In [1]:
```python
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
import numpy as np

from sklearn.preprocessing import KBinsDiscretizer

from sklearn import model_selection

from sklearn.linear_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.svm import SVC

from sklearn.metrics import accuracy_score

from sklearn.metrics import confusion_matrix

from sklearn.metrics import classification_report

from sklearn.model_selection import cross_val_score, cross_val_predict, cross_validate

from sklearn import metrics

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier

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

In [2]:
```python
listings = pd.read_csv("D:\Trent Notes\Data Minining\Assignments\Assignment 2\seattle\listings.csv")
print(listings.head(3))
```

```
        id                          listing_url       scrape_id last_scraped  \
0   241032   https://www.airbnb.com/rooms/241032  20160104002432   2016-01-04
1   953595   https://www.airbnb.com/rooms/953595  20160104002432   2016-01-04
2  3308979  https://www.airbnb.com/rooms/3308979  20160104002432   2016-01-04

                                  name  \
0         Stylish Queen Anne Apartment
1   Bright & Airy Queen Anne Apartment
2  New Modern House-Amazing water view

                                             summary  \
0                                                NaN
1  Chemically sensitive? We've removed the irrita...
2  New modern house built in 2013.  Spectacular s...

                                               space  \
0  Make your self at home in this charming one-be...
1  Beautiful, hypoallergenic apartment in an extr...
2  Our house is modern, light and fresh with a wa...

                                         description experiences_offered  \
0  Make your self at home in this charming one-be...                none
1  Chemically sensitive? We've removed the irrita...                none
2  New modern house built in 2013.  Spectacular s...                none

                               neighborhood_overview  ... review_scores_value  \
0                                                NaN  ...                10.0
1  Queen Anne is a wonderful, truly functional vi...  ...                10.0
2  Upper Queen Anne is a charming neighborhood fu...  ...                10.0

  requires_license license jurisdiction_names instant_bookable  \
0                f     NaN         WASHINGTON                f
1                f     NaN         WASHINGTON                f
2                f     NaN         WASHINGTON                f

  cancellation_policy  require_guest_profile_picture  \
0            moderate                              f
1              strict                              t
2              strict                              f

  require_guest_phone_verification calculated_host_listings_count  \
0                                f                              2
1                                t                              6
2                                f                              2

  reviews_per_month
0              4.07
1              1.48
2              1.15

[3 rows x 92 columns]
```

In [3]:
```python
print(listings.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3818 entries, 0 to 3817
Data columns (total 92 columns):
id                                  3818 non-null int64
listing_url                         3818 non-null object
scrape_id                           3818 non-null int64
last_scraped                        3818 non-null object
name                                3818 non-null object
summary                             3641 non-null object
space                               3249 non-null object
description                         3818 non-null object
experiences_offered                 3818 non-null object
neighborhood_overview               2786 non-null object
notes                               2212 non-null object
transit                             2884 non-null object
thumbnail_url                       3498 non-null object
medium_url                          3498 non-null object
picture_url                         3818 non-null object
xl_picture_url                      3498 non-null object
host_id                             3818 non-null int64
host_url                            3818 non-null object
host_name                           3816 non-null object
host_since                          3816 non-null object
host_location                       3810 non-null object
host_about                          2959 non-null object
host_response_time                  3295 non-null object
host_response_rate                  3295 non-null object
host_acceptance_rate                3045 non-null object
host_is_superhost                   3816 non-null object
host_thumbnail_url                  3816 non-null object
host_picture_url                    3816 non-null object
host_neighbourhood                  3518 non-null object
host_listings_count                 3816 non-null float64
host_total_listings_count           3816 non-null float64
host_verifications                  3818 non-null object
host_has_profile_pic                3816 non-null object
host_identity_verified              3816 non-null object
street                              3818 non-null object
neighbourhood                       3402 non-null object
neighbourhood_cleansed              3818 non-null object
neighbourhood_group_cleansed        3818 non-null object
city                                3818 non-null object
state                               3818 non-null object
zipcode                             3811 non-null object
market                              3818 non-null object
smart_location                      3818 non-null object
country_code                        3818 non-null object
country                             3818 non-null object
latitude                            3818 non-null float64
longitude                           3818 non-null float64
is_location_exact                   3818 non-null object
property_type                       3817 non-null object
room_type                           3818 non-null object
accommodates                        3818 non-null int64
bathrooms                           3802 non-null float64
bedrooms                            3812 non-null float64
beds                                3817 non-null float64
bed_type                            3818 non-null object
amenities                           3818 non-null object
square_feet                         97 non-null float64
price                               3818 non-null object
weekly_price                        2009 non-null object
monthly_price                       1517 non-null object
security_deposit                    1866 non-null object
cleaning_fee                        2788 non-null object
guests_included                     3818 non-null int64
extra_people                        3818 non-null object
minimum_nights                      3818 non-null int64
maximum_nights                      3818 non-null int64
calendar_updated                    3818 non-null object
has_availability                    3818 non-null object
availability_30                     3818 non-null int64
availability_60                     3818 non-null int64
availability_90                     3818 non-null int64
availability_365                    3818 non-null int64
calendar_last_scraped               3818 non-null object
number_of_reviews                   3818 non-null int64
first_review                        3191 non-null object
last_review                         3191 non-null object
review_scores_rating                3171 non-null float64
review_scores_accuracy              3160 non-null float64
review_scores_cleanliness           3165 non-null float64
review_scores_checkin               3160 non-null float64
review_scores_communication         3167 non-null float64
review_scores_location              3163 non-null float64
review_scores_value                 3162 non-null float64
requires_license                    3818 non-null object
license                             0 non-null float64
jurisdiction_names                  3818 non-null object
instant_bookable                    3818 non-null object
cancellation_policy                 3818 non-null object
require_guest_profile_picture       3818 non-null object
require_guest_phone_verification    3818 non-null object
calculated_host_listings_count      3818 non-null int64
reviews_per_month                   3191 non-null float64
dtypes: float64(17), int64(13), object(62)
memory usage: 2.7+ MB
None
```

In [4]:
```python
print(listings.describe())
```

```
                 id     scrape_id       host_id  host_listings_count  \
count  3.818000e+03  3.818000e+03  3.818000e+03          3816.000000
mean   5.550111e+06  2.016010e+13  1.578556e+07             7.157757
std    2.962660e+06  0.000000e+00  1.458382e+07            28.628149
min    3.335000e+03  2.016010e+13  4.193000e+03             1.000000
25%    3.258256e+06  2.016010e+13  3.275204e+06             1.000000
50%    6.118244e+06  2.016010e+13  1.055814e+07             1.000000
75%    8.035127e+06  2.016010e+13  2.590309e+07             3.000000
max    1.034016e+07  2.016010e+13  5.320861e+07           502.000000

       host_total_listings_count     latitude    longitude  accommodates  \
count                3816.000000  3818.000000  3818.000000   3818.000000
mean                    7.157757    47.628961  -122.333103      3.349398
std                    28.628149     0.043052     0.031745      1.977599
min                     1.000000    47.505088  -122.417219      1.000000
25%                     1.000000    47.609418  -122.354320      2.000000
50%                     1.000000    47.623601  -122.328874      3.000000
75%                     3.000000    47.662694  -122.310800      4.000000
max                   502.000000    47.733358  -122.240607     16.000000

         bathrooms     bedrooms  ...  review_scores_rating  \
count  3802.000000  3812.000000  ...           3171.000000
mean      1.259469     1.307712  ...             94.539262
std       0.590369     0.883395  ...              6.606083
min       0.000000     0.000000  ...             20.000000
25%       1.000000     1.000000  ...             93.000000
50%       1.000000     1.000000  ...             96.000000
75%       1.000000     2.000000  ...             99.000000
max       8.000000     7.000000  ...            100.000000

       review_scores_accuracy  review_scores_cleanliness  \
count             3160.000000                3165.000000
mean                 9.636392                   9.556398
std                  0.698031                   0.797274
min                  2.000000                   3.000000
25%                  9.000000                   9.000000
50%                 10.000000                  10.000000
75%                 10.000000                  10.000000
max                 10.000000                  10.000000

       review_scores_checkin  review_scores_communication  \
count            3160.000000                  3167.000000
mean                9.786709                     9.809599
std                 0.595499                     0.568211
min                 2.000000                     2.000000
25%                10.000000                    10.000000
50%                10.000000                    10.000000
75%                10.000000                    10.000000
max                10.000000                    10.000000

       review_scores_location  review_scores_value  license  \
count             3163.000000          3162.000000      0.0
mean                 9.608916             9.452245      NaN
std                  0.629053             0.750259      NaN
min                  4.000000             2.000000      NaN
25%                  9.000000             9.000000      NaN
50%                 10.000000            10.000000      NaN
75%                 10.000000            10.000000      NaN
max                 10.000000            10.000000      NaN

       calculated_host_listings_count  reviews_per_month
count                     3818.000000        3191.000000
mean                         2.946307           2.078919
std                          5.893029           1.822348
min                          1.000000           0.020000
25%                          1.000000           0.695000
50%                          1.000000           1.540000
75%                          2.000000           3.000000
max                         37.000000          12.150000

[8 rows x 30 columns]
```

In [5]:
```python
# To keep the graph of everything uniform
plt.rcParams['figure.figsize']= (20,7)
```

In [ ]:

Performing few data manipulation to ensure data is fit for modelling

In [6]:
```python
listings.price = listings.price.str.strip("$").str.replace(",", "")
listings.monthly_price = listings.monthly_price.str.strip("$").str.replace(",", "")
listings.weekly_price = listings.weekly_price.str.strip("$").str.replace(",", "")
print(listings.price.head(3))
print(listings.monthly_price.head(3))
print(listings.weekly_price.head(5))
```

```
0     85.00
1    150.00
2    975.00
Name: price, dtype: object
0        NaN
1    3000.00
2        NaN
Name: monthly_price, dtype: object
0        NaN
1    1000.00
2        NaN
3     650.00
4        NaN
Name: weekly_price, dtype: object
```

In [7]:
```python
columns = ['price','bathrooms','bedrooms','beds','last_review']
null_columns =listings[columns]
```

In [8]:
```python
# mean is calculated for price and then replacd the mean in place of nulls
listings.price = listings.price.astype(np.float64)
price_mean = listings.price.mean()
print(price_mean)
listings["price"]=listings["price"].fillna(listings["price"].mean())

#Mode is calculated for last review  and then replacd with the mode in place of nulls
last_review_mode = listings.last_review.mode()[0]
print(last_review_mode)
listings["last_review"]=listings["last_review"].fillna(listings["last_review"].mode()[0])


#mode is calculated for bathrooms and all the nulls are replaced by nulls
bathrooms_mode = listings.bathrooms.mode()
print(bathrooms_mode)
listings["bathrooms"]=listings["bathrooms"].fillna(listings["bathrooms"].mode()[0])


#mode is calculated for bedrooms and all the nulls are replaced by nulls
bedrooms_mode = listings.bedrooms.mode()
print(bedrooms_mode)
listings["bedrooms"]=listings["bedrooms"].fillna(listings["bedrooms"].mode()[0])


#mode is calculated for bedrooms and all the nulls are replaced by nulls
beds_mode = listings.beds.mode()
print(beds_mode)
listings['beds'] =listings['beds'].fillna(listings['beds'].mode()[0])
```

```
127.97616553169199
2016-01-02
0    1.0
dtype: float64
0    1.0
dtype: float64
0    1.0
dtype: float64
```

Converting all the necessary columns to appropriate data types

In [10]:
```python
listings.monthly_price = listings.monthly_price.astype(np.float64)

listings.weekly_price = listings.weekly_price.astype(np.float64)

listings.bedrooms = listings.bedrooms.astype(int)

listings.beds = listings.beds.astype(int)

listings.accommodates = listings.accommodates.astype(int)
```

In [11]:
```python
Room =listings[['room_type','review_scores_cleanliness','review_scores_communication']]
print(Room)
```

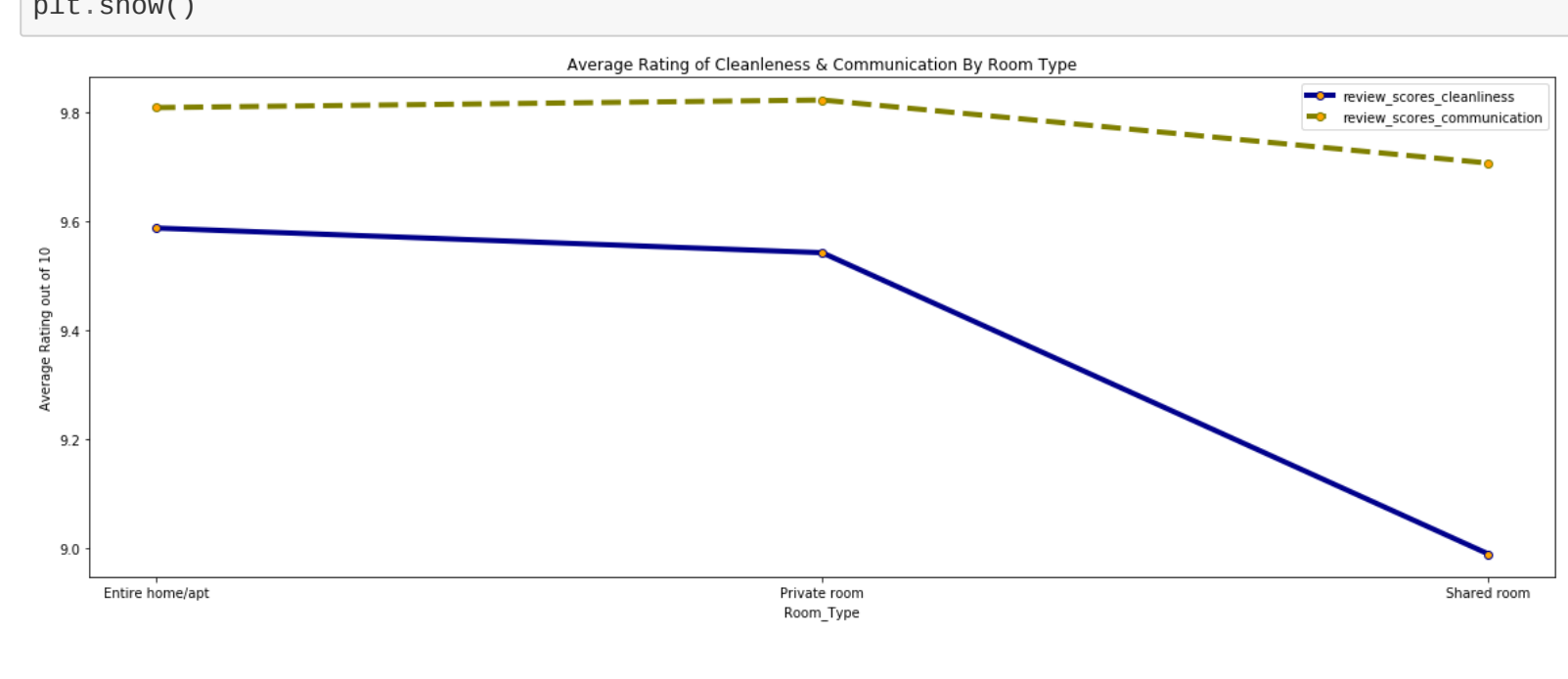
```
            room_type  review_scores_cleanliness  review_scores_communication
0     Entire home/apt                       10.0                         10.0
1     Entire home/apt                       10.0                         10.0
2     Entire home/apt                       10.0                         10.0
3     Entire home/apt                        NaN                          NaN
4     Entire home/apt                        9.0                         10.0
...               ...                        ...                          ...
3813  Entire home/apt                       10.0                          8.0
3814  Entire home/apt                       10.0                         10.0
3815  Entire home/apt                        NaN                          NaN
3816  Entire home/apt                        NaN                          NaN
3817  Entire home/apt                        NaN                          NaN

[3818 rows x 3 columns]
```

In [12]:
```python
#grouping the dataset by room to perform analysis
room =Room.groupby('room_type').mean()
room

#removing the index of the column
room = room.reset_index()
```

In [13]:
```python
room.review_scores_communication
```

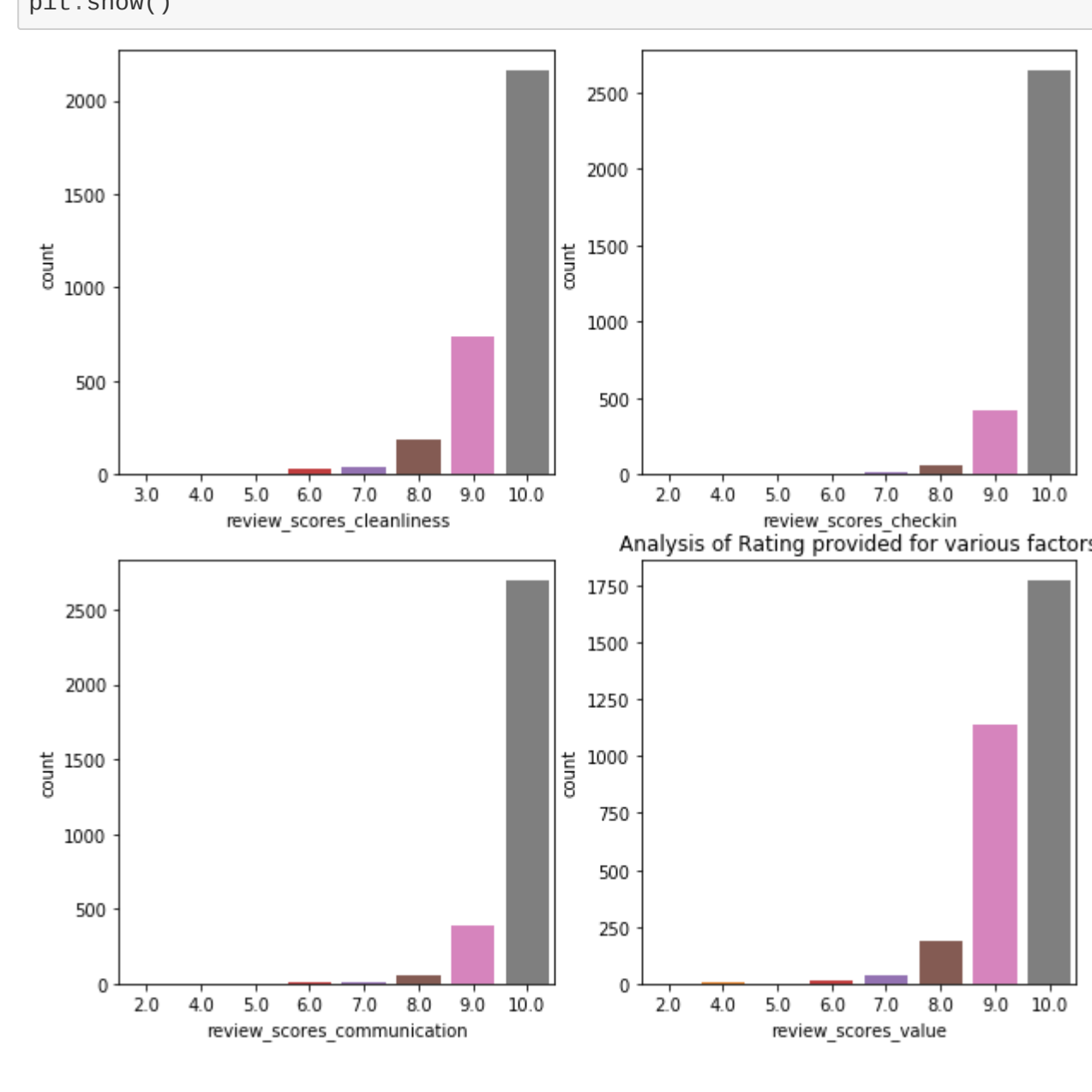
Out[13]:
```
0    9.808380
1    9.822292
2    9.706522
Name: review_scores_communication, dtype: float64
```

In [14]:
```python
plt.plot( 'room_type', 'review_scores_cleanliness', data=room, marker='o', markerfacecolor='orange', color='darkblue', linewidth=4)
plt.plot( 'room_type', 'review_scores_communication', data=room, marker='o',  markerfacecolor='orange',color='olive', linestyle='dashed',linewidth=4)
plt.legend()
plt.xlabel("Room_Type")
plt.ylabel("Average Rating out of 10")
plt.title("Average Rating of Cleanleness & Communication By Room Type")
plt.show()
```



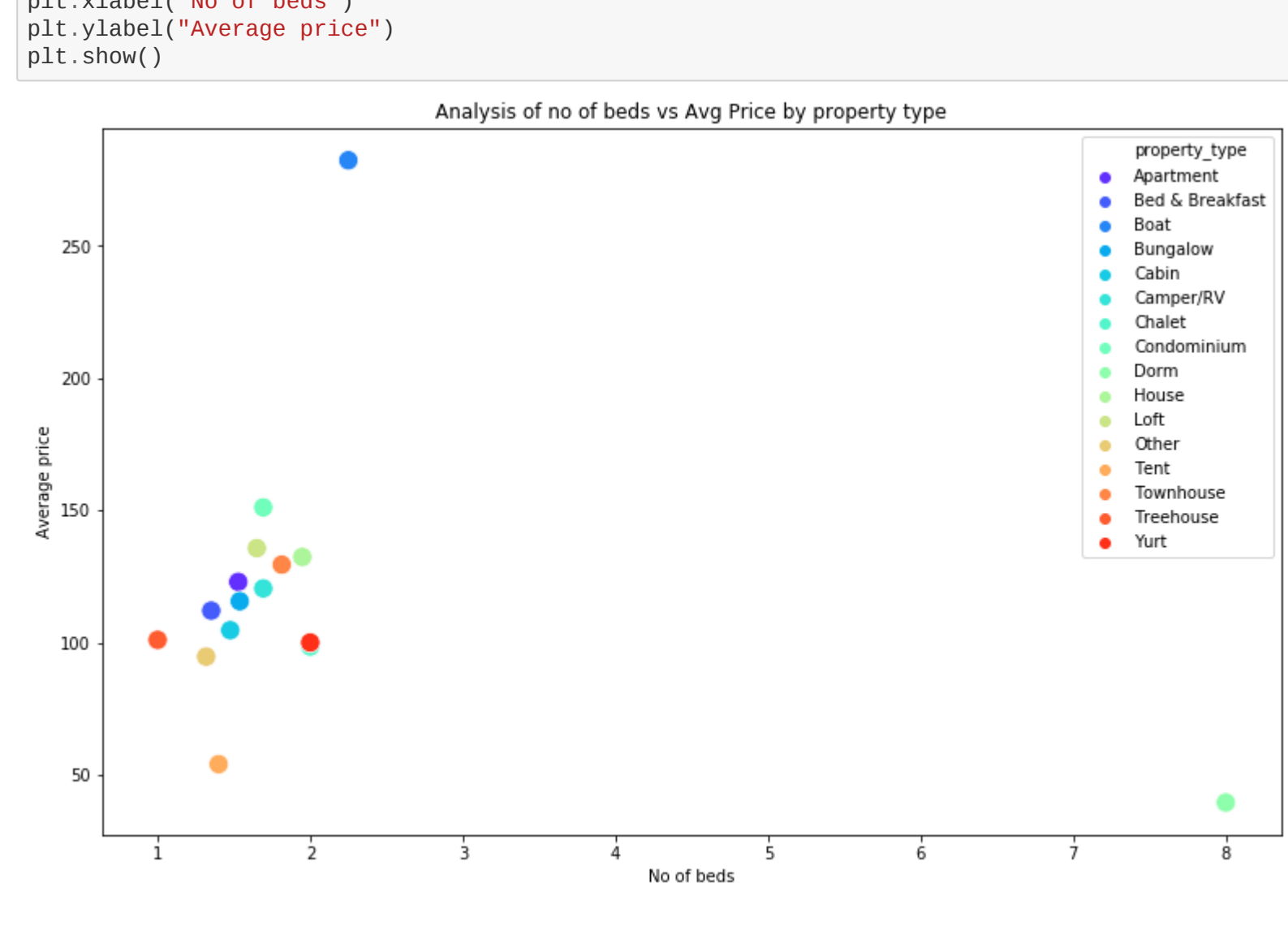
We can see from the graph that the shared room has overall Cleanliness & Communication rating less

In [15]:
```python
fig,axes= plt.subplots(nrows=2, ncols= 2,figsize=(10,10))
# graph to analyse the count of feedbacks recieved for teh below mentioned categories rated
 among the scale of 1 to 10
sb.countplot(listings['review_scores_cleanliness'],ax=axes[0][0])
sb.countplot(listings['review_scores_checkin'],ax=axes[0][1])
sb.countplot(listings['review_scores_communication'],ax=axes[1][0])
#sb.countplot(listings['review_scores_location'],ax=axes[1][1])
sb.countplot(listings['review_scores_value'],ax=axes[1][1])
plt.title("Analysis of Rating provided for various factors")
plt.show()
```



This above graphs is used to anlyse the total no of records that are having very less ratings

In [16]:
```python
property= listings[['beds', 'price', 'property_type']]
price= property.groupby('property_type', as_index= False).agg({'beds':'mean','price':'mean'})

plt.figure(figsize=(13,8))
sb.scatterplot(x='beds',y='price',hue='property_type',data= price,s =150 ,palette="rainbow")
plt.title("Analysis of no of beds vs Avg Price by property type")
plt.xlabel("No of beds")
plt.ylabel("Average price")
plt.show()
```

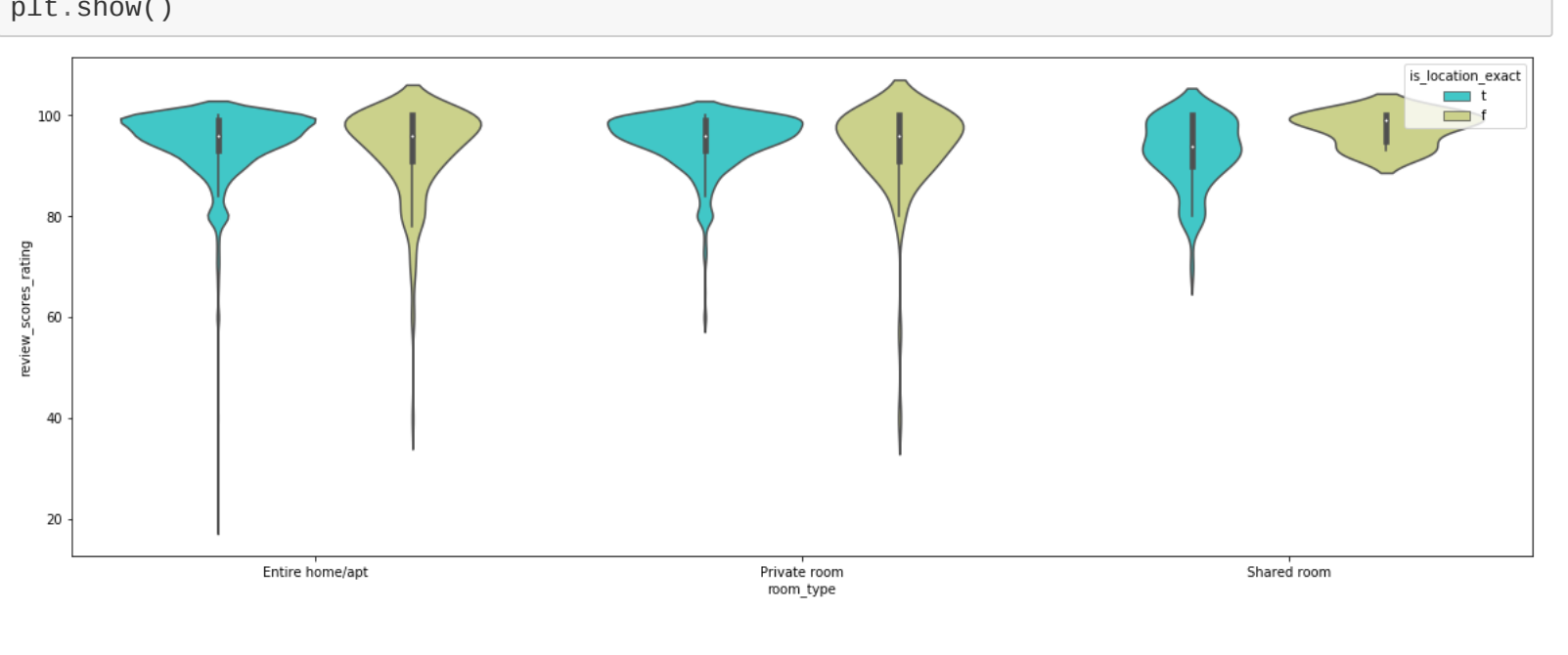


The above graph is used to Analysis of no of beds vs Avg Price by property type

In [17]:
```python
columns = ['accommodates','bathrooms','bedrooms','guests_included','beds','price']
sb.heatmap(listings[columns].corr(),annot=True)
plt.show()
```

The above graph is used to analyse the co relation between various variables mentioned

In [18]:
```python
#Analysis of Rating for various Room types based on is loaction exact
sb.violinplot("room_type", "review_scores_rating", hue="is_location_exact", data=listings,palette='rainbow')
plt.show()
```

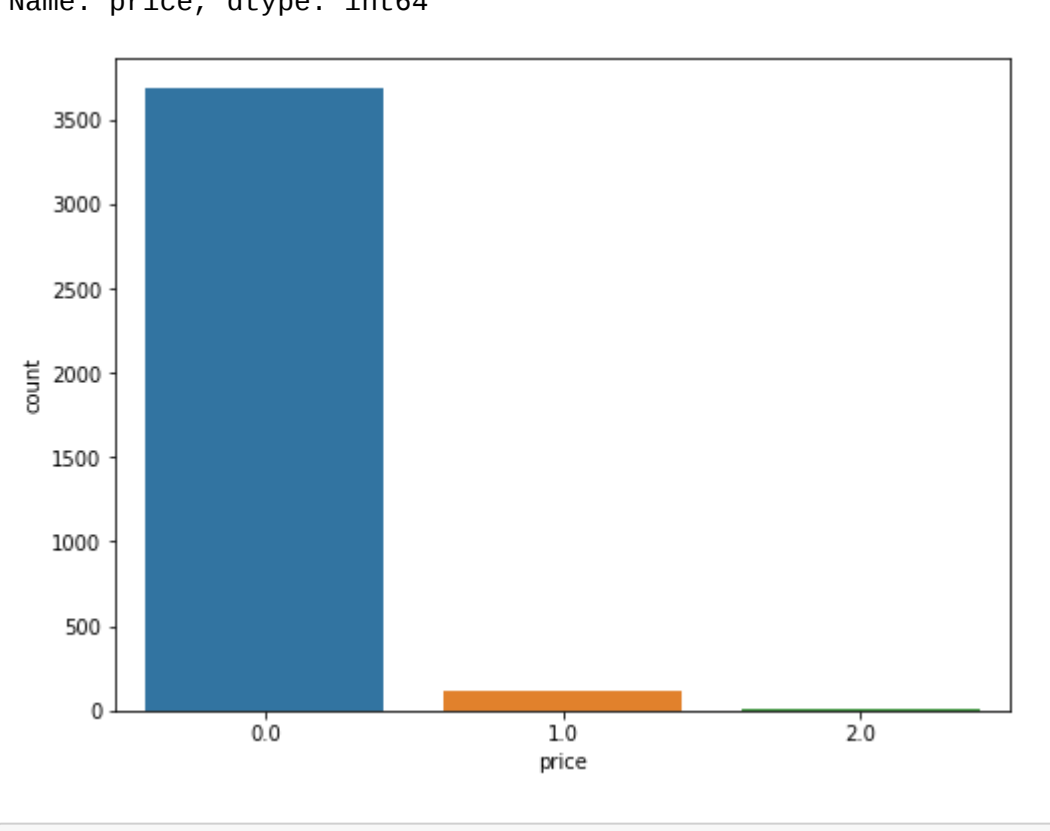


The above graph is used to analyse the distribution of values for various room types

Pre Processing Methods

In [19]:
```python
# binning the price column

bins = KBinsDiscretizer(n_bins=3, encode='ordinal', strategy='uniform')

# i have used encode = ordianl to ensure the output to be of farm integer, strategy is choosen to keep the bin width same for all

listings['price']=bins.fit_transform(listings[['price']])

print(listings['price'].unique())

# printing the number of values per bin
print(listings["price"].value_counts())

plt.figure(figsize=(8,6))
sb.countplot(listings["price"])
plt.show()
```

```
[0. 2. 1.]
0.0    3684
1.0     121
2.0      13
Name: price, dtype: int64
```



In [20]:
```python
#first converting the last review column to date farm and then subtracting it from todays date to calculate no of days
listings['last_review']= pd.to_datetime(listings['last_review']).dt.date

listings['no_days']= (pd.datetime.now().date()-listings['last_review']).dt.days

print(listings[['last_review', 'no_days']].head())
```

```
  last_review  no_days
0  2016-01-02     1551
1  2015-12-29     1555
2  2015-09-03     1672
3  2016-01-02     1551
4  2015-10-24     1621
```

In [21]:
```python
#binning the availability_30 into 10 equal bins
bins = KBinsDiscretizer(n_bins=10, encode='ordinal', strategy='uniform')

listings['availability_30']=bins.fit_transform(listings[['availability_30']])

print(listings['availability_30'].unique())

#binning the availability_60 into 10 equal bins
bins = KBinsDiscretizer(n_bins=10, encode='ordinal', strategy='uniform')

listings['availability_60']=bins.fit_transform(listings[['availability_60']])

print(listings['availability_60'].unique())

#binning the availability_90 into 10 equal bins
bins = KBinsDiscretizer(n_bins=10, encode='ordinal', strategy='uniform')

listings['availability_90']=bins.fit_transform(listings[['availability_90']])

print(listings['availability_90'].unique())

#binning the availability_365 into 10 equal bins
bins = KBinsDiscretizer(n_bins=10, encode='ordinal', strategy='uniform')

listings['availability_365']=bins.fit_transform(listings[['availability_365']])

print(listings['availability_365'].unique())
```

```
[4. 0. 9. 6. 7. 2. 8. 3. 5. 1.]
[6. 2. 1. 0. 9. 8. 7. 3. 5. 4.]
[7. 1. 0. 9. 3. 4. 5. 2. 6. 8.]
[9. 7. 6. 3. 8. 2. 4. 1. 5. 0.]
```

In [ ]:

3. Modelling Techniques

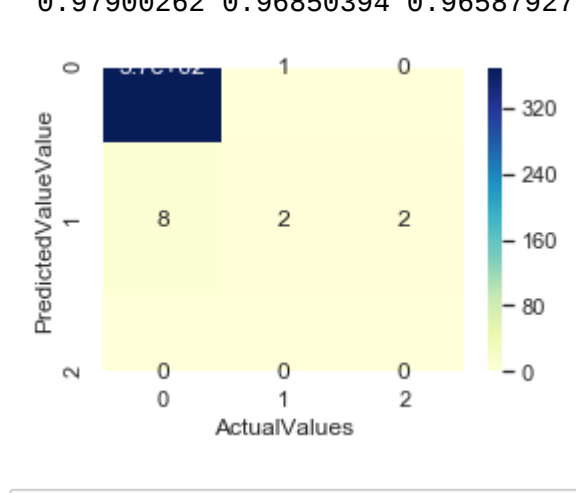
Creating a Traininng and Testing set

In [22]:
```python
X= listings[['accommodates', 'bathrooms', 'bedrooms','beds']]

predictor= listings[['price']]

X_train, X_test, y_train, y_test = train_test_split(X, predictor, test_size=0.1, random_state=101)

print ("number of training samples {}".format(X_train.shape))
print ("number of tesing {}".format( y_train.shape))
```

```
number of training samples (3436, 4)
number of tesing (3436, 1)
```

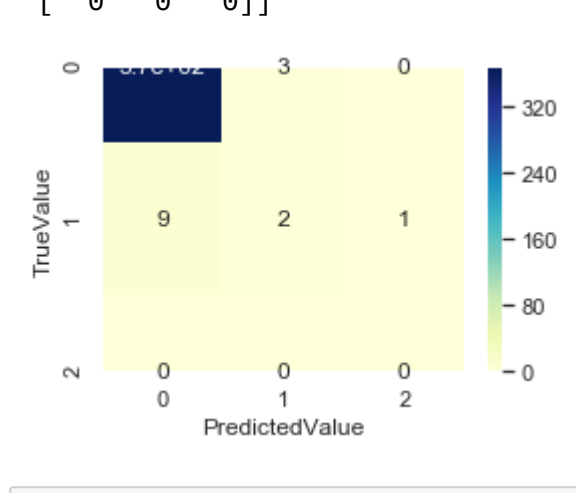
In [23]:
```python
# 1. Applying Decision Tree algorithm to predict the price based on the given training variables

decision= DecisionTreeClassifier()
decission_model= decision.fit(X_train, y_train)
predict= decision.predict(X_test)
print(accuracy_score(y_test, predict))
# creating confusion matrix
confuson_matrix =confusion_matrix(y_test, predict)
print(confuson_matrix)
print(classification_report(y_test, predict))

#performing 10 fold cross validation
cross_val_scores = cross_val_score(decission_model, X, predictor, cv=10)
print(cross_val_scores)

#creation of confusion matrix plot
sb.set(font_scale=1.0)
sb.set(rc={'figure.figsize':(4,3)})
sb.heatmap(confuson_matrix, annot=True, cmap="YlGnBu")
plt.ylabel('PredictedValueValue')
plt.xlabel('ActualValues')
plt.tight_layout()
plt.show()
```

```
0.9712041884816754
[[369   1   0]
 [  8   2   2]
 [  0   0   0]]
              precision    recall  f1-score   support

         0.0       0.98      1.00      0.99       370
         1.0       0.67      0.17      0.27        12
         2.0       0.00      0.00      0.00         0

    accuracy                           0.97       382
   macro avg       0.55      0.39      0.42       382
weighted avg       0.97      0.97      0.97       382

[0.96354167 0.95822454 0.96605744 0.97905759 0.96587927 0.96325459
 0.97900262 0.96850394 0.96587927 0.97112861]
```



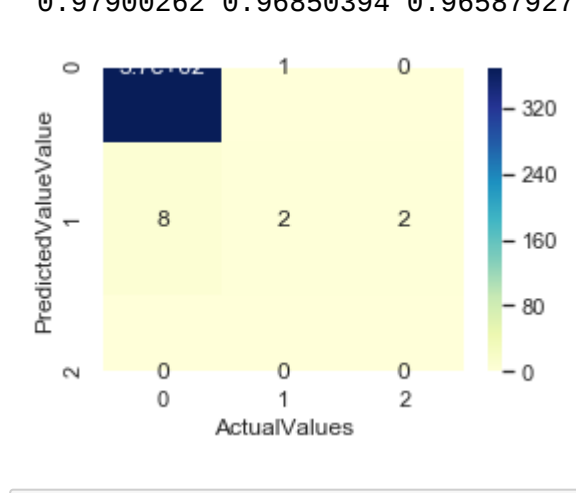
In [24]:
```python
#Random forest classifier

random = RandomForestClassifier(random_state = 0)
# training the model with training data
rand_forest =random.fit(X_train,y_train)
# prediction form test data
randfor_pred = random.predict(X_test)
print(accuracy_score(y_test, randfor_pred))
# 10 fold validation
cv_randfor  = cross_validate(rand_forest, X, predictor, cv=10)
print(cv_randfor)

confusion_matrix_randfor = confusion_matrix(y_test, randfor_pred)
print(confusion_matrix_randfor)
# Plotting of the confusion matrix
sb.set(font_scale=1.0)
sb.heatmap(confusion_matrix_randfor, annot=True, cmap="YlGnBu")
plt.ylabel('TrueValue')
plt.xlabel('PredictedValue')
plt.tight_layout()
plt.show()
```

```
0.9659685863874345
{'fit_time': array([0.09094119, 0.08495331, 0.09997225, 0.07995129, 0.0789845 ,
       0.09491515, 0.07692552, 0.07697988, 0.07592511, 0.09194493]), 'score_time': array([0.01002502, 0.01495981, 0.01097012, 0.00899529, 0.01099443,
       0.01002693, 0.01199913, 0.01099324, 0.01099443, 0.00999618]), 'test_score': array([0.9609375 , 0.96083551, 0.96083551, 0.97905759, 0.96325459,
       0.95013123, 0.9816273 , 0.97112861, 0.96850394, 0.96850394])}
[[367   3   0]
 [  9   2   1]
 [  0   0   0]]
```



In [28]:
```python
# 1. Applying Knn to predict the price based on the given training variables

Knn= KNeighborsClassifier(n_neighbors = 11)
knn_model= decision.fit(X_train, y_train)
predict= decision.predict(X_test)
print(accuracy_score(y_test, predict))
# creating confusion matrix
confuson_matrix =confusion_matrix(y_test, predict)
print(confuson_matrix)
print(classification_report(y_test, predict))

#performing 10 fold cross validation
cross_val_scores = cross_val_score(knn_model, X, predictor, cv=10)
print(cross_val_scores)

#creation of confusion matrix plot
sb.set(font_scale=1.0)
sb.set(rc={'figure.figsize':(4,3)})
sb.heatmap(confuson_matrix, annot=True, cmap="YlGnBu")
plt.ylabel('PredictedValueValue')
plt.xlabel('ActualValues')
plt.tight_layout()
plt.show()
```

```
0.9712041884816754
[[369   1   0]
 [  8   2   2]
 [  0   0   0]]
              precision    recall  f1-score   support

         0.0       0.98      1.00      0.99       370
         1.0       0.67      0.17      0.27        12
         2.0       0.00      0.00      0.00         0

    accuracy                           0.97       382
   macro avg       0.55      0.39      0.42       382
weighted avg       0.97      0.97      0.97       382

[0.9609375  0.95822454 0.96344648 0.97905759 0.96850394 0.96587927
 0.97900262 0.96850394 0.96587927 0.97112861]
```



In [ ]:
```
i have choosen the value of k = 11 for the best accurecy , we can even plot the graph to know the optimal graph
```