Flat Price Prediction

In [246]:

```
# I have used the dataset("resale-flat-prices-based-on-approval-date-1990-1999.csv")
# for the flat price prediction by considering the number of rooms
# according to the rules of Singapore Housing and Development Board (HDB).

# For more details: https://www.hdb.gov.sg/residential/buying-a-flat/resale/getting-started/types-of
-flats
# Datasets: https://data.gov.sg/dataset/resale-flat-prices?resource_id=42ff9cfe-abe5-4b54-beda-c88f9
bb438ee
```

In [247]:

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

In [248]:

```
#reading .csv file and storing it in "dataset" dataframe
dataset=pd.read_csv("/home/ankit/Desktop/resale-flat-prices-based-on-approval-date-1990-1999.csv")
```

In [249]:

```
print(dataset)
# There are total 9 features(predictors) including both qualitative and quantitative features.
```

```
          month        town  flat_type block       street_name storey_range  \
0       1990-01  ANG MO KIO     1 ROOM   309  ANG MO KIO AVE 1     10 TO 12
1       1990-01  ANG MO KIO     1 ROOM   309  ANG MO KIO AVE 1     04 TO 06
2       1990-01  ANG MO KIO     1 ROOM   309  ANG MO KIO AVE 1     10 TO 12
3       1990-01  ANG MO KIO     1 ROOM   309  ANG MO KIO AVE 1     07 TO 09
4       1990-01  ANG MO KIO     3 ROOM   216  ANG MO KIO AVE 1     04 TO 06
...         ...         ...        ...   ...               ...          ...
287195  1999-12      YISHUN  EXECUTIVE   611      YISHUN ST 61     10 TO 12
287196  1999-12      YISHUN  EXECUTIVE   324       YISHUN CTRL     01 TO 03
287197  1999-12      YISHUN  EXECUTIVE   392      YISHUN AVE 6     07 TO 09
287198  1999-12      YISHUN  EXECUTIVE   356    YISHUN RING RD     04 TO 06
287199  1999-12      YISHUN  EXECUTIVE   358    YISHUN RING RD     01 TO 03

        floor_area_sqm      flat_model  lease_commence_date  resale_price
0                 31.0        IMPROVED                 1977          9000
1                 31.0        IMPROVED                 1977          6000
2                 31.0        IMPROVED                 1977          8000
3                 31.0        IMPROVED                 1977          6000
4                 73.0  NEW GENERATION                 1976         47200
...                ...             ...                  ...           ...
287195           142.0       APARTMENT                 1987        456000
287196           142.0       APARTMENT                 1988        408000
287197           146.0      MAISONETTE                 1988        469000
287198           146.0      MAISONETTE                 1988        440000
287199           145.0      MAISONETTE                 1988        484000

[287200 rows x 10 columns]
```

In [250]:

```
print(dataset.shape)
# Total 287200 rows and 10 columns are present in this dataset.
```

```
(287200, 10)
```

In [251]:

```
dataset.flat_type.unique() # to find the unique values in flat_type column
```

Out[251]:

```
array(['1 ROOM', '3 ROOM', '4 ROOM', '5 ROOM', '2 ROOM', 'EXECUTIVE',
       'MULTI GENERATION'], dtype=object)
```

In [252]:

```
n1 = len(pd.unique(dataset['flat_type']))
n1
```

Out[252]:

```
7
```

In [253]:

```
dataset.storey_range.unique() # to find the unique values in storey_range column
```

Out[253]:

```
array(['10 TO 12', '04 TO 06', '07 TO 09', '01 TO 03', '13 TO 15',
       '19 TO 21', '16 TO 18', '25 TO 27', '22 TO 24'], dtype=object)
```

In [254]:

```
dataset.describe()
# We get the statistic about the dataset.
# On average, floor area is 93.35 sqm and resale price is 219541$ and we can also check the other de
tails here.
# From this output, I will try to see the nature of the dataset.
```

Out[254]:

	floor_area_sqm	lease_commence_date	resale_price
count	287200.000000	287200.000000	287200.000000
mean	93.351439	1983.206741	219541.850313
std	27.361839	6.085734	128144.384286
min	28.000000	1967.000000	5000.000000
25%	68.000000	1979.000000	127000.000000
50%	91.000000	1984.000000	195000.000000
75%	113.000000	1987.000000	298000.000000
max	307.000000	1997.000000	900000.000000

In [255]:

```
#summary statistics of columns in dataframe
dataset.describe().transpose() # Rowwise summary
```

Out[255]:

	count	mean	std	min	25%	50%	75%	max
floor_area_sqm	287200.0	93.351439	27.361839	28.0	68.0	91.0	113.0	307.0
lease_commence_date	287200.0	1983.206741	6.085734	1967.0	1979.0	1984.0	1987.0	1997.0
resale_price	287200.0	219541.850313	128144.384286	5000.0	127000.0	195000.0	298000.0	900000.0

In [256]:

```
dataset.dtypes # To see the datatypes of the column data
```

Out[256]:

```
month                   object
town                    object
flat_type               object
block                   object
street_name             object
storey_range            object
floor_area_sqm         float64
flat_model              object
lease_commence_date      int64
resale_price             int64
dtype: object
```

Data Preprocessing

In [257]:

```
data = dataset.to_numpy() # storing dataset as numpy array
```

In [258]:

```
#dataset['flat_type'] = dataset['flat_type'].map(lambda x: x.rstrip('ROOM'))
```

In [259]:

```
# https://www.hdb.gov.sg/residential/buying-a-flat/resale/getting-started/types-of-flats
# Converting the string type flat_type data into numerical data, so that machine learning algorithm
# will work on this numerical data.
# Used the number of bedrooms in each flat_type according to the rules of HDB(singapore) and assumed
 number
# of bedrooms in "1 ROOM" flat_type is 1 as it is not mentioned on the site.
for i in range(len(data)):
    if data[i][2]=="1 ROOM":
        data[i][2]=1
    if data[i][2]=="2 ROOM":
        data[i][2]=1
    if data[i][2]=="3 ROOM":
        data[i][2]=2
    if data[i][2]=="4 ROOM":
        data[i][2]=3
    if data[i][2]=="5 ROOM":
        data[i][2]=3
    if data[i][2]=="EXECUTIVE":
        data[i][2]=3
    if data[i][2]=="MULTI GENERATION":
        data[i][2]=4
```

In [260]:

```
# In the storey_range column, on taking the average of minimum and maximum number of storeys, so tha
t
# string get converted into numerical data.
# Extracted first 2 digits and last 2 digits and have taken the average.
for i in range(len(data)):
    string=data[i][5]
    p=int(string[0])
    q=int(string[1])
    x=10*p + q
    #print(x)
    r=int(string[-1])
    s=int(string[-2])
    y=10*s+r
    #print((x+y)/2)
    avg=round((x+y)/2)
    data[i][5]=avg
```

In [261]:

```
# From numpy array i.e. "data"(list of lists) to dataframe:
dataset1 = pd.DataFrame(data, columns =['month','town','flat_type','block','street_name','storey_ran
ge','floor_area_sqm','flat_model','lease_commence_date','resale_price'])
```

In [262]:

```
dataset1
```

Out[262]:

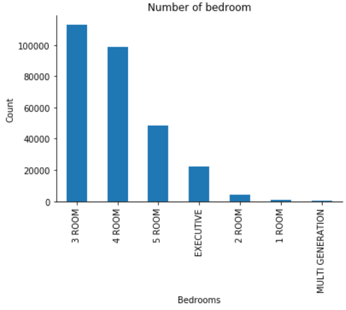
	month	town	flat_type	block	street_name	storey_range	floor_area_sqm	flat_model	lease_commence_date	resale_price
0	1990-01	ANG MO KIO	1	309	ANG MO KIO AVE 1	11	31	IMPROVED	1977	9000
1	1990-01	ANG MO KIO	1	309	ANG MO KIO AVE 1	5	31	IMPROVED	1977	6000
2	1990-01	ANG MO KIO	1	309	ANG MO KIO AVE 1	11	31	IMPROVED	1977	8000
3	1990-01	ANG MO KIO	1	309	ANG MO KIO AVE 1	8	31	IMPROVED	1977	6000
4	1990-01	ANG MO KIO	2	216	ANG MO KIO AVE 1	5	73	NEW GENERATION	1976	47200
...	...	...	...	...	...	...	...	...	...	...
287195	1999-12	YISHUN	3	611	YISHUN ST 61	11	142	APARTMENT	1987	456000
287196	1999-12	YISHUN	3	324	YISHUN CTRL	2	142	APARTMENT	1988	408000
287197	1999-12	YISHUN	3	392	YISHUN AVE 6	8	146	MAISONETTE	1988	469000
287198	1999-12	YISHUN	3	356	YISHUN RING RD	5	146	MAISONETTE	1988	440000
287199	1999-12	YISHUN	3	358	YISHUN RING RD	2	145	MAISONETTE	1988	484000

287200 rows × 10 columns

Exploratory Data Analysis

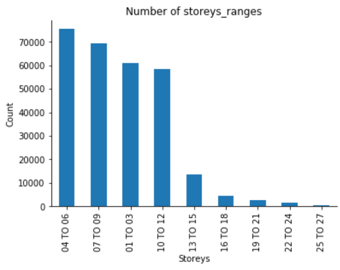
In [263]:

```
dataset['flat_type'].value_counts().plot(kind='bar')
plt.title('Number of bedroom')
plt.xlabel('Bedrooms')
plt.ylabel('Count')
sns.despine()
```



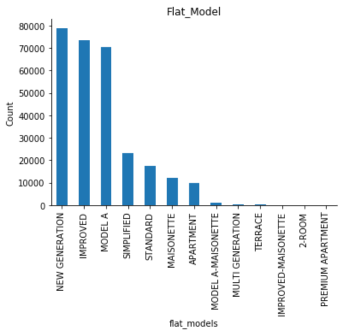
In [264]:
```
# As we can see from the visualization 3 and 4 bedroom houses are most commonly sold.
# So, for a builder having this data , it can make a new flat with more 3 and 4 bedrooms
# to attract more buyers.
```

In [265]:
```
dataset['storey_range'].value_counts().plot(kind='bar')
plt.title('Number of storeys_ranges')
plt.xlabel('Storeys')
plt.ylabel('Count')
sns.despine()
```



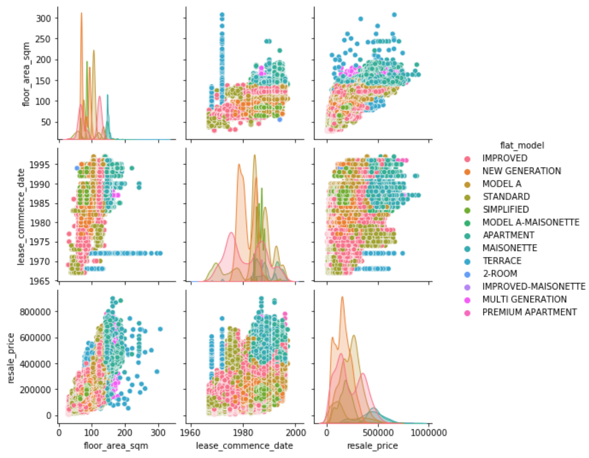
In [266]:
```
# As we can see 4 to 6, 7 to 9 , 1 to 3 and 10 to 12 storey_range flats have more count.
# So, to predict resale flat prices of the flat, we should have to consider these storey range flat
s.
```

In [267]:
```
dataset['flat_model'].value_counts().plot(kind='bar')
plt.title('Flat_Model')
plt.xlabel('flat_models')
plt.ylabel('Count')
sns.despine()
```



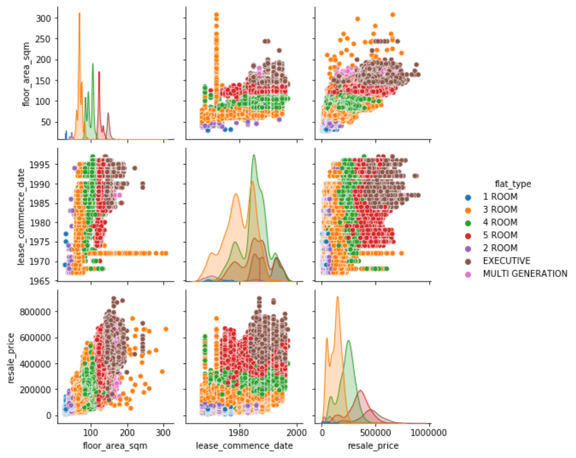
In [268]:
```
# Here, "NEW GENERATION", "IMPROVED" and "MODEL A" flat models have more count compared to other fla
t models.
# So, while predicting flat prices, we should have to concentrate these flat models.
```

In [269]:
```
sns.pairplot(dataset,hue='flat_model', diag_kws={'bw': 0.2})
plt.show()
```



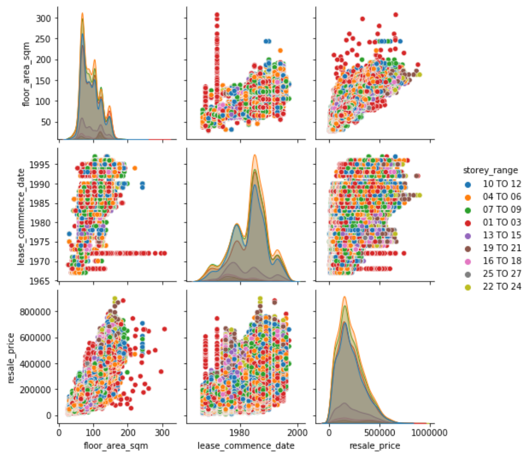
In [270]:
```
# As we can see, there is a spike in the scatter plot between floor_area_sqm and lease commence_dat
e.
# For lease_commence year between 1960 and 1980, for 2-ROOM flat model, floor area is very high and
 this
# 2-ROOM flat model is used between these years only.
# Similarly, APARTMENT,MODEL A-MAISONETTE and MAISONETTE flat models were used between 1980 and 2000
# lease_commence year.
# For "MODEL A" AND "STANDARD" flat models, flat area is under 150 square meters.
# There is approximate a linear relationship between resale_price and floor_area_sqm
# MODEL A and STANDARD flat models have floor_area between 100 and 200 sqm for which resale price is
 between
# 200000 and 700000
# PREMIUM APARTMENT have floor_area between 0 and 150 sqm for which resale_prices are under 600000$.
# For "most" 2-ROOM and TERRACE flat models, lease_commence year is between 1980 and 1998 and
# resale_prices are above 400000$.
```

In [271]:
```
sns.pairplot(dataset,hue='flat_type', diag_kws={'bw': 0.2})
plt.show()
```



In [272]:
```
# There is a spike for "3-ROOM" flat_type for earlier lease_commence_year of 1980 which shows
# total flat area in sqm is maximum in that year for "3-ROOM" flat type
# floor area for "4 ROOM" and "5 ROOM" flat_type is less than 150 sqm.
# floor area for "1 ROOM" and "2 ROOM" flat_type is less than 50 sqm.
# EXECUTIVE flat type are implemented after 1980 lease commence_year and mostly floor are is between

# 150 and 200 sqm except 2-3 flats.
# Mostly EXECUTIVE flats have resale price more than 400000$ with floor area around 100 sqm.
# "4 ROOM" flats have resale price less than 600000$
```

In [273]:
```
sns.pairplot(dataset,hue='storey_range', diag_kws={'bw': 0.2})
plt.show()
```



In [274]:
```
dataset
```

Out[274]:

	month	town	flat_type	block	street_name	storey_range	floor_area_sqm	flat_model	lease_commence_date	resale_pri
0	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977	90

1	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	04 TO 06	31.0	IMPROVED	1977	60
2	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977	80
3	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	07 TO 09	31.0	IMPROVED	1977	60
4	1990-01	ANG MO KIO	3 ROOM	216	ANG MO KIO AVE 1	04 TO 06	73.0	NEW GENERATION	1976	472
...	...	...	...	...	...	...	...	...	...	
287195	1999-12	YISHUN	EXECUTIVE	611	YISHUN ST 61	10 TO 12	142.0	APARTMENT	1987	4560
287196	1999-12	YISHUN	EXECUTIVE	324	YISHUN CTRL	01 TO 03	142.0	APARTMENT	1988	4080
287197	1999-12	YISHUN	EXECUTIVE	392	YISHUN AVE 6	07 TO 09	146.0	MAISONETTE	1988	4690
287198	1999-12	YISHUN	EXECUTIVE	356	YISHUN RING RD	04 TO 06	146.0	MAISONETTE	1988	4400
287199	1999-12	YISHUN	EXECUTIVE	358	YISHUN RING RD	01 TO 03	145.0	MAISONETTE	1988	4840

287200 rows × 10 columns

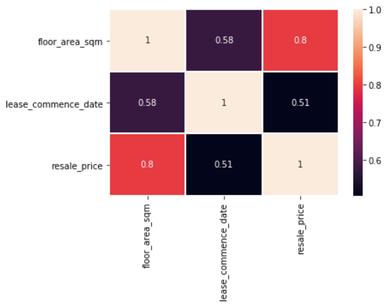
In [275]:
```
dataset.corr() # Finding Correlation between features:
```

Out[275]:

	floor_area_sqm	lease_commence_date	resale_price
floor_area_sqm	1.000000	0.578498	0.797008
lease_commence_date	0.578498	1.000000	0.505054
resale_price	0.797008	0.505054	1.000000

In [276]:
```
sns.heatmap(dataset.corr(),annot=True,lw=1)
```

Out[276]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc367ce110>
```

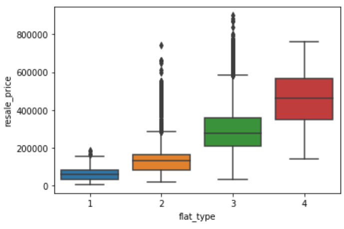


In [277]:
```
# Correlation is a statistical measure to explain the relationship between two or more than
# two variables which are used to predict the values of target variable.
# If two variables or features are positively correlated with each other,
# it means when the value of one variable increases then the value of the other variable(s) also inc
reases.
```

In [278]:
```
# resale_price and floor_area_sqm are highly correlated
```

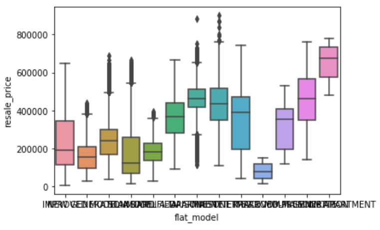
In [279]:
```
# Box-plots (another way of visualizing and analysing data with min,max,25,50 and 75 percentile valu
es)
sns.boxplot(y='resale_price',x='flat_type',data=dataset1)
```

Out[279]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc363a3d50>
```



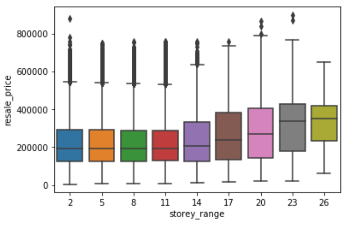
In [280]:
```
sns.boxplot(y='resale_price',x='flat_model',data=dataset1)
```

Out[280]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc336a4d90>
```

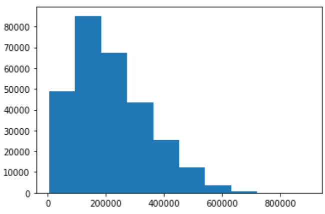


In [281]:
```
sns.boxplot(y='resale_price',x='storey_range',data=dataset1)
```

Out[281]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc36c34cd0>
```



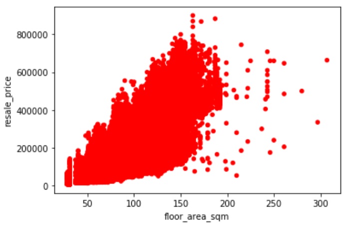
In [282]:
```
import matplotlib.pyplot as plt
plt.hist(dataset.resale_price)
plt.show()
```



In [283]:
```
# flats which have resale prices are between 100000$ and 200000$ have highest count which is 80000
# and then comes those flats which have resale prices 200000$ and 300000$ with 70000 count
# and then flats with resale prices between 0 and 100000$ comes with count ~50000
```

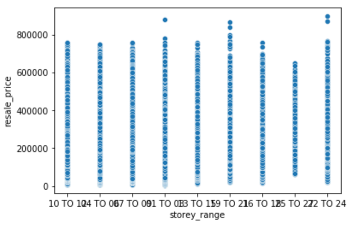
In [284]:
```
colors = np.where(dataset.resale_price > 1, 'r', 'k')
#plt.scatter(dataset.resale_price, dataset.floor_area_sqm, s=20, c=colors)
# OR (with pandas 0.13 and up)
dataset.plot(kind='scatter', x='floor_area_sqm', y='resale_price', s=20, c=colors)
```

Out[284]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc36fd1d50>
```



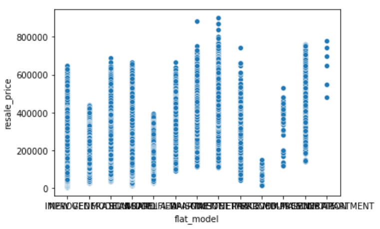
In [285]:
```
import seaborn as sns
sns.scatterplot(x="storey_range", y="resale_price", data=dataset)
```

Out[285]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc36bd5150>
```



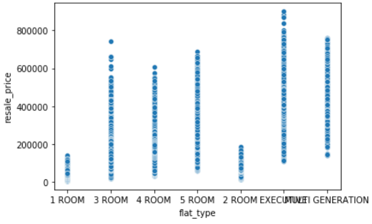
In [286]:
```
import seaborn as sns
sns.scatterplot(x="flat_model", y="resale_price", data=dataset)
```

Out[286]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc36771110>
```



In [287]:
```
sns.scatterplot(x="flat_type", y="resale_price", data=dataset)
```

Out[287]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcc36769310>
```



In [288]:

```
# Based on parameters "floor_area_sqm", "flat_type","flat_model","storey_range" as above, we can see

# the range of resale flat prices.
```

On Adding latitude and longitude columns based on the address given in dataset

In [289]:

```
# As the record size is 287200 in the given dataset and there is a problem of time out if we use geo
py
# library to convert given address into latitude and longitude. So, just to analyze the data, I am c
onsidring
# less record size with 1000 rows.
```

In [290]:

```
modified_dataset=dataset=pd.read_csv("/home/ankit/Desktop/resale-flat-prices-based-on-approval-date-
1990-1999.csv", nrows = 1000)
```

In [291]:

```
modified_dataset.shape
```

Out[291]:

```
(1000, 10)
```

In [292]:

```
dataset["address"] = dataset["town"] + " " + dataset["block"] + " " + dataset["street_name"]
```

In [293]:

```
from geopy.geocoders import Nominatim
from geopy.exc import GeocoderTimedOut, GeocoderQuotaExceeded
import time
Address_info= dataset[['town','block','street_name']].copy()
Address_info = Address_info.apply(lambda x: x.str.strip(), axis=1)
Address_info['Full_Address'] = Address_info[Address_info.columns[1:]].apply(lambda x: ','.join(x.dro
pna().astype(str)), axis=1)

locator = Nominatim(user_agent="myGeocoder")
def geocode_me(location):
    time.sleep(1.1)
    try:
        return locator.geocode(location)
    except (GeocoderTimedOut, GeocoderQuotaExceeded) as e:
        if GeocoderQuotaExceeded:
            print(e)
        else:
            print(f'Location not found: {e}')
            return None

Address_info['location'] = Address_info['Full_Address'].apply(lambda x: geocode_me(x))
Address_info['point'] = Address_info['location'].apply(lambda loc: tuple(loc.point) if loc else None
)
Address_info[['latitude', 'longitude', 'altitude']] =   pd.DataFrame(Address_info['point'].tolist(),
 index=Address_info.index)
#Ref:Stackoverflow
```

In [294]:

```
modified_dataset=pd.concat([modified_dataset,Address_info], axis=1)
```

In [295]:

```
modified_dataset
```

Out[295]:

	month	town	flat_type	block	street_name	storey_range	floor_area_sqm	flat_model	lease_commence_date	resa
0	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977	
1	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	04 TO 06	31.0	IMPROVED	1977	
2	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977	
3	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	07 TO 09	31.0	IMPROVED	1977	
4	1990-01	ANG MO KIO	3 ROOM	216	ANG MO KIO AVE 1	04 TO 06	73.0	NEW GENERATION	1976	
...	...	...	...	...	...	...	...	...	...	
995	1990-01	KALLANG/WHAMPOA	3 ROOM	11	UPP BOON KENG RD	13 TO 15	65.0	IMPROVED	1974	
996	1990-01	KALLANG/WHAMPOA	3 ROOM	98	WHAMPOA DR	13 TO 15	65.0	IMPROVED	1974	
997	1990-01	KALLANG/WHAMPOA	3 ROOM	98	WHAMPOA DR	13 TO 15	65.0	IMPROVED	1974	
998	1990-01	KALLANG/WHAMPOA	3 ROOM	65	KALLANG BAHRU	07 TO 09	65.0	IMPROVED	1981	
999	1990-01	KALLANG/WHAMPOA	3 ROOM	65	KALLANG BAHRU	13 TO 15	65.0	IMPROVED	1981	

1000 rows × 20 columns

In [296]:

```
new_dataset=modified_dataset.dropna() #Removing where values are undefined in the form of 'NaN'
```

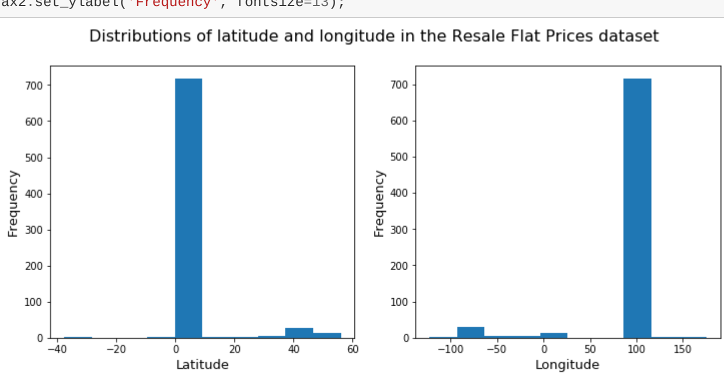
In [297]:
```
new_dataset
```
Out[297]:

	month	town	flat_type	block	street_name	storey_range	floor_area_sqm	flat_model	lease_commence_date
0	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977
1	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	04 TO 06	31.0	IMPROVED	1977
2	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977
3	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	07 TO 09	31.0	IMPROVED	1977
4	1990-01	ANG MO KIO	3 ROOM	216	ANG MO KIO AVE 1	04 TO 06	73.0	NEW GENERATION	1976
...	...	...	...	...	...	...	...	...	...
992	1990-01	KALLANG/WHAMPOA	3 ROOM	82	WHAMPOA DR	13 TO 15	66.0	IMPROVED	1974
996	1990-01	KALLANG/WHAMPOA	3 ROOM	98	WHAMPOA DR	13 TO 15	65.0	IMPROVED	1974
997	1990-01	KALLANG/WHAMPOA	3 ROOM	98	WHAMPOA DR	13 TO 15	65.0	IMPROVED	1974
998	1990-01	KALLANG/WHAMPOA	3 ROOM	65	KALLANG BAHRU	07 TO 09	65.0	IMPROVED	1981
999	1990-01	KALLANG/WHAMPOA	3 ROOM	65	KALLANG BAHRU	13 TO 15	65.0	IMPROVED	1981

770 rows × 20 columns

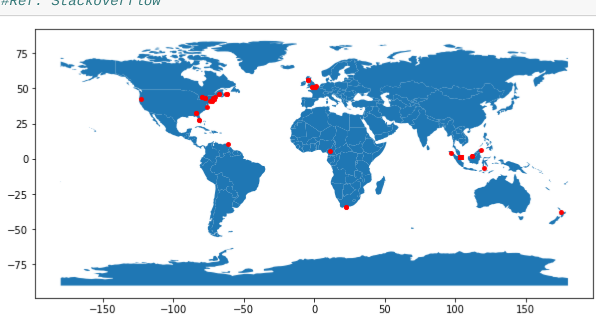
Now, We are going to see the common locations where the flats are placed.

In [298]:
```python
import matplotlib.pyplot as plt
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 5))
fig.suptitle('Distributions of latitude and longitude in the Resale Flat Prices dataset', fontsize=16)
ax1.hist(new_dataset.latitude)
ax1.set_xlabel('Latitude', fontsize=13)
ax1.set_ylabel('Frequency', fontsize=13)
ax2.hist(new_dataset.longitude)
ax2.set_xlabel('Longitude', fontsize=13)
ax2.set_ylabel('Frequency', fontsize=13);
```



In [299]:
```python
# As we can see with latitude range 0 to 10, maximum flats were sold and same for longitude around 100.
# So, these locations might be ideal location for flat sale in future also.
```

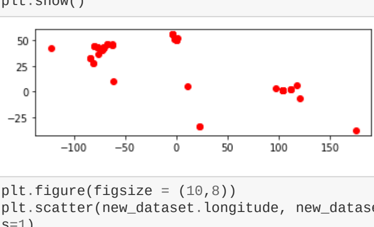
In [300]:
```python
from shapely.geometry import Point
import geopandas as gpd
from geopandas import GeoDataFrame
geometry = [Point(xy) for xy in zip(new_dataset['longitude'], new_dataset['latitude'])]
gdf = GeoDataFrame(new_dataset, geometry=geometry)
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
gdf.plot(ax=world.plot(figsize=(10, 6)), marker='o', color='red', markersize=15);
#Ref: Stackoverflow
```



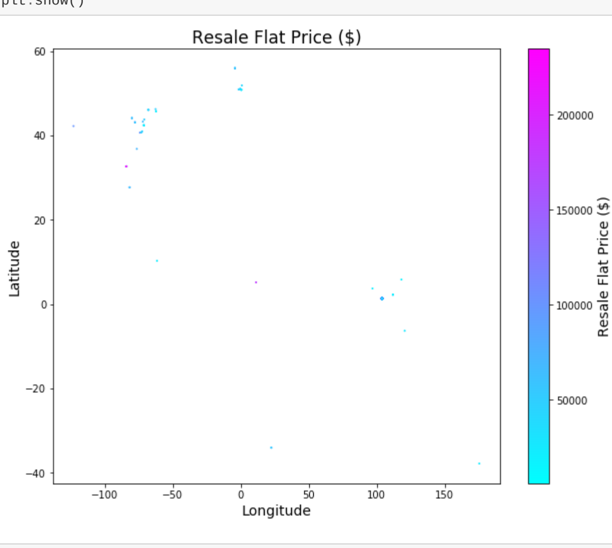
In [301]:
```python
import geopandas
gdf = geopandas.GeoDataFrame(new_dataset, geometry=geopandas.points_from_xy(new_dataset.longitude, new_dataset.latitude))
```

In [302]:
```python
print(gdf.head())
```
```
     month        town flat_type block       street_name storey_range  \
0  1990-01  ANG MO KIO    1 ROOM   309  ANG MO KIO AVE 1     10 TO 12
1  1990-01  ANG MO KIO    1 ROOM   309  ANG MO KIO AVE 1     04 TO 06
2  1990-01  ANG MO KIO    1 ROOM   309  ANG MO KIO AVE 1     10 TO 12
3  1990-01  ANG MO KIO    1 ROOM   309  ANG MO KIO AVE 1     07 TO 09
4  1990-01  ANG MO KIO    3 ROOM   216  ANG MO KIO AVE 1     04 TO 06

   floor_area_sqm      flat_model  lease_commence_date  resale_price  ...  \
0            31.0        IMPROVED                 1977          9000  ...
1            31.0        IMPROVED                 1977          6000  ...
2            31.0        IMPROVED                 1977          8000  ...
3            31.0        IMPROVED                 1977          6000  ...
4            73.0  NEW GENERATION                 1976         47200  ...

         town block       street_name          Full_Address  \
0  ANG MO KIO   309  ANG MO KIO AVE 1  309,ANG MO KIO AVE 1
1  ANG MO KIO   309  ANG MO KIO AVE 1  309,ANG MO KIO AVE 1
2  ANG MO KIO   309  ANG MO KIO AVE 1  309,ANG MO KIO AVE 1
3  ANG MO KIO   309  ANG MO KIO AVE 1  309,ANG MO KIO AVE 1
4  ANG MO KIO   216  ANG MO KIO AVE 1  216,ANG MO KIO AVE 1

                                            location  \
0  (Ang Mo Kio Avenue 1, Ang Mo Kio, Singapore, C...
1  (Ang Mo Kio Avenue 1, Ang Mo Kio, Singapore, C...
2  (Ang Mo Kio Avenue 1, Ang Mo Kio, Singapore, C...
3  (Ang Mo Kio Avenue 1, Ang Mo Kio, Singapore, C...
4  (Ang Mo Kio Avenue 1, Ang Mo Kio, Singapore, C...

                               point  latitude   longitude  altitude  \
0  (1.3645119, 103.8420761, 0.0)  1.364512  103.842076       0.0
1  (1.3645119, 103.8420761, 0.0)  1.364512  103.842076       0.0
2  (1.3645119, 103.8420761, 0.0)  1.364512  103.842076       0.0
3  (1.3645119, 103.8420761, 0.0)  1.364512  103.842076       0.0
4  (1.3645119, 103.8420761, 0.0)  1.364512  103.842076       0.0

                    geometry
0  POINT (103.84208 1.36451)
1  POINT (103.84208 1.36451)
2  POINT (103.84208 1.36451)
3  POINT (103.84208 1.36451)
4  POINT (103.84208 1.36451)

[5 rows x 21 columns]
```

In [303]:
```python
world = geopandas.read_file(geopandas.datasets.get_path('naturalearth_lowres'))

# We restrict to Singapore.
ax = world[world.continent == 'Singapore'].plot(color='white', edgecolor='black')
gdf.plot(ax=ax, color='red')

plt.show()
```



In [304]:
```python
plt.figure(figsize = (10,8))
plt.scatter(new_dataset.longitude, new_dataset.latitude ,c=new_dataset.resale_price, cmap = 'cool', s=1)
plt.colorbar().set_label('Resale Flat Price ($)', fontsize=14)
plt.xlabel('Longitude', fontsize=14)
plt.ylabel('Latitude', fontsize=14)
plt.title('Resale Flat Price ($)', fontsize=17)
plt.show()
```



In [2]:
```python
# As we can see Locations for which longitude is between -100 to 50 and latitude between 30 to 50,
# Flat prices are below 5000$.
```

Building the Model: Predicting the resale flat price

In [306]:
```python
## Once we get a good fit, we will use this model to predict the sale price of the flat.
```

In [307]:
```python
#modified_dataset=pd.concat([modified_dataset,Address_info], axis=1)
```

In [308]:
```python
#modified_dataset
```

In [309]:
```python
#array_train_data=train_dataset.to_numpy()
```

In [310]:
```python
columns_to_remove = (0,1,3,4,7,8)
new_object = [[x for i,x in enumerate(l) if i not in columns_to_remove] for l in data]
```

In [1]:
```python
#new_object
```

In [312]:
```python
index_values = [i for i in range(len(data))]

# creating a list of column names
column_values = ['flat_type','floor_area_sqm', 'number_of_storeys', 'resale_price']

# creating the dataframe
df = pd.DataFrame(data = new_object,
                  index = index_values,
                  columns = column_values)

# displaying the dataframe
#print(df)
```

In [313]:
```python
i = list(df.columns)
a, b = i.index('floor_area_sqm'), i.index('number_of_storeys')
i[b], i[a] = i[a], i[b]
df = df[i]
```

In [314]:
```python
df = df.rename(columns={'floor_area_sqm': 'number_of_storeys','number_of_storeys': 'floor_area_sqm'})
```

In [315]:
```python
df
```
Out[315]:

	flat_type	floor_area_sqm	number_of_storeys	resale_price
0	1	31.0	11	9000
1	1	31.0	5	6000
2	1	31.0	11	8000
3	1	31.0	8	6000
4	2	73.0	5	47200
...	...	...	...	...
287195	3	142.0	11	456000
287196	3	142.0	2	408000
287197	3	146.0	8	469000
287198	3	146.0	5	440000
287199	3	145.0	2	484000

287200 rows × 4 columns

Implementation from scratch:

Equation of Best Fit Hyperplane: $z^* = (A^TA)^{-1}A^TB$ for system of equations $Az = b$

where vector b is not in plane of column vectors of matrix A and to get the

approximate solution, we have projected the vector b in plane which is $\hat{b}$

$\text{and so solving $Az^ = \hat{b},wegetz^ = (A^TA)^{-1} A^TB }

In [316]:
```python
dataset=df.to_numpy() #converting dataframe to numpy array
```

In [317]:
```python
# writing it in z= ax+by+c form and then convert it into matrix form
# I am writing it in matrix equation form directly

A=[]
for i in range(10):
    temp=[]
    temp.append(dataset[i][0])
    temp.append(dataset[i][1])
    temp.append(1) # for coefficient of c i.e. 1
    A.append(temp)

B=[]
for i in range(10):
    B.append(dataset[i][-1])
```

In [318]:
```python
# Printing matrix A and vector B
print(A)
print(B)
```
```
[[1.0, 31.0, 1], [1.0, 31.0, 1], [1.0, 31.0, 1], [1.0, 31.0, 1], [2.0, 73.0, 1], [2.0, 67.0, 1], [2.0, 67.0, 1], [2.0, 67.0, 1], [2.0, 67.0, 1], [2.0, 67.0, 1]]
[9000.0, 6000.0, 8000.0, 6000.0, 47200.0, 46000.0, 42000.0, 38000.0, 40000.0, 47000.0]
```

In [319]:
```python
#writing function for transpose of a matrix
def transpose(A,m,n):
    trans=[]
    for j in range(n):
        temp=[]
        for i in range(m):
            temp.append(A[i][j])
        trans.append(temp)
    return trans
```

In [320]:
```python
trans_A= transpose(A,10,3)
print(transpose(A,10,3)) # printing transpose of matrix A
```
```
[[1.0, 1.0, 1.0, 1.0, 2.0, 2.0, 2.0, 2.0, 2.0, 2.0], [31.0, 31.0, 31.0, 31.0, 73.0, 67.0, 67.0, 67.0, 67.0, 67.0], [1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]
```

In [321]:
```python
mul = np.dot(trans_A, A) # multiplying A^T and A
inv = np.linalg.inv(mul) # inverse of A^T*A
prod= np.dot(inv,trans_A) # multiplying (A^T*A)^-1 and A^T
res = np.dot(prod,B) # finding (A^T*A)^-1 * A^T* B
```

In [322]:
```python
# So, our result matrix is
print(res) # It shows the values of a,b,c
```

Using already implemented Linear Regression

Conclusion