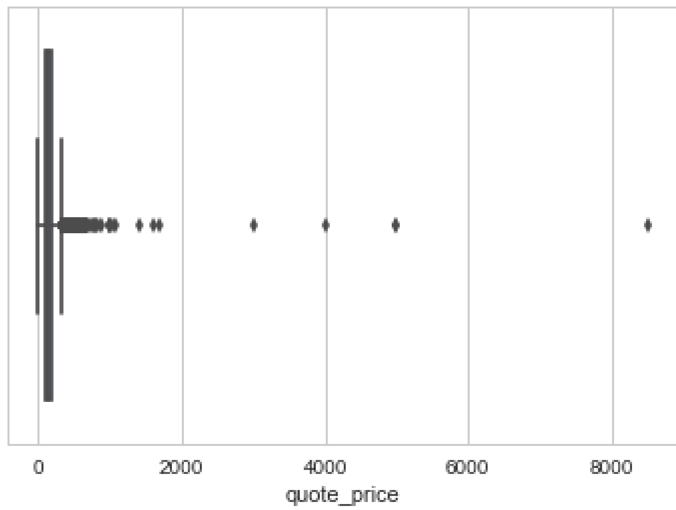
In [64]:
```
overall_data.groupby('category_name')['quote_price'].mean()
```

Out[64]:
```
category_name
House Cleaning (One Time)        151.982718
Local Moving (under 50 miles)    350.821409
Name: quote_price, dtype: float64
```

In [65]:
```
overall_cleaning_data = overall_data.loc[overall_data.category_name ==
'House Cleaning (One Time)']
overall_moving_data = overall_data.loc[overall_data.category_name == 'Lo
cal Moving (under 50 miles)']
```

In [66]:
```
sns.boxplot(overall_cleaning_data.quote_price)
```

Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x126c533c8>



Since there are very few quotes above 800 dollars, we shall filter the quotes to below 800 dollars to obtain quote prices distributions

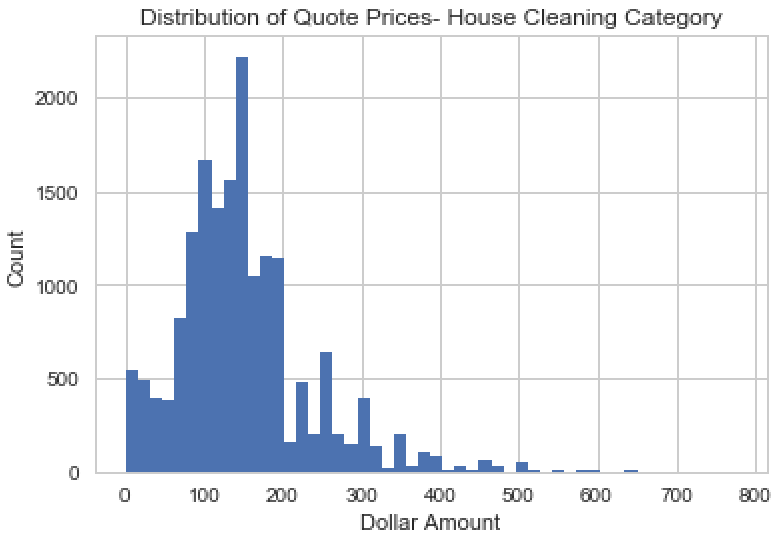
In [67]:
```
cleaning_quote_price = overall_cleaning_data.quote_price.loc[overall_cle
aning_data.quote_price < 800]
```

In [68]:
```
g = sns.boxplot(cleaning_quote_price)
plt.title('Distribution of Quote Prices- House Cleaning Category')
```

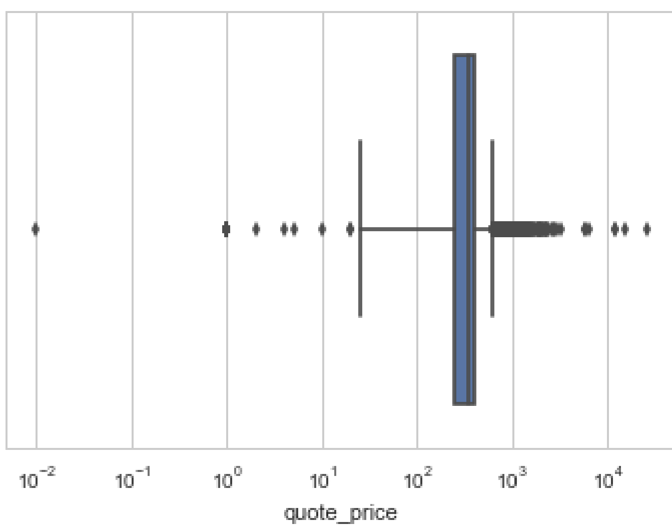
Out[68]: <matplotlib.text.Text at 0x12982c748>

In [69]:
```
cleaning_quote_price.hist(bins=50)
plt.title('Distribution of Quote Prices- House Cleaning Category')
plt.xlabel('Dollar Amount')
plt.ylabel('Count')
```

Out[69]: <matplotlib.text.Text at 0x12971db00>



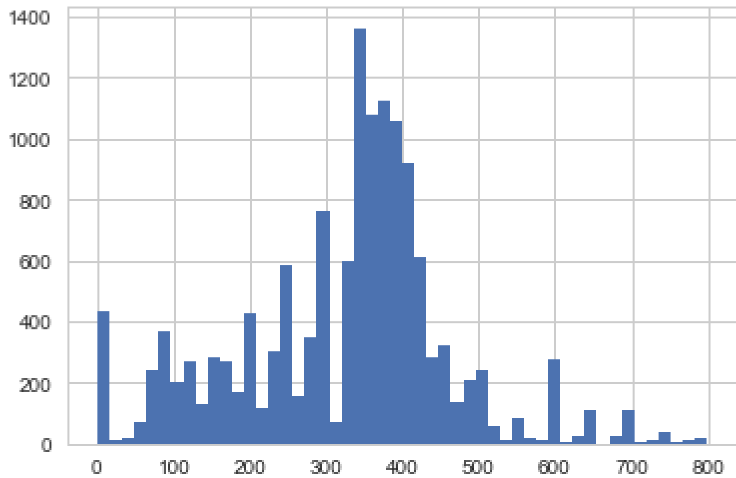
In [499]:
```
g = sns.boxplot(overall_moving_data.quote_price)
g.set_xscale('log')
```



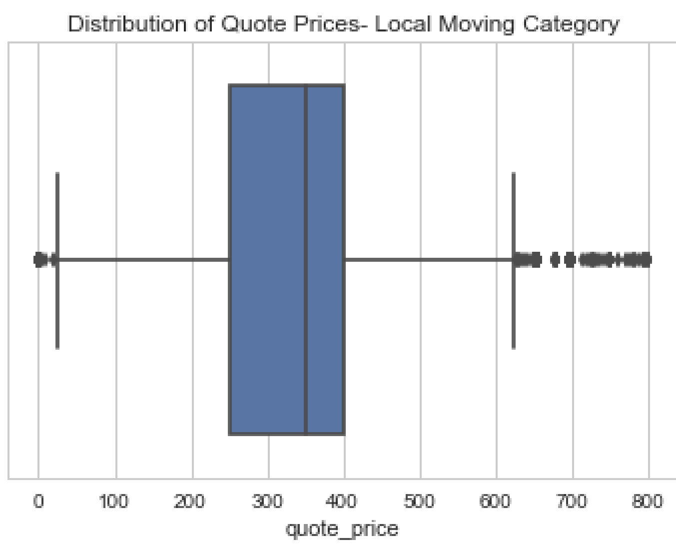
In [70]:
```
moving_quote = overall_moving_data.quote_price.loc[overall_moving_data.q
uote_price < 800]
```

In [71]:
```
moving_quote.hist(bins=50)
```

Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x127815630>

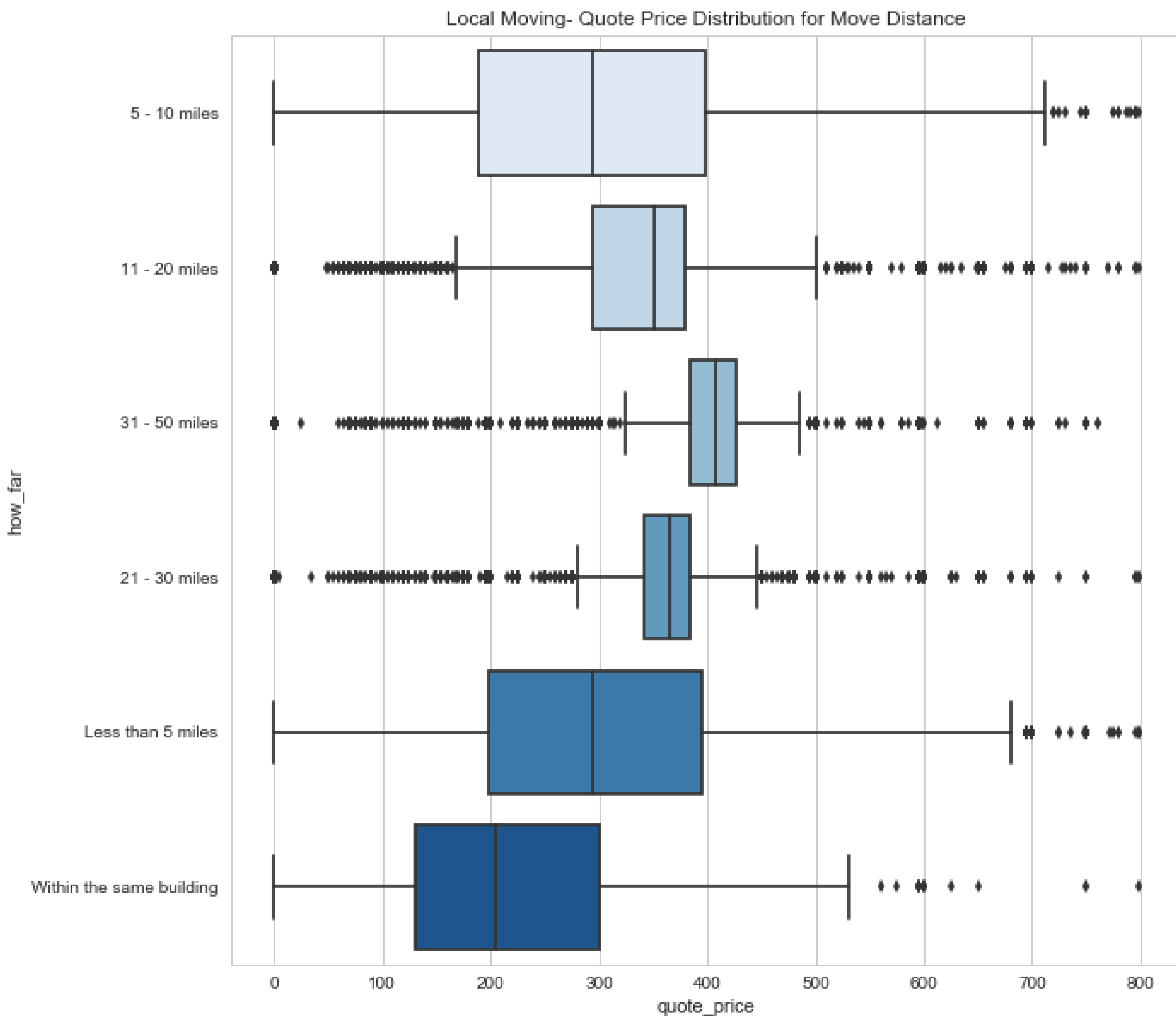


In [72]:
```
sns.boxplot(moving_quote)
plt.title('Distribution of Quote Prices- Local Moving Category')
plt.savefig('moving_price_dist.png',dpi=300,bbox_inches='tight')
```



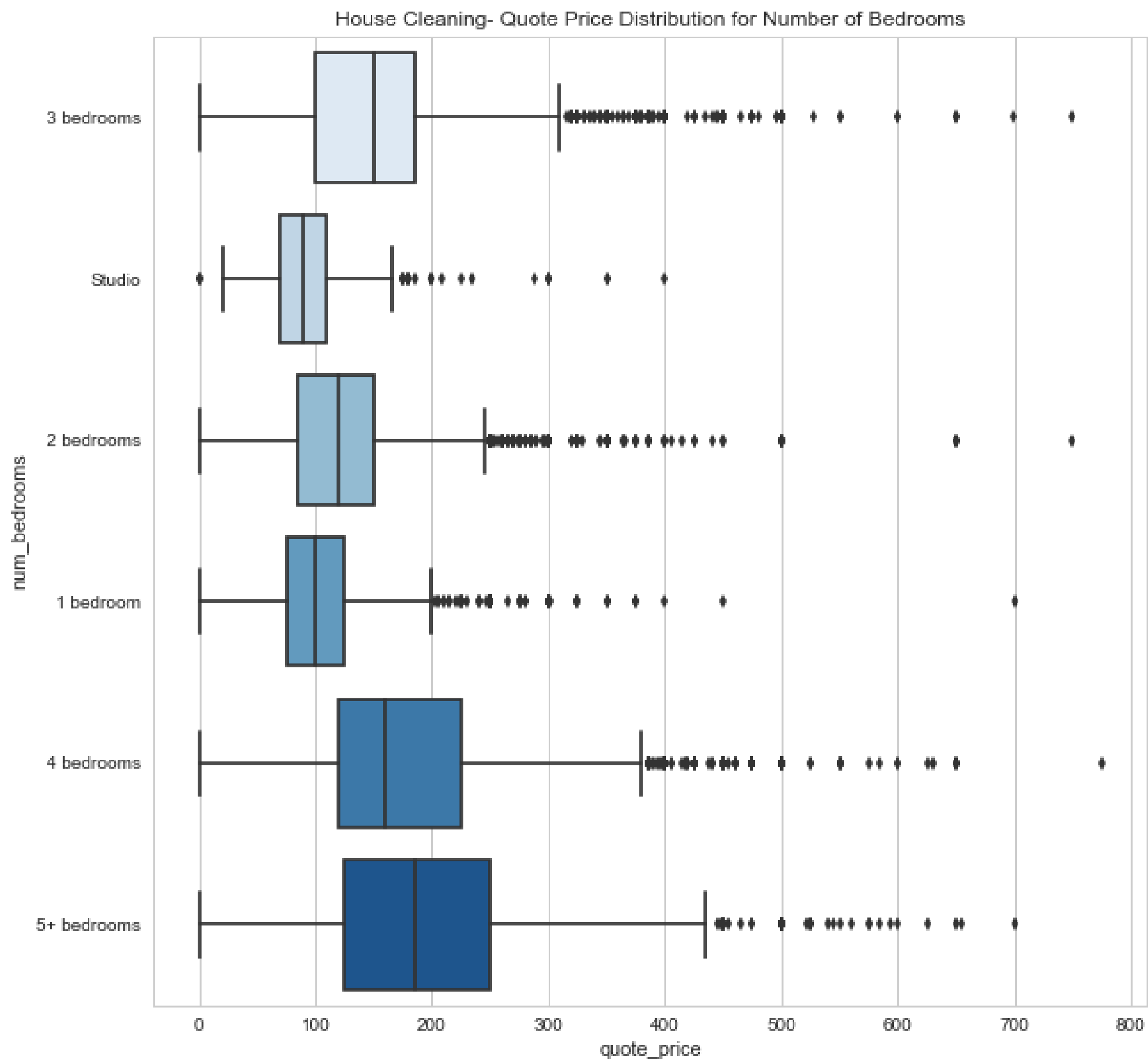
In [73]:
```
less_than_800_moving = overall_moving_data.loc[overall_moving_data.quote
_price < 800]
plt.figure(figsize=(10,10))
g = sns.boxplot(x='quote_price',y='how_far',data=less_than_800_moving,pa
lette='Blues')
plt.title('Local Moving- Quote Price Distribution for Move Distance')
```

Out[73]: <matplotlib.text.Text at 0x12722c3c8>



In [74]:
```
less_than_800_cleaning = overall_cleaning_data.loc[overall_cleaning_data
.quote_price < 800]
plt.figure(figsize=(10,10))
g = sns.boxplot(x='quote_price',y='num_bedrooms',data=less_than_800_clea
ning,palette='Blues')
plt.title('House Cleaning- Quote Price Distribution for Number of Bedroo
ms')
```

Out[74]: <matplotlib.text.Text at 0x12149c550>



In [569]:
```
overall_data.groupby(['category_name','num_bedrooms'])['quote_price'].ag
g(['mean','median'])
```

Out[569]:

		mean	median
category_name	**num_bedrooms**		
House Cleaning (One Time)	**1 bedroom**	104.936083	100.0
	2 bedrooms	129.694420	120.0
	3 bedrooms	155.215701	150.0
	4 bedrooms	179.951035	162.0
	5+ bedrooms	205.888405	186.0
	Studio	101.130453	90.0
Local Moving (under 50 miles)	**1 bedroom**	107.512821	100.0
	2 bedrooms	137.029265	125.0
	3 bedrooms	153.368049	150.0
	4 bedrooms	165.452381	155.5
	5+ bedrooms	211.666667	202.5
	Studio	96.181818	100.0

In [76]:
```
# Cleaning quote prices that have the maximum occurence
overall_cleaning_data.quote_price.value_counts().head(5)
```

Out[76]:
```
150.0    1427
100.0    1145
120.0     870
200.0     775
125.0     690
Name: quote_price, dtype: int64
```

In [77]:
```
# Moving quote prices that have the maximum occurence
overall_moving_data.quote_price.value_counts().head(5)
```

Out[77]:
```
250.0    498
350.0    409
300.0    326
400.0    319
340.0    298
Name: quote_price, dtype: int64
```

For Local Moving

- A large volume of quote prices in the 250 - 400 range (250 and 350- most quoted price)
- As moving distance increases, the quote price ranges also increase
- < 5 miles and 5 - 10 miles price ranges are almost similar

For House Cleaning

- A large volume of quote prices in the 100 - 200 range (100 and 150 - most quoted price)
- Similar to Local Moving, the range of quote prices increase as the number of bedrooms increase
- Single Family Homes have higher quote price ranges

In [ ]:

```

```