### The Problem Statement:

To build an application which predicts the monthly rental of a house based on the given attributes.

**Attributes:**

- Id: listing id
- url: listing URL
- region: craigslist region
- region_url: region URL
- price: rent per month (Target Column)
- type: housing type
- sqfeet: total square footage
- beds:number of beds
- baths:number of bathrooms
- cats_allowed: cats allowed boolean (1 = yes, 0 = no)
- dogs_allowed: dogs allowed boolean
- smoking_allowed: smoking allowed boolean
- wheelchair_access: has wheelchair access boolean
- electric_vehicle_charge: has electric vehicle charger boolean
- comes_furnished: comes with furniture boolean
- laundry_options: laundry options available
- parking_options: parking options available
- image_url: image URL
- description: description by poster
- lat: latitude
- long: longitude
- state: state of listing

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeRegressor


import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
house = pd.read_csv("housing_train.csv")
house.head(3)
```

Out[2]:

| | id | url | region | region_url | price | type | sqfeet | beds | baths | cats_allowed | ... | wheelchair_access | electric_ve |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 7039061606 | https://bham.craigslist.org /apa/d/birmingham-h... | birmingham | https://bham.craigslist.org | 1195 | apartment | 1908 | 3 | 2.0 | 1 | ... | 0 | |
| **1** | 7041970863 | https://bham.craigslist.org /apa/d/birmingham-w... | birmingham | https://bham.craigslist.org | 1120 | apartment | 1319 | 3 | 2.0 | 1 | ... | 0 | |
| **2** | 7041966914 | https://bham.craigslist.org /apa/d/birmingham-g... | birmingham | https://bham.craigslist.org | 825 | apartment | 1133 | 1 | 1.5 | 1 | ... | 0 | |

3 rows × 22 columns

In [3]:
```python
house.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 265190 entries, 0 to 265189
Data columns (total 22 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   id                       265190 non-null  int64  
 1   url                      265190 non-null  object 
 2   region                   265190 non-null  object 
 3   region_url               265190 non-null  object 
 4   price                    265190 non-null  int64  
 5   type                     265190 non-null  object 
 6   sqfeet                   265190 non-null  int64  
 7   beds                     265190 non-null  int64  
 8   baths                    265190 non-null  float64
 9   cats_allowed             265190 non-null  int64  
 10  dogs_allowed             265190 non-null  int64  
 11  smoking_allowed          265190 non-null  int64  
 12  wheelchair_access        265190 non-null  int64  
 13  electric_vehicle_charge  265190 non-null  int64  
 14  comes_furnished          265190 non-null  int64  
 15  laundry_options          210879 non-null  object 
 16  parking_options          170055 non-null  object 
 17  image_url                265190 non-null  object 
 18  description              265188 non-null  object 
 19  lat                      263771 non-null  float64
 20  long                     263771 non-null  float64
 21  state                    265189 non-null  object 
dtypes: float64(3), int64(10), object(9)
memory usage: 44.5+ MB
```

***Drop unwanted columns***

In [4]:
```python
house.drop(columns=['id','url','lat','long','region_url','image_url','description'], inplace=True)
```

Shape of the data

In [5]:
```python
house.shape
```

Out[5]:
```
(265190, 15)
```

***Lets check the statical values of data***

In [6]:
```python
house.describe().round(2).T
```

Out[6]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **price** | 265190.0 | 12272.85 | 5376351.72 | 0.0 | 817.0 | 1060.0 | 1450.0 | 2.768307e+09 |
| **sqfeet** | 265190.0 | 1093.68 | 23068.88 | 0.0 | 752.0 | 950.0 | 1156.0 | 8.388607e+06 |
| **beds** | 265190.0 | 1.91 | 3.69 | 0.0 | 1.0 | 2.0 | 2.0 | 1.100000e+03 |
| **baths** | 265190.0 | 1.48 | 0.63 | 0.0 | 1.0 | 1.0 | 2.0 | 7.500000e+01 |
| **cats_allowed** | 265190.0 | 0.72 | 0.45 | 0.0 | 0.0 | 1.0 | 1.0 | 1.000000e+00 |
| **dogs_allowed** | 265190.0 | 0.70 | 0.46 | 0.0 | 0.0 | 1.0 | 1.0 | 1.000000e+00 |
| **smoking_allowed** | 265190.0 | 0.73 | 0.44 | 0.0 | 0.0 | 1.0 | 1.0 | 1.000000e+00 |
| **wheelchair_access** | 265190.0 | 0.08 | 0.27 | 0.0 | 0.0 | 0.0 | 0.0 | 1.000000e+00 |
| **electric_vehicle_charge** | 265190.0 | 0.01 | 0.12 | 0.0 | 0.0 | 0.0 | 0.0 | 1.000000e+00 |
| **comes_furnished** | 265190.0 | 0.05 | 0.22 | 0.0 | 0.0 | 0.0 | 0.0 | 1.000000e+00 |

Checking null values

In [7]:
```python
house.isna().sum()
```

Out[7]:
```
region                         0
price                          0
type                           0
sqfeet                         0
beds                           0
baths                          0
cats_allowed                   0
dogs_allowed                   0
smoking_allowed                0
wheelchair_access              0
electric_vehicle_charge        0
comes_furnished                0
laundry_options            54311
parking_options            95135
state                          1
dtype: int64
```

Remove Null values and Duplicate

In [8]:
```python
house.dropna(inplace=True)
```

In [9]:
```python
house.drop_duplicates(inplace=True)
```

Check the unique values to see the data in categorial values and some continuous values

In [10]:
```python
print('Unique values of beds \n ',house.beds.unique(),'\n',
      'Unique values of baths \n ',house.baths.unique(),'\n',
      'Available laundry options \n ',house.laundry_options.unique(),'\n',
      'Available parking options \n ',house.parking_options.unique())
```

```
Unique values of beds
  [   3    1    2    4    0    5    7    6    8 1000 1100]
 Unique values of baths
  [ 2.   1.5  1.   2.5  3.5  0.   3.   4.   4.5  5.   6.5  6.   5.5  7.
 35.  75.   7.5  8. ]
 Available laundry options
  ['laundry on site' 'w/d hookups' 'laundry in bldg' 'w/d in unit'
 'no laundry on site']
 Available parking options
  ['street parking' 'off-street parking' 'carport' 'attached garage'
 'detached garage' 'no parking' 'valet parking']
```

Baths values are uneven and lets replace with next values of the uneven values

In [11]:
```python
house.baths.replace(to_replace=(1.5,2.5,3.5,4.5), value=(2,3,4,5), inplace=True )
```

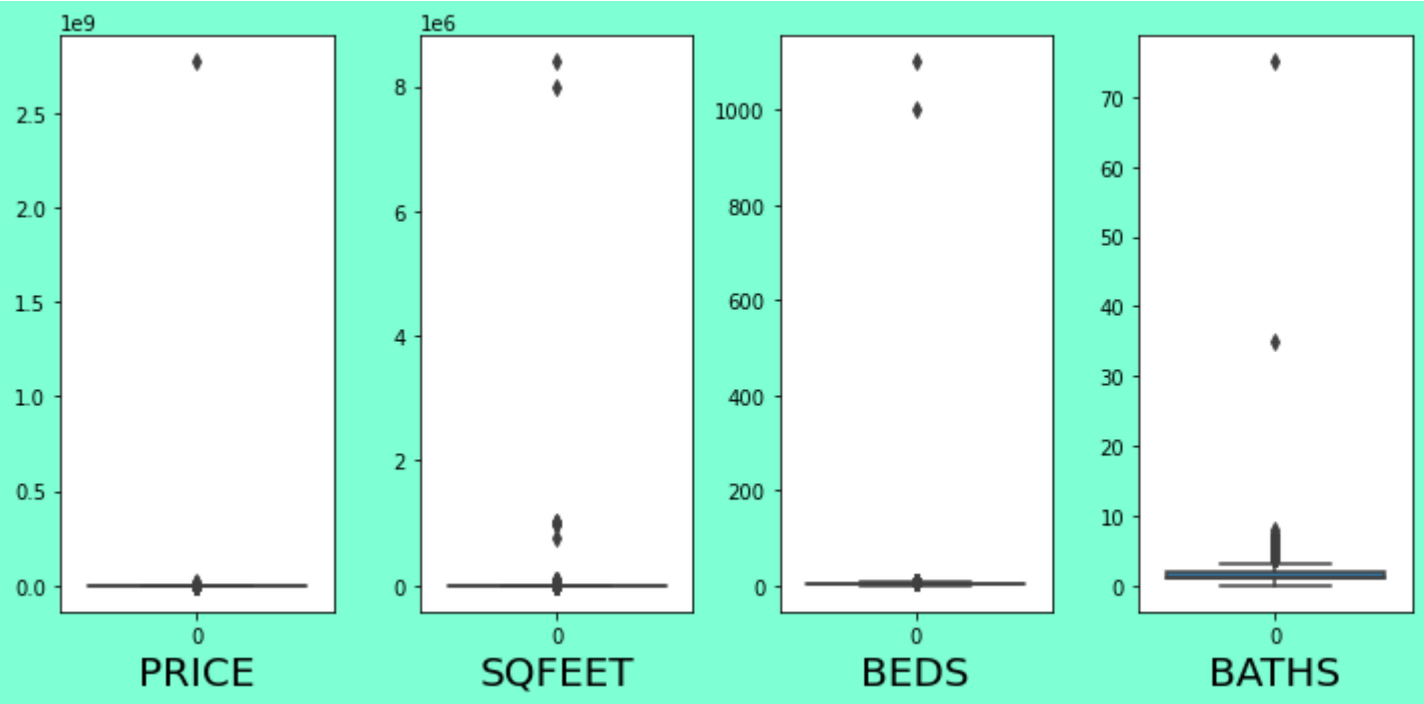
**Describe function**

Difference between mean and standard deviation shows that there so many variances in data,

Min and Max Values of Sqfeet, Beds, Baths and Price are to exterme, seems like there are outliers

**lets check data with box plot**

In [12]:
```python
house_cont= house[['price','sqfeet','beds','baths']]

plt.figure(figsize=(10,5), facecolor='aquamarine')
plotnumber =1

for column in house_cont:
    if plotnumber<=4:
        ax=plt.subplot(1,4,plotnumber)
        sns.boxplot(house_cont[column])
        plt.xlabel(column.upper(), fontsize = 20)

    plotnumber+=1
plt.tight_layout()
plt.show()
```



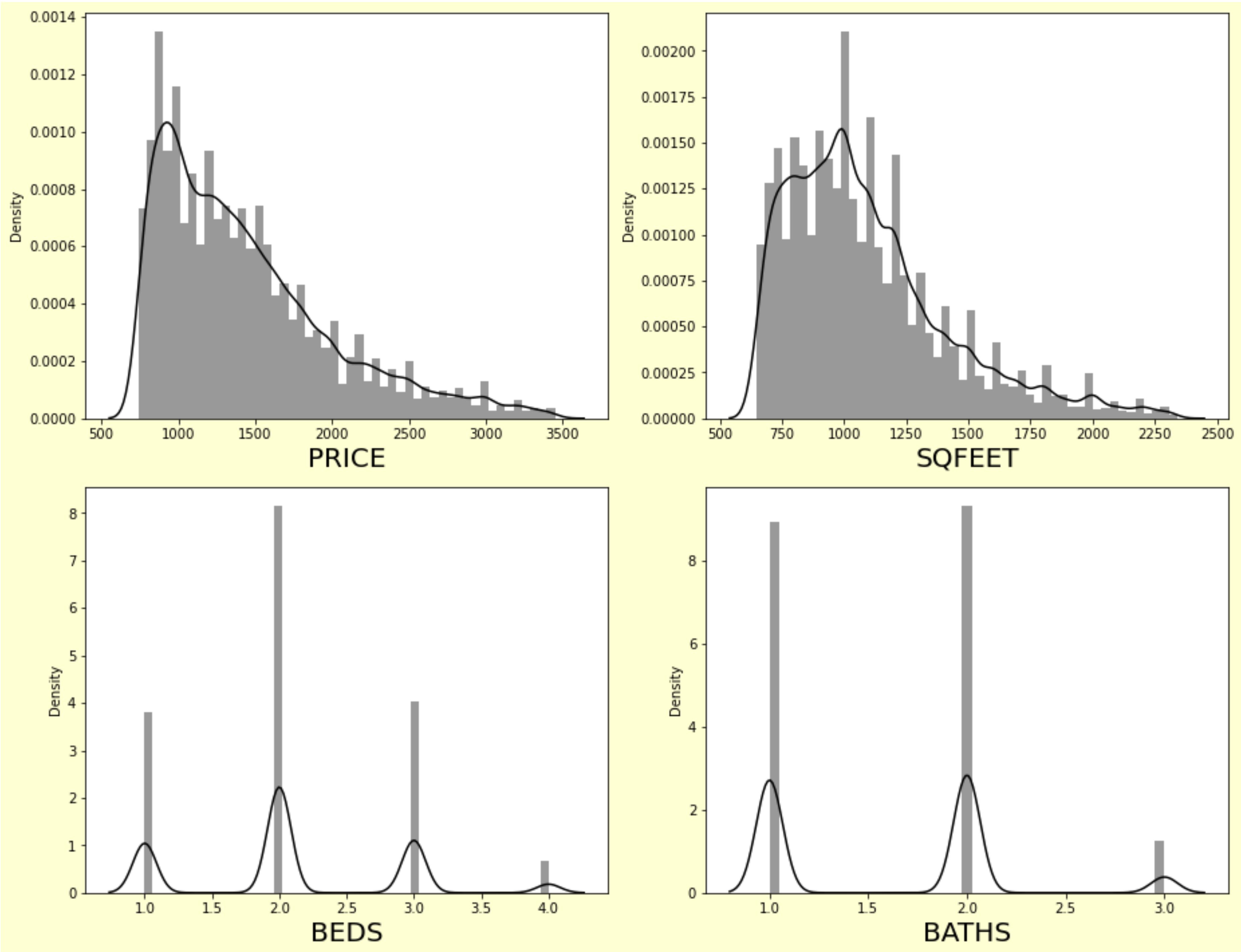

Bar plot can also shows the outliers present in Price, Sqfeet, Beds and Baths

Lets remove data of price, sqfeet, beds and baths which isn't less than 12.5% and more than 97.5%

In [13]:
```
qua_low = house.quantile(0.125)
qua_high = house.quantile(0.975)

h1= house[(house.price>qua_high.price)|
          (house.price<qua_low.price)|
          (house.sqfeet>qua_high.sqfeet)|
         (house.sqfeet<qua_low.sqfeet)|
         (house.beds>qua_high.beds)|
         (house.beds<qua_low.beds)|
         (house.baths>qua_high.baths)|
         (house.baths<qua_low.baths)].index

house.drop(h1, inplace=True)
```

Lets see the Disturbance plot and how values are distributed

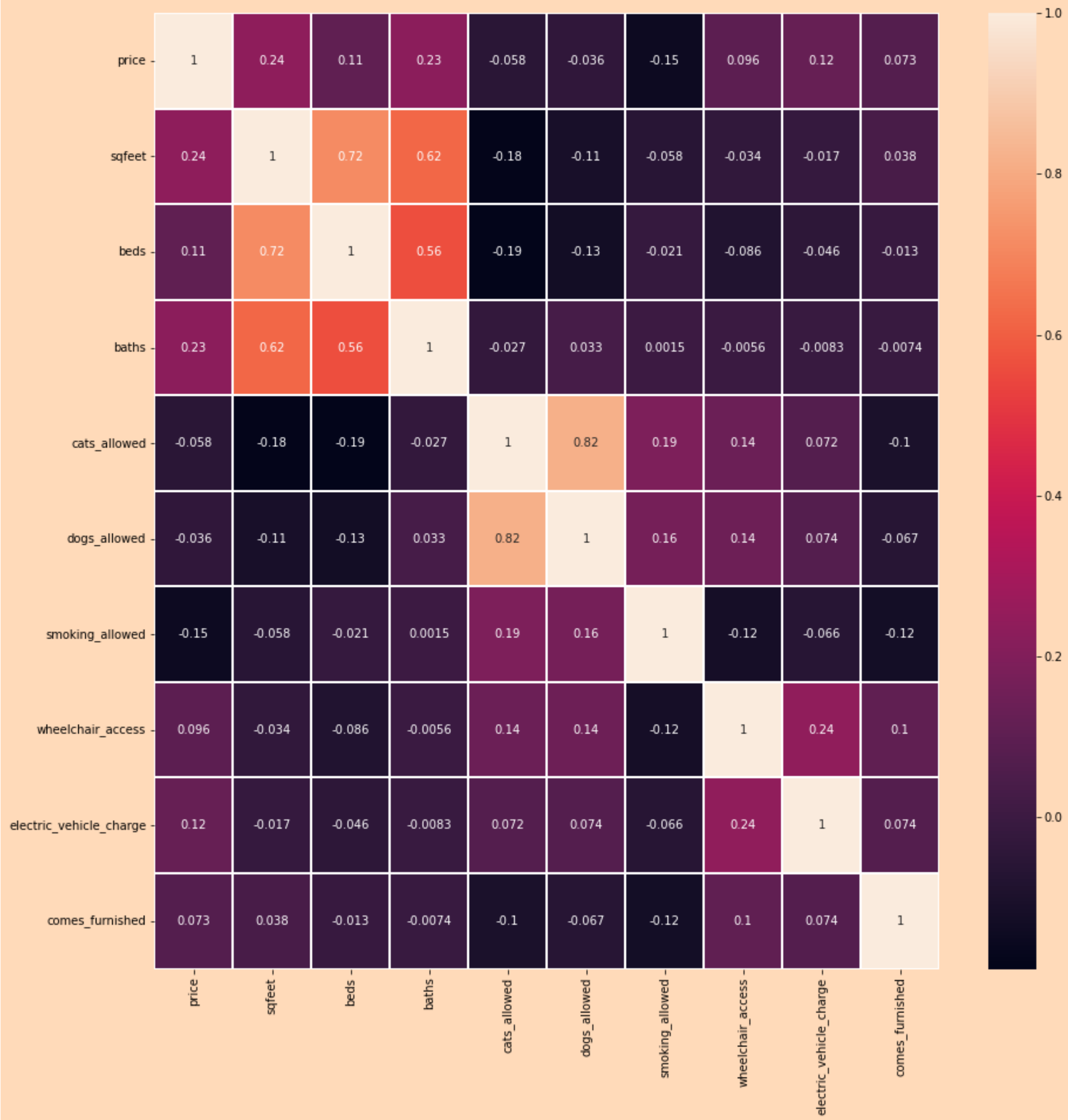
In [14]:
```
house_cont= house[['price','sqfeet','beds','baths']]

plt.figure(figsize=(13,10), facecolor='xkcd:eggshell')
plotnumber =1

for column in house_cont:
    if plotnumber<=10:
        ax=plt.subplot(2,2,plotnumber)
        sns.distplot(house_cont[column], color='k')
        plt.xlabel(column.upper(), fontsize = 20)

    plotnumber+=1
plt.tight_layout()
plt.show()
```




Using Heat map and Correlations

Lets check the dependency of columns with each others

In [15]:
```
plt.figure(figsize=(15,15), facecolor='#ffdab9')
sns.heatmap(house.corr(), annot=True, linewidths=0.005);
```




Lets use get_dummies and convert object data to do further model application

In [16]:
```
house = pd.get_dummies(data=house)
house.shape
```

Out[16]: (58974, 363)

***Iinitializing Linear Model***

In [17]:
```
lr = LinearRegression()
```

## Simple linear model

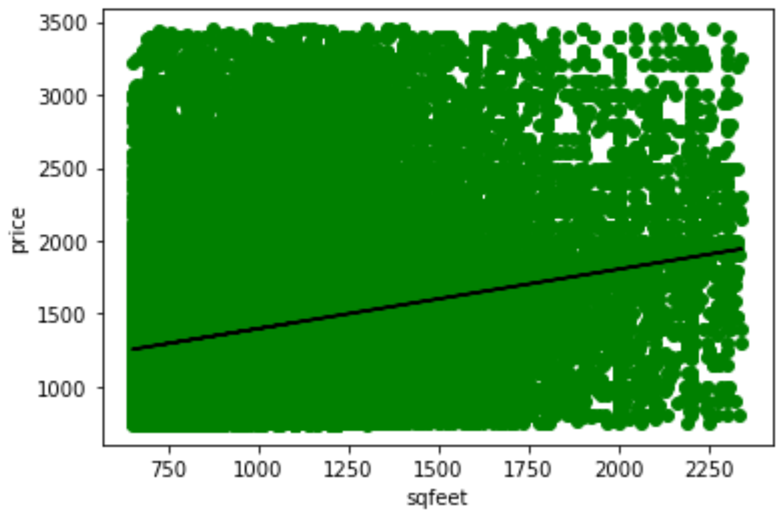
Lets check the result

In [18]:
```
# Separating feature and output/result
X = house[['sqfeet']]
y = house[['price']]

# Splting train and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=20)

# Fitting linear modle
lr.fit(X_train, y_train)


print('Intercept',lr.intercept_)
print('Coefficient ',lr.coef_)
```

```
Intercept [991.48092574]
Coefficient  [[0.40689659]]
```

Lets plot the scatter plot and see the predicted line

In [19]:
```
plt.scatter(X, y, color='g')
plt.plot(X_test, lr.predict(X_test), color ='k')
plt.xlabel('sqfeet')
plt.ylabel('price');
```




Lets see the MAE, MSE, RMSE and R2Score the view the model perfomance

In [20]:
```
# Predict the model
y_pred= lr.predict(X_test)

print('Mean Absolute Error',mean_absolute_error(y_test, y_pred))
print('Mean Squared Error',mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error',np.sqrt(mean_squared_error(y_test, y_pred)))
print('R2 Score',r2_score(y_test, y_pred))
```

```
Mean Absolute Error 426.76385520718
Mean Squared Error 300213.8346956622
Root Mean Squared Error 547.9177262104797
R2 Score 0.055662803476350886
```

R2 score is very less, Lets do Multi Linear Regression and check R2 score

## Multi Linear Regression

In [21]:
```
# Sepearting Feature and result
X= house[['sqfeet','beds','baths']]
y = house[['price']]

# Spliting data into train and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=20)

# Applying linear model to data
lr.fit(X_train, y_train)

print('Intercept',lr.intercept_)
print('Coefficient ',lr.coef_)

# Predict the model
y_pred= lr.predict(X_test)


print('Mean Absolute Error',mean_absolute_error(y_test, y_pred))
print('Mean Squared Error',mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error',np.sqrt(mean_squared_error(y_test, y_pred)))
print('R2 score',r2_score(y_test, y_pred))
```

```
Intercept [961.3255184]
Coefficient  [[   0.42499237 -114.16746469  154.85637623]]
Mean Absolute Error 421.019551527462
Mean Squared Error 293008.7912622138
Root Mean Squared Error 541.3028646351447
R2 score 0.07832661749968284
```

R2 score has not improved much,

Lets make data scaler and apply Multi Regreesion model too

In [22]:
```
# Initialize Scaler Model
scaler = StandardScaler()

# Apply scaler model
X_scaled = scaler.fit_transform(X)

# Spliting data into train and test data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=200)

# Applying linear model to data
lr.fit(X_train, y_train)

print('Intercept',lr.intercept_)
print('Coefficient ',lr.coef_)

# Predict the model
y_pred= lr.predict(X_test)


print('Mean Absolute Error',mean_absolute_error(y_test, y_pred))
print('Mean Squared Error',mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error',np.sqrt(mean_squared_error(y_test, y_pred)))
print('R2 score',r2_score(y_test, y_pred))
```

```
Intercept [1437.43484598]
Coefficient  [[142.98260846 -92.13740545  90.10055812]]
Mean Absolute Error 418.1886532532226
Mean Squared Error 288534.5851372588
Root Mean Squared Error 537.1541539793384
R2 score 0.08115875324956545
```

R2 score has not improved much,

Lets make data scaler and apply Decision Tree Regreesion model

## Decision Tree

In [23]:
```
# Seperating Feature and result
X= house.drop(['price'], axis=1)
y = house[['price']]

# Apply scaler model
X_scaled = scaler.fit_transform(X)

# Spliting data into train and test data
X_train,X_test,y_train,y_test = train_test_split(X_scaled,y, test_size=0.2, random_state=100)

# Initializing Decision Tree
reg_tree = DecisionTreeRegressor(criterion= 'squared_error', max_depth= 3)

# Applying Decision Tree model to data
reg_tree.fit(X_train,y_train)

# Predict the model
y_pred = reg_tree.predict(X_test)


print('Mean Absolute Error',mean_absolute_error(y_test, y_pred))
print('Mean Squared Error',mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error',np.sqrt(mean_squared_error(y_test, y_pred)))
print('R2 score',r2_score(y_test, y_pred))
```

```
Mean Absolute Error 361.91216965499547
Mean Squared Error 224819.10073259717
Root Mean Squared Error 474.15092611171514
R2 score 0.31015164172673015
```

R2 score has improved very little, Lets do HyperParamete tuning and check best fit values to improve the R2

***Hyperparameter Tuning***

In [24]:
```
grid_param = {
    'criterion': ['squared_error','friedman_mse'],
    'max_depth' : range(20,22),
    'min_samples_leaf' : range(12,18),
}
```

In [25]:
```
grid_search = GridSearchCV(estimator=reg_tree,
                     param_grid=grid_param,
                     cv=5,
                    n_jobs =-1)
```

In [26]:
```
grid_search.fit(X_train,y_train)
```

Out[26]:
```
▸ GridSearchCV
▸ estimator: DecisionTreeRegressor
  ▸ DecisionTreeRegressor
```

In [27]:
```
print(grid_search.best_params_)
```

```
{'criterion': 'squared_error', 'max_depth': 21, 'min_samples_leaf': 15}
```

In [28]:
```
grid_search.best_score_
```

Out[28]:
```
0.6552040149302076
```

Applying Grid Search values to verify the result and check model score

In [29]:
```
# Initializing Decision Tree
reg_tree = DecisionTreeRegressor(criterion= 'squared_error', max_depth= 21, min_samples_leaf=15 )

# Applying Decision Tree model to data
reg_tree.fit(X_train,y_train)

# Predict the model
y_pred = reg_tree.predict(X_test)


print('Mean Absolute Error',mean_absolute_error(y_test, y_pred))
print('Mean Squared Error',mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error',np.sqrt(mean_squared_error(y_test, y_pred)))
print('R2 score',r2_score(y_test, y_pred))
```

```
Mean Absolute Error 234.4015763883326
Mean Squared Error 110268.52863392427
Root Mean Squared Error 332.06705442413926
R2 score 0.6616454598410717
```

In [ ]: