IBM Datascience Capstone

Analysing Berling AirBnB rental Datascience

We're using the [Berlin AirBnB (https://www.kaggle.com/brittabettendorf/berlin-airbnb-data)](https://www.kaggle.com/brittabettendorf/berlin-airbnb-data) dataset to evaluate two questions:

1. Which neighbourhood attracts high-paying tourists?
2. Is location really everything?

These questions are important for city planning with several regards. Positive aspects on tourism include attracting cashflow to local businesses. However, AirBnB can attract commercial usage of living space that should be available to normal tenants and therefore contribute to shortages and price hikes in apartments in popular cities and areas.

We'll start out with importing, loading and cleaning the data. I decided to exclude AirBnB offers over 1000 Euro per night for visualization purposes. The long tail (up to 9000 Euro) makes the plots quite unreadable.

In [1]:

```
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import folium
from folium import plugins
```

In [2]:

```
berlin_raw = pd.read_csv("data/listings.csv")
berlin_raw.neighbourhood_group = berlin_raw.neighbourhood_group.str.replace(" ", "")
berlin_raw.neighbourhood_group = berlin_raw.neighbourhood_group.str.replace("Charlotten
burg-Wilm.", "Charlottenburg-Wilmersdorf")
berlin_airbnb = berlin_raw[berlin_raw.price > 0] # Price 0 seems buggy
berlin_airbnb = berlin_airbnb[berlin_airbnb.price < 1000] # To get around the long tail
outliers
berlin_airbnb[["neighbourhood_group", "neighbourhood", "room_type"]] = berlin_airbnb[[
"neighbourhood_group", "neighbourhood", "room_type"]].astype("category")
```

In [3]:

```
berlin_airbnb.shape
```

Out[3]:

```
(22503, 16)
```

In [4]:

```
berlin_airbnb.room_type.unique()
```

Out[4]:

```
[Entire home/apt, Private room, Shared room]
Categories (3, object): [Entire home/apt, Private room, Shared room]
```

In [5]:

```
berlin_airbnb.neighbourhood_group.unique()
```

Out[5]:

```
[Mitte, Pankow, Tempelhof-Schöneberg, Friedrichshain-Kreuzberg, Neukölln,
..., Steglitz-Zehlendorf, Reinickendorf, Lichtenberg, Marzahn-Hellersdorf,
Spandau]
Length: 12
Categories (12, object): [Mitte, Pankow, Tempelhof-Schöneberg, Friedrichsh
ain-Kreuzberg, ..., Reinickendorf, Lichtenberg, Marzahn-Hellersdorf, Spand
au]
```

The dataset contains 22503 individual appartments on AirBnB in a city with 1.95 million apartments total. The dataset shows 12 different neighbourhoods and some review data, as well as, exact location of each. Therefore, a geospatial analysis will be quite interesting.

Exploratory Data analysis

We can now explore the data and analyze how different areas are represented in the data. In the first map map we explore the average price of AirBnB lettings per neighbourhood.

In [6]:

```
berlin_airbnb["price_norm"] = (berlin_airbnb.price-berlin_airbnb.price.min())/(berlin_a
irbnb.price.max()-berlin_airbnb.price.min())
```

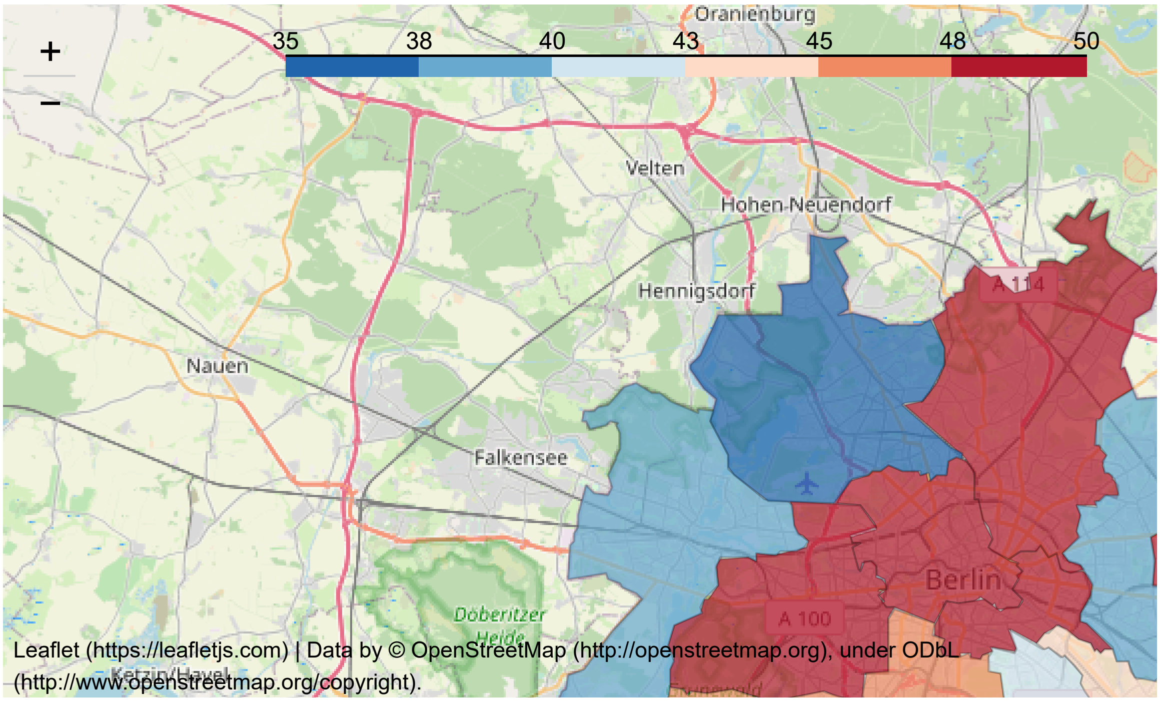
In [7]:

```
berlin_lat = berlin_airbnb.latitude.mean()
berlin_long = berlin_airbnb.longitude.mean()
colors = ["#3333DD", "#B00000"]
```

In [8]:

```
berlin_map = folium.Map(location=[berlin_lat, berlin_long], zoom_start=10)

belin_boroughs = "https://raw.githubusercontent.com/funkeinteraktiv/Berlin-Geodaten/mas
ter/berlin_bezirke.geojson"
berlin_price = berlin_airbnb.groupby(by="neighbourhood_group").median().reset_index()

folium.Choropleth(
    geo_data=belin_boroughs,
    name='choropleth',
    data=berlin_price,
    columns=['neighbourhood_group', 'price'],
    key_on='feature.properties.name',
    fill_color='RdBu_r',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend = "Median Price (Euro)"
).add_to(berlin_map)

folium.LayerControl().add_to(berlin_map)

berlin_map
```

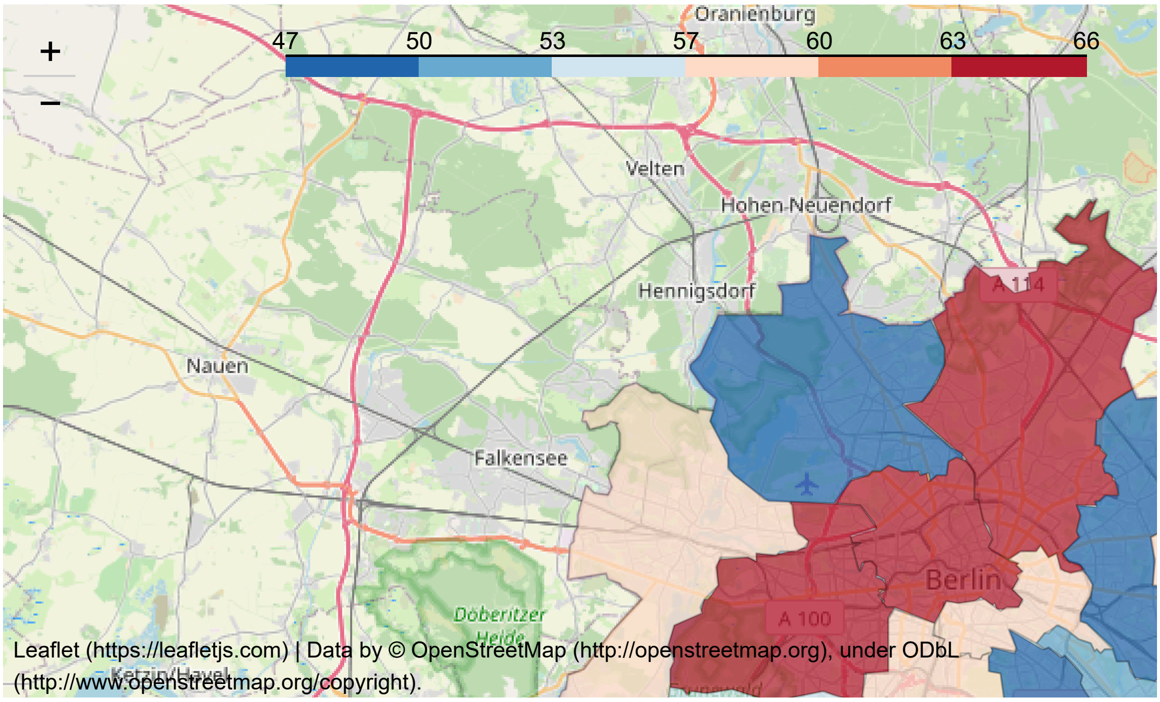
Out[8]:



In [9]:

```
berlin_map = folium.Map(location=[berlin_lat, berlin_long], zoom_start=10)

belin_boroughs = "https://raw.githubusercontent.com/funkeinteraktiv/Berlin-Geodaten/master/berlin_bezirke.geojson"
berlin_price = berlin_airbnb.groupby(by="neighbourhood_group").mean().reset_index()

folium.Choropleth(
    geo_data=belin_boroughs,
    name='choropleth',
    data=berlin_price,
    columns=['neighbourhood_group', 'price'],
    key_on='feature.properties.name',
    fill_color='RdBu_r',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend = "Mean Average Price (Euro)"
).add_to(berlin_map)

folium.LayerControl().add_to(berlin_map)

berlin_map
```

Out[9]:



We can see that central locations are especially expensive, with some of the East/West divide still existing. It is also visible that Tegel airport is somewhat of a barrier behind which there is a low-cost AirBnB neighbourhood (and a lot of forests and not a lot of public transportation). There is a clear discrepancy betweenthe mean and median data. It seems Kreuzberg has some really cheap flats available but most commonly it is just as expensive as Mitte.

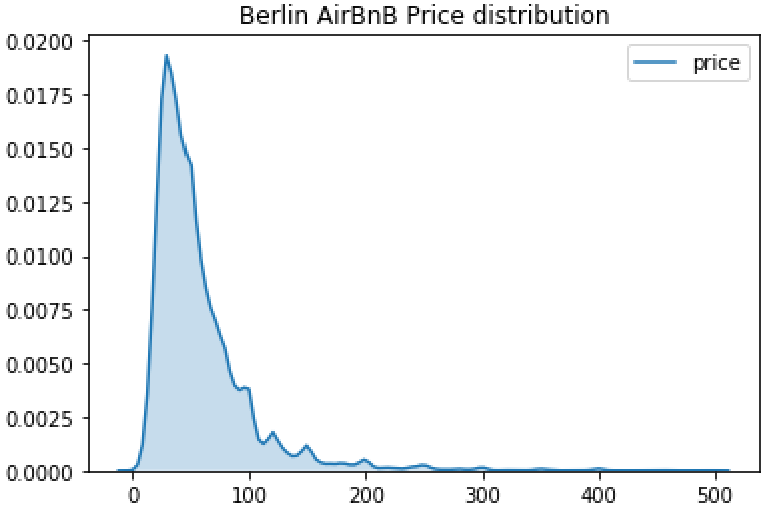
But let's have a look at the distributions of price. Is it really just about location?

In [10]:

```
sns.kdeplot(berlin_airbnb.price, shade=True, clip=(0, 500))
plt.title("Berlin AirBnB Price distribution")
```

Out[10]:

```
Text(0.5, 1.0, 'Berlin AirBnB Price distribution')
```

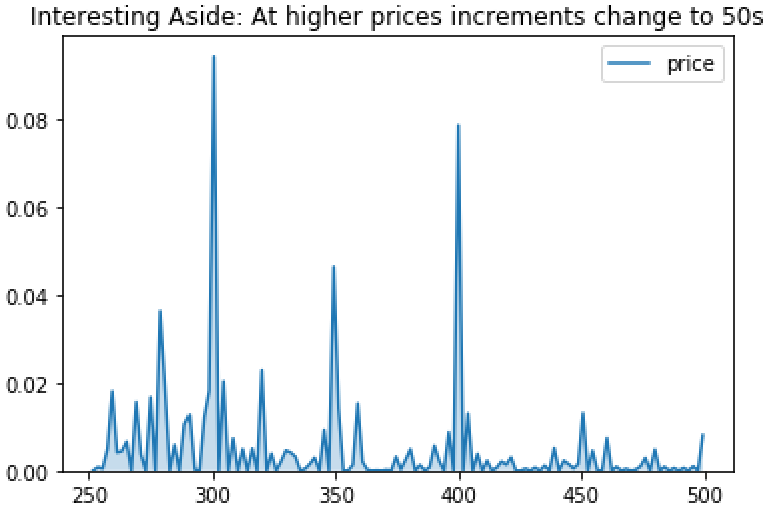


In [11]:

```
sns.kdeplot(berlin_airbnb.price, bw=.1, shade=True, clip=(250, 500))
plt.title("Interesting Aside: At higher prices increments change to 50s")
```

Out[11]:

```
Text(0.5, 1.0, 'Interesting Aside: At higher prices increments change to 5
0s')
```

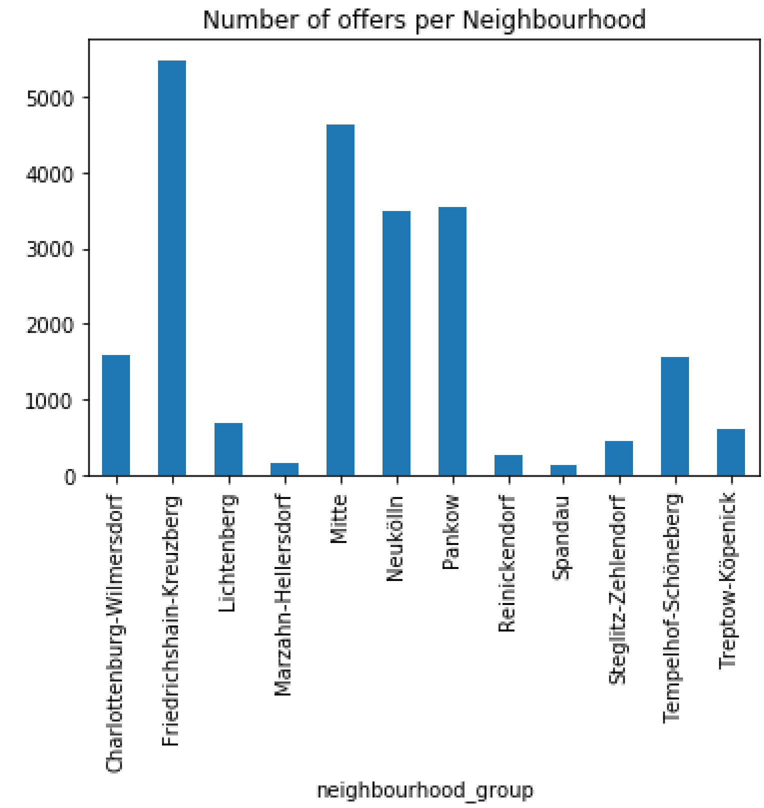


In [12]:

```
berlin_airbnb.groupby(by="neighbourhood_group").id.count().plot(kind="bar", title="Numb
er of offers per Neighbourhood")
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x223d96a6588>
```

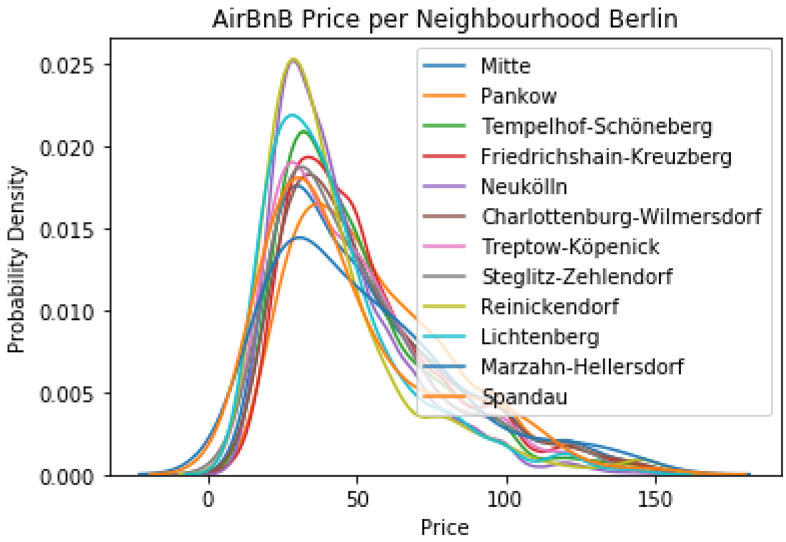


In [13]:

```
# Plotting the KDE Plot
for hood in berlin_airbnb.neighbourhood_group.unique():
    sns.kdeplot(berlin_airbnb[berlin_airbnb.neighbourhood_group==hood].price, shade=Fal
se, clip=(0, 150), Label=hood)


plt.xlabel('Price')
plt.ylabel('Probability Density')
plt.title('AirBnB Price per Neighbourhood Berlin')
```

Out[13]:

```
Text(0.5, 1.0, 'AirBnB Price per Neighbourhood Berlin')
```



The distributions are remarkably similar! Yes Mitte and Pankow (central districts) are somewhat wider, but that's also due to the number of available lettings. The very sharp spike is Reinickendorf, which does not have many offers on AirBnB. Generally, the spikes are in very similar areas below 100€. An interesting outlier is Frierichhain-Kreuzberg, which has a second peak close to 50€. So what is causing the divide between places actually?

There seems to be a slight bias, but is that actually enough? How about we compare the type of letting. People generally pay less for staying in a shared room.

Type of apartment

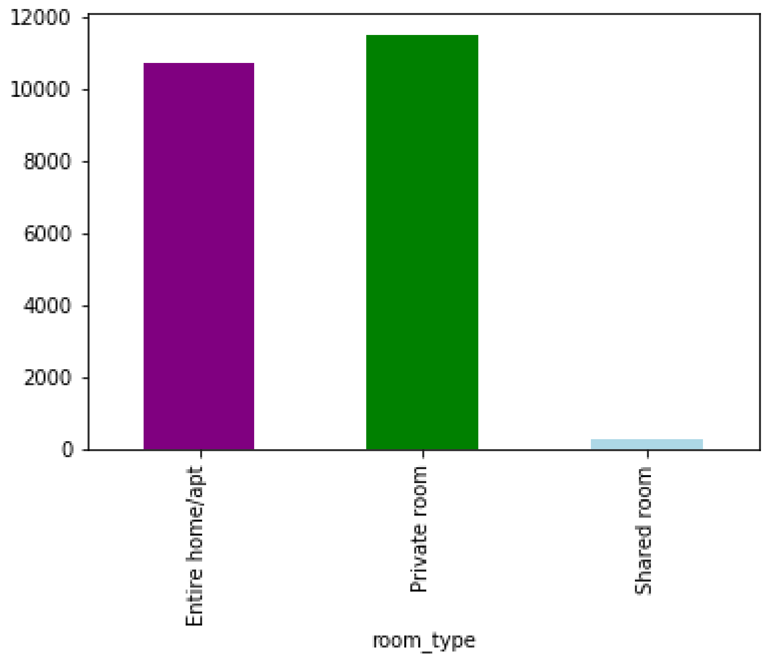
- puple: Entire Apartment
- green: Private Room
- yellow: Shared Room

In [14]:

```
colors = ["purple", "green", "lightblue"]
features = ["neighbourhood_group", "room_type", "price", "number_of_reviews", "reviews_per_month"]

berlin_airbnb.groupby(by="room_type").count().id.plot(kind="bar", color=colors)
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x223d97b4c48>
```

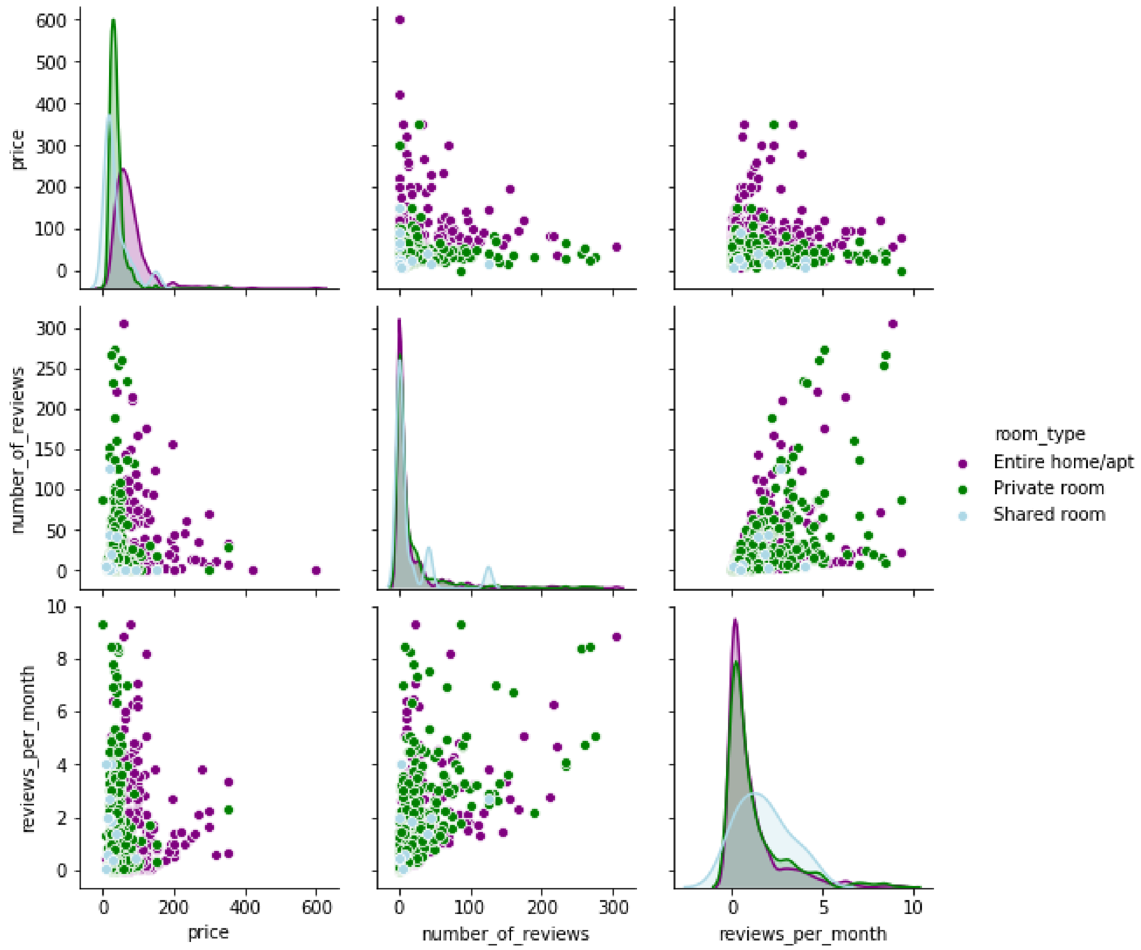


In [15]:

```
sns.pairplot(berlin_airbnb[features].sample(1000), hue="room_type", palette=colors)
```

Out[15]:

```
<seaborn.axisgrid.PairGrid at 0x223d971c848>
```



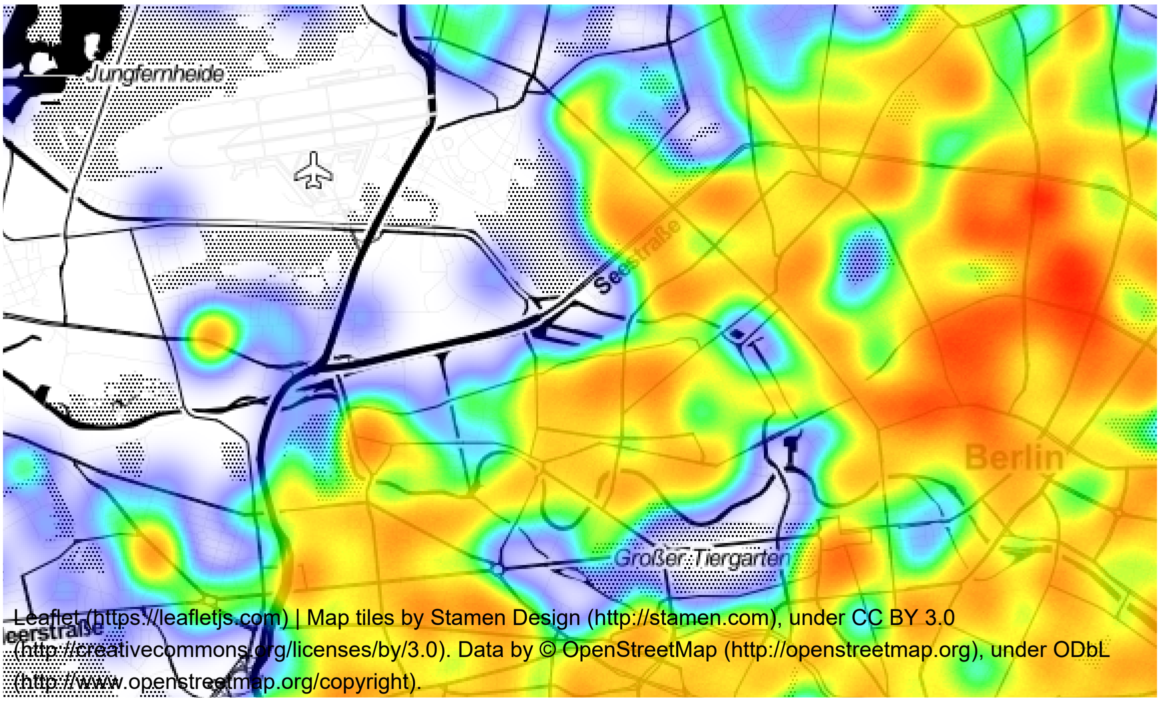
Now this looks like a difference. The data on room type shows a change in the price distribution! Shared rooms tend to have fewer reviews and a lower rate of monthly reviews. A lot more full apartment lettings have a lot more reviews! The 500 Euro lettings have 100 of reviews even. How are these room types distributed then?

In [16]:

```
heatmap = folium.Map(location=[berlin_lat, berlin_long], zoom_start=12, tiles='Stamen Toner',)

# plot heatmap
heatmap.add_children(folium.plugins.HeatMap(berlin_airbnb[berlin_airbnb.room_type == "Entire home/apt"][['latitude', 'longitude']].values, radius=15))
heatmap
```

```
C:\tools\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: FutureWarning: Method `add_children` is deprecated. Please use `add_child` instead.
  after removing the cwd from sys.path.
```

Out[16]:

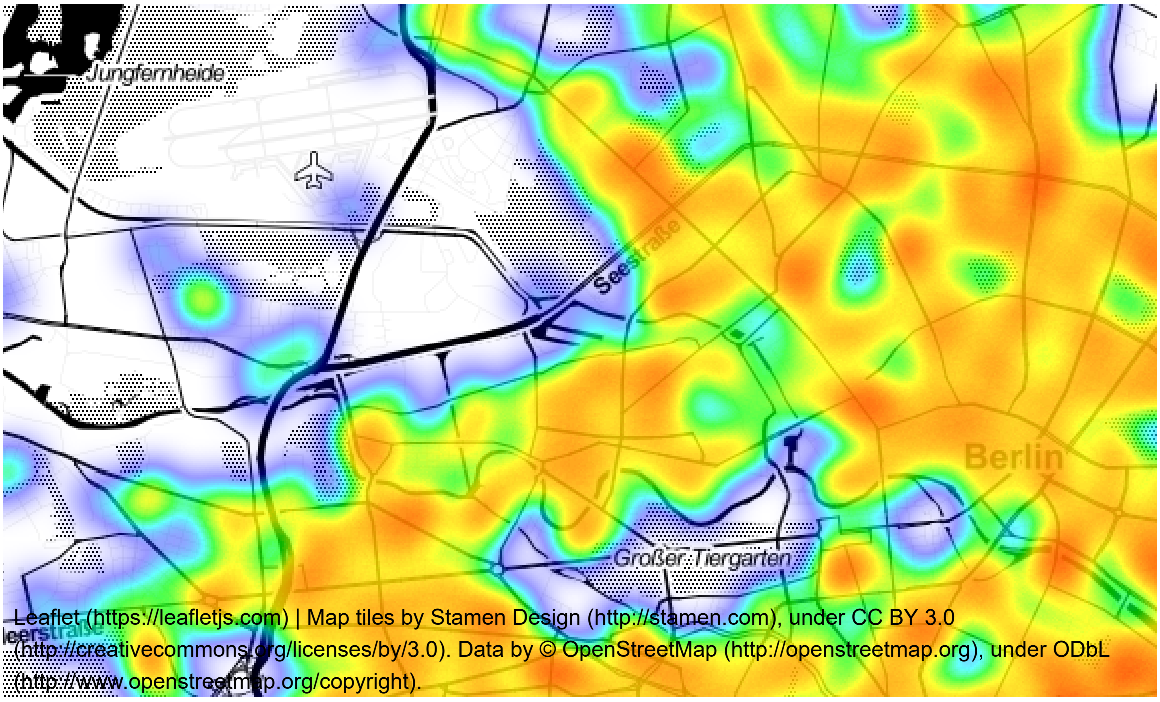


In [17]:

```
heatmap = folium.Map(location=[berlin_lat, berlin_long], zoom_start=12, tiles='Stamen Toner',)

# plot heatmap
heatmap.add_children(folium.plugins.HeatMap(berlin_airbnb[berlin_airbnb.room_type == "Private room"][['latitude', 'longitude']].values, radius=15))
heatmap
```

```
C:\tools\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: FutureWarning: Method `add_children` is deprecated. Please use `add_child` instead.
  after removing the cwd from sys.path.
```

Out[17]:



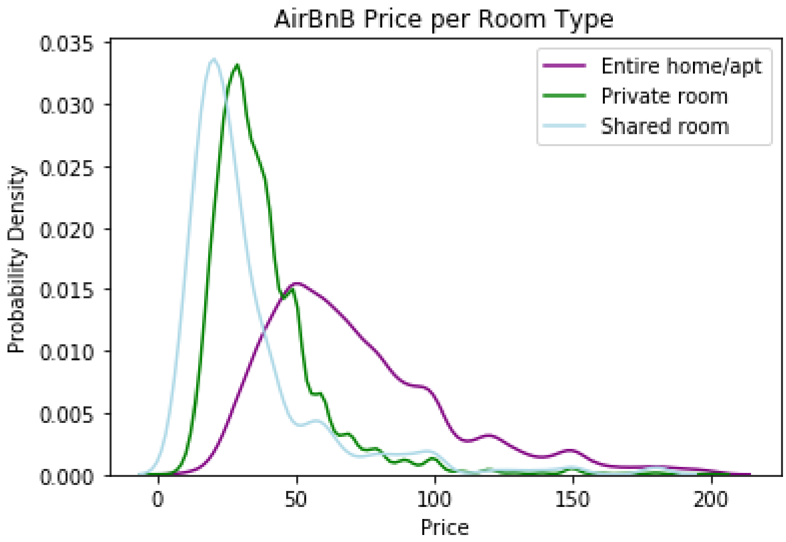
So that's interesting, there are a lot of full apartments available in Mitte, whereas private rooms are more common toward the east. Shared apartments are sprinkled across Berlin, but then again there was not a lot of data available. Let's look at the price distribution by apartment type in detail to finish this out. And see how many apartment types are in each neighbourhood.

In [18]:

```
# Plotting the KDE Plot
for i, room in enumerate(berlin_airbnb.room_type.unique()):
    sns.kdeplot(berlin_airbnb[berlin_airbnb.room_type==room].price, shade=False, clip=(
0, 200), Label=room, color=colors[i])

plt.xlabel('Price')
plt.ylabel('Probability Density')
plt.title('AirBnB Price per Room Type')
```

Out[18]:

```
Text(0.5, 1.0, 'AirBnB Price per Room Type')
```

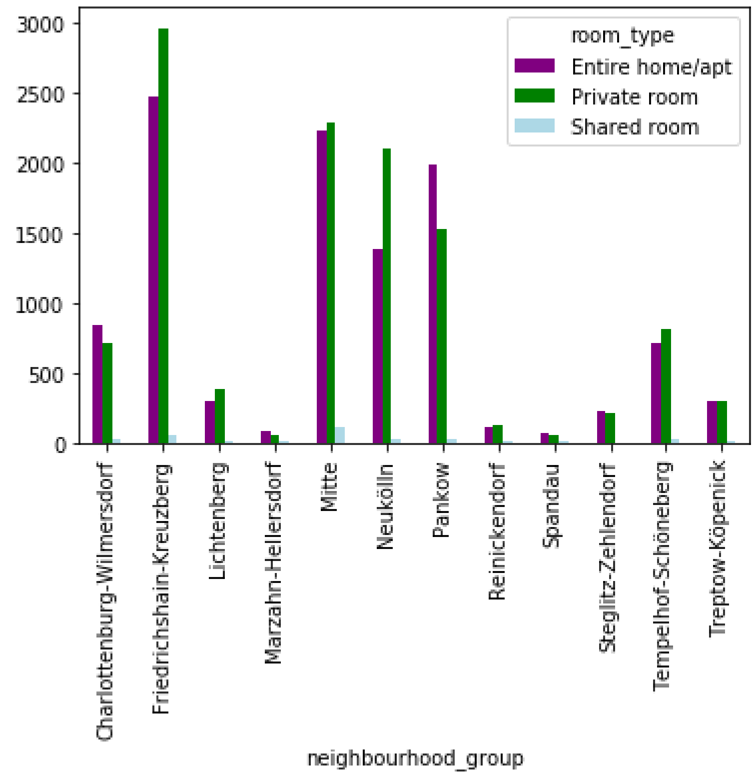


In [19]:

```
pd.pivot_table(berlin_airbnb, index="neighbourhood_group", columns="room_type", values=
'id', aggfunc='count').plot(kind = 'bar', color=colors)
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x223db5671c8>
```



Modeling Step

Let's build a linear model to predict price and round it off with a random forest model that works well on categorical features. We also have to consider that the classes are relatively unbalanced, regarding distribution among neighbourhoods.

In [20]:

```
df_train = pd.get_dummies(berlin_airbnb[["neighbourhood_group", "room_type"]])
target = berlin_airbnb["price"]
```

In [21]:

```
import numpy as np
from sklearn.preprocessing import OrdinalEncoder
from sklearn.model_selection import StratifiedKFold
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.inspection import permutation_importance
from sklearn.metrics import mean_squared_error
```

In [22]:

```python
scores = []
mse = []
skf = StratifiedKFold(n_splits=10)
for train, test in skf.split(df_train, target):
    clf = LinearRegression()
    clf.fit(df_train.iloc[train], target.iloc[train])
    scores.append(clf.score(df_train.iloc[test], target.iloc[test]))
    mse.append(mean_squared_error(target.iloc[test], clf.predict(df_train.iloc[test])))

print("Average R2 score: \t", np.mean(scores),)
print("Average MSE: \t\t", np.mean(mse), "\n")

r = permutation_importance(clf, df_train.iloc[test], target.iloc[test],
                           n_repeats=30,
                           random_state=0)

print("Normalized importances")
sorted_idx = r.importances_mean.argsort()
max_i = sorted_idx[-1]

rel_max = r.importances_mean[max_i]

for i in sorted_idx[::-1]:
    if r.importances_mean[i] - 2 * r.importances_std[i] > 0:
        print(f"{df_train.columns[i]:<50}"
              f"{r.importances_mean[i]/rel_max:.3f}"
              f" +/- {r.importances_std[i]/rel_max:.3f}")
```

```
C:\tools\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:66
7: UserWarning: The least populated class in y has only 1 members, which i
s less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)

Average R2 score:        0.1688816089848335
Average MSE:             2146.3158415682396

Normalized importances
room_type_Private room                            1.000 +/- 0.020
room_type_Entire home/apt                         0.984 +/- 0.018
neighbourhood_group_Friedrichshain-Kreuzberg      0.219 +/- 0.005
neighbourhood_group_Mitte                         0.212 +/- 0.004
neighbourhood_group_Pankow                        0.148 +/- 0.003
neighbourhood_group_Neukölln                      0.141 +/- 0.003
room_type_Shared room                             0.100 +/- 0.002
neighbourhood_group_Charlottenburg-Wilmersdorf    0.099 +/- 0.002
neighbourhood_group_Tempelhof-Schöneberg          0.092 +/- 0.002
neighbourhood_group_Lichtenberg                   0.058 +/- 0.001
neighbourhood_group_Steglitz-Zehlendorf           0.036 +/- 0.001
neighbourhood_group_Treptow-Köpenick              0.033 +/- 0.001
neighbourhood_group_Reinickendorf                 0.014 +/- 0.000
neighbourhood_group_Spandau                       0.013 +/- 0.000
neighbourhood_group_Marzahn-Hellersdorf           0.012 +/- 0.000
```

In [23]:

```python
scores = []
mse = []
skf = StratifiedKFold(n_splits=10)
for train, test in skf.split(df_train, target):
    clf = RandomForestRegressor()
    clf.fit(df_train.iloc[train], target.iloc[train])
    scores.append(clf.score(df_train.iloc[test], target.iloc[test]))
    mse.append(mean_squared_error(target.iloc[test], clf.predict(df_train.iloc[test])))

print("Average R2 score: \t", np.mean(scores),)
print("Average MSE: \t\t", np.mean(mse), "\n")

r = permutation_importance(clf, df_train.iloc[test], target.iloc[test],
                           n_repeats=30,
                           random_state=0)

print("Normalized importances")
sorted_idx = r.importances_mean.argsort()
max_i = sorted_idx[-1]

rel_max = r.importances_mean[max_i]

for i in sorted_idx[::-1]:
    if r.importances_mean[i] - 2 * r.importances_std[i] > 0:
        print(f"{df_train.columns[i]:<50}"
              f"{r.importances_mean[i]/rel_max:.3f}"
              f" +/- {r.importances_std[i]/rel_max:.3f}")
```

```
C:\tools\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:66
7: UserWarning: The least populated class in y has only 1 members, which i
s less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)

Average R2 score:        0.17293195509076958
Average MSE:             2136.0282403208503

Normalized importances
room_type_Entire home/apt                         1.000 +/- 0.060
neighbourhood_group_Mitte                         0.056 +/- 0.010
neighbourhood_group_Neukölln                      0.020 +/- 0.009
room_type_Private room                            0.010 +/- 0.003
neighbourhood_group_Lichtenberg                   0.008 +/- 0.003
neighbourhood_group_Charlottenburg-Wilmersdorf    0.005 +/- 0.002
neighbourhood_group_Reinickendorf                 0.005 +/- 0.002
neighbourhood_group_Friedrichshain-Kreuzberg      0.001 +/- 0.000
```

In [24]:

```
mse = []
scores = []
skf = StratifiedKFold(n_splits=10)
enc = OrdinalEncoder()

df_rf = berlin_airbnb[["neighbourhood_group", "room_type"]]

enc.fit(df_rf)

for train, test in skf.split(df_rf, target):
    clf = RandomForestRegressor()
    clf.fit(enc.transform(df_rf.iloc[train]), target.iloc[train])
    scores.append(clf.score(enc.transform(df_rf.iloc[test]), target.iloc[test]))
    mse.append(mean_squared_error(target.iloc[test], clf.predict(enc.transform(df_rf.il
oc[test]))))

print("Average R2 score: \t", np.mean(scores),)
print("Average MSE: \t\t", np.mean(mse), "\n")

r = permutation_importance(clf, enc.transform(df_rf.iloc[test]), target.iloc[test],
                           n_repeats=30,
                           random_state=0)

print("Normalized importances")
sorted_idx = r.importances_mean.argsort()
max_i = sorted_idx[-1]

rel_max = r.importances_mean[max_i]

for i in sorted_idx[::-1]:
    if r.importances_mean[i] - 2 * r.importances_std[i] > 0:
        print(f"{df_rf.columns[i]:<50}"
              f"{r.importances_mean[i]/rel_max:.3f}"
              f" +/- {r.importances_std[i]/rel_max:.3f}")
```

```
C:\tools\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:66
7: UserWarning: The least populated class in y has only 1 members, which i
s less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)

Average R2 score:        0.17300974989333984
Average MSE:             2135.834610356241

Normalized importances
room_type                                         1.000 +/- 0.060
neighbourhood_group                               0.120 +/- 0.017
```

Conclusion

The initial analysis showed that the price of an AirBnB let is in part influenced by the centrality, but that type of room may have an even larger influence on the price. The geospatial analysis shows that more full apartments are available in Mitte and more private rooms are available in Kreuzberg. The linear regression model shows that prices can be predicted with a moderate R2 score of ~0.17 using location and room type. Using the permutation importance the most important features are in fact whether a room is private or a full apartment, all other features being 5 times less influential on the prediction result. This suggests the initial analysis was in fact correct. The non-linear Random Forest model confirms this idea, with a slightly better R2 score, where centrality of the apartment and whether the entire apartment was available are the main predictive features. Considering the similar performance of both models it is advisable to use the simpler linear model over the non-linear model. If more features are important it may be good to use Random Forests because ordinal categories (as shown in the last code cell) are possible.