Prediction with Machine Learning for Economists

Central European University, 2021/22 Fall

Instructor: Prof Gábor Békés, TA: János Bíró

Student: Mingming Li

Email: Li_Mingming@phd.ceu.edu (mailto:Li_Mingming@phd.ceu.edu)

Tasks for Assignment 2

I discuss my idea and steps before the codes

Help company set to price their new apartments (small and mid-size apartments hosting 2-6 guests) not on the market in Berlin

In [1]:

```
import re
import pandas as pd
import numpy as np
from plotnine import *
from mizani.formatters import percent_format
from sklearn.linear_model import LinearRegression, Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
from py_helper_functions import *
import warnings

warnings.filterwarnings("ignore")
```

Data Prepare

In [2]:

```
data = pd.read_csv('listings.csv')
```

We need a small and middle apartment, 2-6persons according to assignment

In [3]:

```
data=data.loc[(data.accommodates < 7) & (data.accommodates > 1)]
```

We need deal with missing values:

For those not miss too many: use mean to replace it

For those miss not too many: drop the colloums

In [4]:

```
# show the columns of missing value
na_filter=data.isna().sum()
na_filter[na_filter > 0].index
```

Out[4]:

```
Index(['name', 'description', 'neighborhood_overview', 'host_name',
       'host_since', 'host_location', 'host_about', 'host_response_tim
e',
       'host_response_rate', 'host_acceptance_rate', 'host_is_superhos
t',
       'host_thumbnail_url', 'host_picture_url', 'host_neighbourhood',
       'host_listings_count', 'host_total_listings_count',
       'host_has_profile_pic', 'host_identity_verified', 'neighbourhoo
d',
       'bathrooms', 'bathrooms_text', 'bedrooms', 'beds', 'calendar_up
dated',
       'first_review', 'last_review', 'review_scores_rating',
       'review_scores_accuracy', 'review_scores_cleanliness',
       'review_scores_checkin', 'review_scores_communication',
       'review_scores_location', 'review_scores_value', 'license',
       'reviews_per_month'],
      dtype='object')
```

In [5]:

```
# process the missing value
# fill median strategy with these attributes:
data['host_listings_count']=data['host_listings_count'].fillna(np.nanmedian(data['ho
data['host_total_listings_count']=data['host_total_listings_count'].fillna(np.nanmed
data['bedrooms']=data['bedrooms'].fillna(np.nanmedian(data['bedrooms']))
data['beds']=data['beds'].fillna(np.nanmedian(data['beds']))

# drop these attributes: Because there are too many missing
data.drop(columns=['bathrooms', 'calendar_updated', 'license', 'neighbourhood',
                   'neighborhood_overview', 'host_about', 'host_response_time',
                   'host_response_rate', 'host_acceptance_rate', 'host_neighbourhood'

# drop rows if no value on these attributes
data.dropna(subset=['review_scores_rating', 'review_scores_accuracy', 'review_scores
                    'review_scores_checkin', 'review_scores_communication', 'review_
                    'review_scores_value', 'reviews_per_month', 'bathrooms_text'], i
```

In [6]:

```
# Because the missing number of these attributes is small, they are assigned randoml
data['host_is_superhost']=data['host_is_superhost'].fillna('t')
data['host_has_profile_pic']=data['host_has_profile_pic'].fillna('t')
data['host_identity_verified']=data['host_identity_verified'].fillna('t')
```

We need to assign the value to dummy variables

In [7]:

```
# object to numerical type
data['host_is_superhost']=(data['host_is_superhost']=='t').astype(int)
data['host_has_profile_pic']=(data['host_has_profile_pic']=='t').astype(int)
data['host_identity_verified']=(data['host_identity_verified']=='t').astype(int)
data['has_availability']=(data['has_availability']=='t').astype(int)
data['instant_bookable']=(data['instant_bookable']=='t').astype(int)
```

In [8]:

```
data.property_type.value_counts()
```

Out[8]:

```
Entire rental unit                       6546
Private room in rental unit              4050
Entire condominium (condo)                352
Entire loft                               275
Entire serviced apartment                 230
Private room in residential home          137
Private room in condominium (condo)       127
Room in hotel                              89
Entire residential home                    85
Private room in loft                       52
Entire guesthouse                          50
Room in boutique hotel                     46
Shared room in hostel                      40
Private room in townhouse                  39
Private room in bed and breakfast          36
Shared room in rental unit                 33
Room in serviced apartment                 30
Private room in hostel                     28
Room in aparthotel                         28
Entire guest suite                         25
Entire bungalow                            20
Private room in serviced apartment         16
Houseboat                                  15
Private room                               13
Entire townhouse                           10
Tiny house                                  8
Private room in pension                     7
Private room in guest suite                 7
Private room in guesthouse                  7
Entire villa                                5
Camper/RV                                   5
Entire place                                5
Room in hostel                              5
Entire cottage                              4
Shared room in boutique hotel               4
Entire cabin                                4
Private room in boat                        4
Private room in tiny house                  3
Room in bed and breakfast                   2
Treehouse                                   2
Shared room in condominium (condo)          2
Private room in casa particular             2
Private room in cottage                     2
Private room in villa                       2
Boat                                        2
Shared room in townhouse                    1
Private room in bungalow                    1
Shared room in tiny house                   1
Private room in houseboat                   1
Shared room in residential home             1
Shared room in boat                         1
Earth house                                 1
Entire chalet                               1
Casa particular                             1
Private room in cave                        1
```

```
Private room in floor                1
Island                               1
Private room in tipi                 1
Name: property type, dtype: int64
```

Two main property types (similar to "Apartment" classfication in London) are chosen for predication and calculation

In [9]:

```
# Rename room type because it is too long, just two classes
data= data.loc[data.property_type.isin(['Entire rental unit', 'Private room in renta
```

In [10]:

```
data.property_type = ['entire uint' if x == 'Entire rental unit' else 'private room'
data['f_property_type'] = data['property_type'].astype('category')
```

In [11]:

```
data.room_type.value_counts()
```

Out[11]:

```
Entire home/apt    6546
Private room       4050
Name: room_type, dtype: int64
```

In [12]:

```
data['f_room_type'] = data['room_type'].astype('category')
data["f_room_type2"] = (
    data["f_room_type"]
    .replace(
        {
            "Entire home/apt": "Entire/Apt",
            "Private room": "Private",
        }
    )
    .astype("category")
)
```

Bathroom and other amenities should be given value using the information

In [13]:

```
# process bathrooms_text to get bathrooms
def process_bathText(text, n_persons):
    texts = text.split(' ')
    if texts[0].isdigit() or (texts[0].split('.')[0].isdigit() and texts[0].split('.
        if texts[1] == 'shared':
            return float(texts[0]) / n_persons
        else:
            return float(texts[0])
    else:
        if texts[0] in ['Half-bath', 'Private']:
            return 0.5
        if texts[0] == 'Shared':
            return 0.5 / n_persons
```

In [14]:

```
data['bathrooms']=data.apply(lambda row: process_bathText(row['bathrooms_text'],
                                                          row['accommodates']), axis
```

In [15]:

```
data['f_neighbourhood_cleansed'] = data['neighbourhood_cleansed'].astype('category')
data['f_neighbourhood_group_cleansed'] = data['neighbourhood_group_cleansed'].astype
```

In [16]:

```
data['n_days_since'] = pd.to_datetime(
    data['calendar_last_scraped'], format='%Y-%m-%d'
) - pd.to_datetime(data["first_review"], format="%Y-%m-%d")
# Previous row creates a timedelta object in each row. Get the elapsed number of day
data['n_days_since'] = [x.days for x in data['n_days_since']]
```

In [17]:

```
# process amenities
amenities = data['amenities'].values
total_map = {}  # all kinds of amenities, hash map
for item in amenities:
    for i in eval(item):
        if i not in total_map.keys():
            total_map[i] = 1
        else:
            total_map[i] += 1

# select top 50 frequency amenities
top50_amenities = sorted(total_map.items(), key=lambda x:-x[1])[:50]
top50_amenities = [x[0] for x in top50_amenities]
# add attributes
for col in top50_amenities:
    data['d_' + col] = 0
```

In [18]:

```
# process the column amenities
def processAmenities(items, amenity):
    for item in items:
        if item == amenity:
            return 1
    return 0


for col in top50_amenities:
    data['d_' + col] = data.apply(lambda row: processAmenities(eval(row['amenities']]
```

In [19]:

```
for column in (
    'accommodates',
    'bathrooms',
    'review_scores_rating',
    'number_of_reviews',
    'reviews_per_month',
    'minimum_nights',
    'beds',
):
    data["n_" + re.sub(r"[^[:alnum:]_]", "", column.lower())] = data[column].astype(
        "float"
    )
```

In [20]:

```
amenities=list(data.filter(regex='^d_.*'))
len(amenities)
```

Out[20]:

```
50
```

In [21]:

```
data.filter(regex=('^d_.*|^n_.*|^f_.*')).columns
```

Out[21]:

```
Index(['f_property_type', 'f_room_type', 'f_room_type2',
       'f_neighbourhood_cleansed', 'f_neighbourhood_group_cleansed',
       'n_days_since', 'd_Kitchen', 'd_Wifi', 'd_Essentials', 'd_Heati
ng',
       'd_Washer', 'd_Long term stays allowed', 'd_Hair dryer', 'd_Han
gers',
       'd_Dedicated workspace', 'd_Hot water', 'd_Iron',
       'd_Dishes and silverware', 'd_Cooking basics', 'd_Smoke alarm',
       'd_Shampoo', 'd_Refrigerator', 'd_Stove', 'd_Oven', 'd_Bed line
ns',
       'd_Coffee maker', 'd_TV', 'd_Free street parking', 'd_Dishwashe
r',
       'd_Host greets you', 'd_Patio or balcony', 'd_Microwave', 'd_El
evator',
       'd_Extra pillows and blankets', 'd_First aid kit', 'd_Private e
ntrance',
       'd_Luggage dropoff allowed', 'd_Carbon monoxide alarm', 'd_Cabl
e TV',
       'd_TV with standard cable', 'd_Bathtub', 'd_Dryer',
       'd_Fire extinguisher', 'd_Lock on bedroom door', 'd_Baking shee
t',
       'd_Free parking on premises', 'd_Room-darkening shades',
       'd_Single level home', 'd_Shower gel', 'd_Paid parking off prem
ises',
       'd_Hot water kettle', 'd_Freezer', 'd_Backyard', 'd_Cleaning pr
oducts',
       'd_Dining table', 'd_High chair', 'n_accommodates', 'n_bathroom
s',
       'n_review_scores_rating', 'n_number_of_reviews', 'n_reviews_per
_month',
       'n_minimum_nights', 'n_beds'],
      dtype='object')
```

In [22]:

```
# keep columns if contain d_, n_,f_, p_, usd_ and some others
data = data.filter(regex=('^d_.*|^n_.*|^f_.*')).join(
    data[
        [
            'price',
            'id',
            'neighbourhood_cleansed',
            'room_type',
            'property_type',
        ]
    ]
)
```

Change the format of price and take logs, I choose the price below 400 as few above it

In [23]:

```
# deal price
data['price']=data['price'].str[1:]  # delete $
data['price']=data['price'].str.replace(",","").astype('float')
```

In [24]:

```
data['ln_price']=np.log(data.price)
```

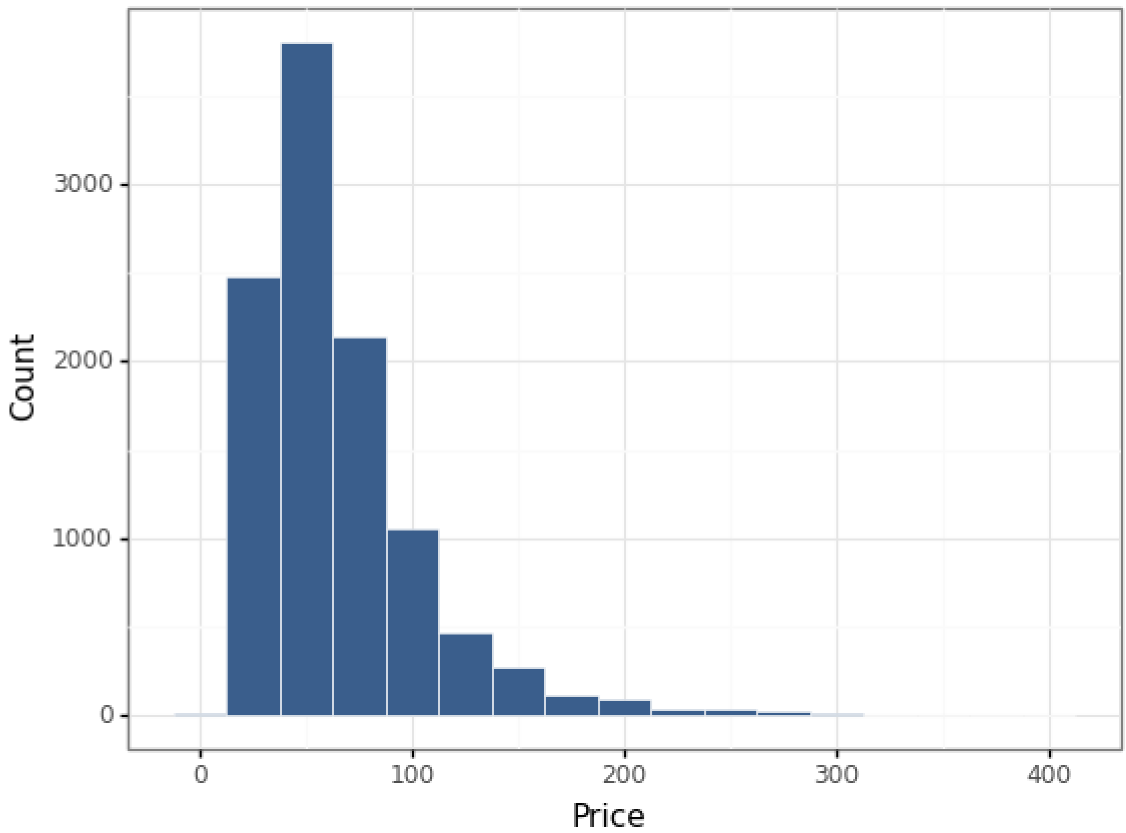
In [25]:

```
# Remove extreme values from prices
data=data.loc[data.price <400]
```

Draw the histograms for the price and lnprice

In [26]:

```
# Histograms
(
    ggplot(data, aes('price'))
    + geom_histogram(
        binwidth=25, fill=color[0], color='white', alpha=0.8, size=0.25, closed='lef
    )
    + ylab('Count')
    + xlab('Price')
    + theme_bw()
)
```

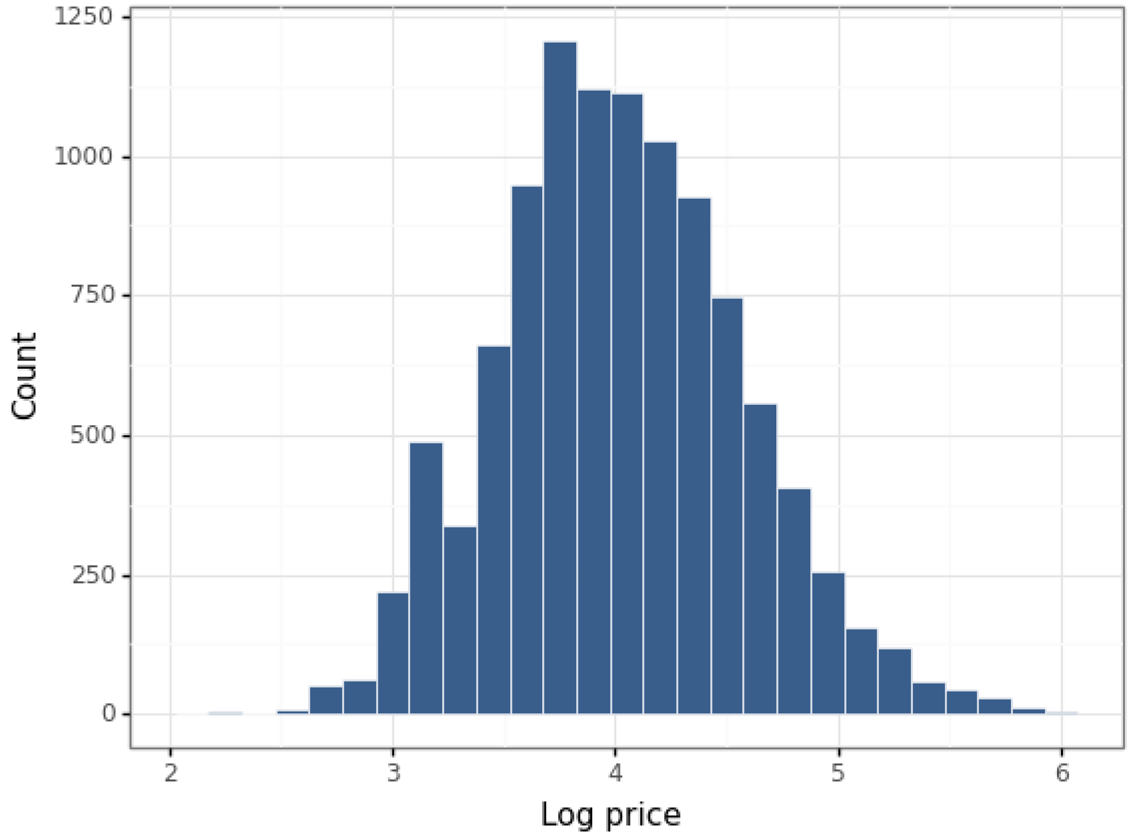


Out[26]:

```
<ggplot: (8764285182853)>
```

In [27]:

```
(
    ggplot(data, aes('ln_price'))
    + geom_histogram(
        binwidth=0.15, fill=color[0], color='white', alpha=0.8, size=0.25, closed='l
    )
    + ylab('Count')
    + xlab('Log price')
    + theme_bw()
)
```



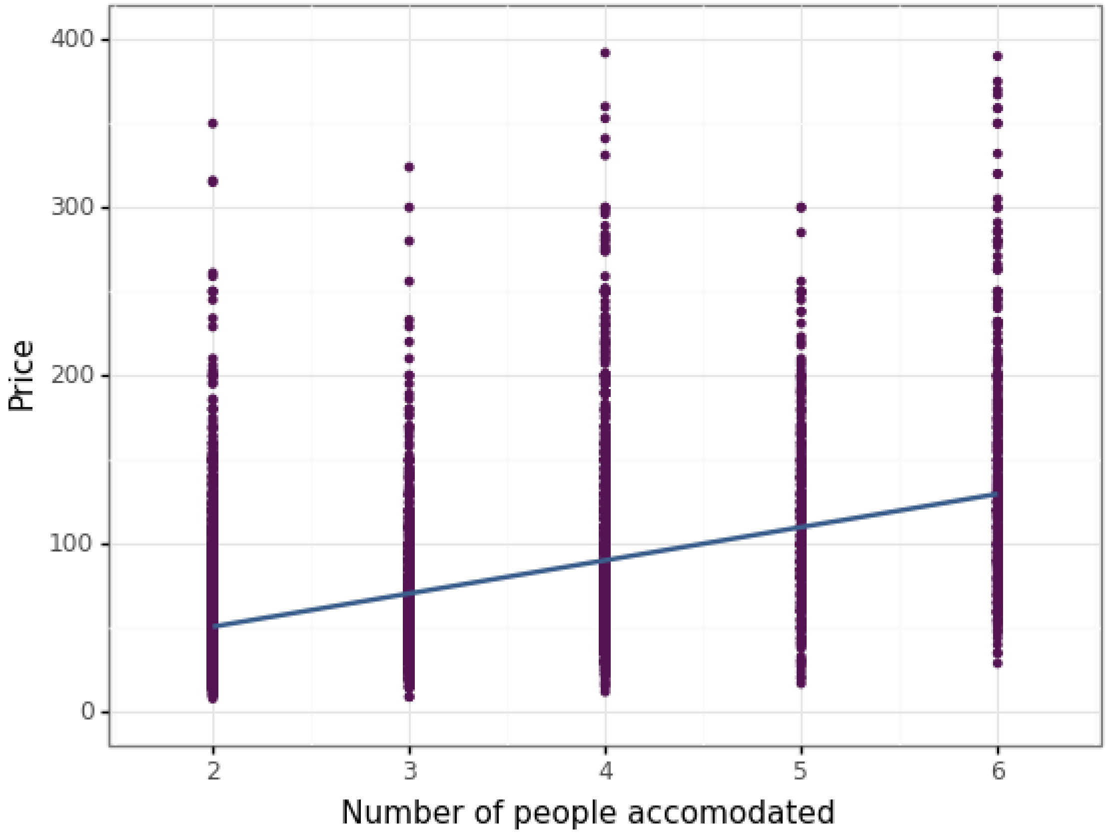
Out[27]:

```
<ggplot: (8764278956304)>
```

Find out the relation bewteen number of people accomodated and price in graph and table

In [28]:

```
(
    ggplot(data, aes(x='n_accommodates', y='price'))
    + geom_point(size=1, colour=color[2])
    + ylim(0, 400)
    + xlim(1.7, 6.3)
    + labs(x='Number of people accomodated', y='Price')
    + geom_smooth(method='lm', colour=color[0], se=False)
    + theme_bw()
)
```



Out[28]:

```
<ggplot: (8764278981798)>
```

In [29]:

```
data.groupby('n_accommodates').agg(mean_price=('price', np.mean))
```

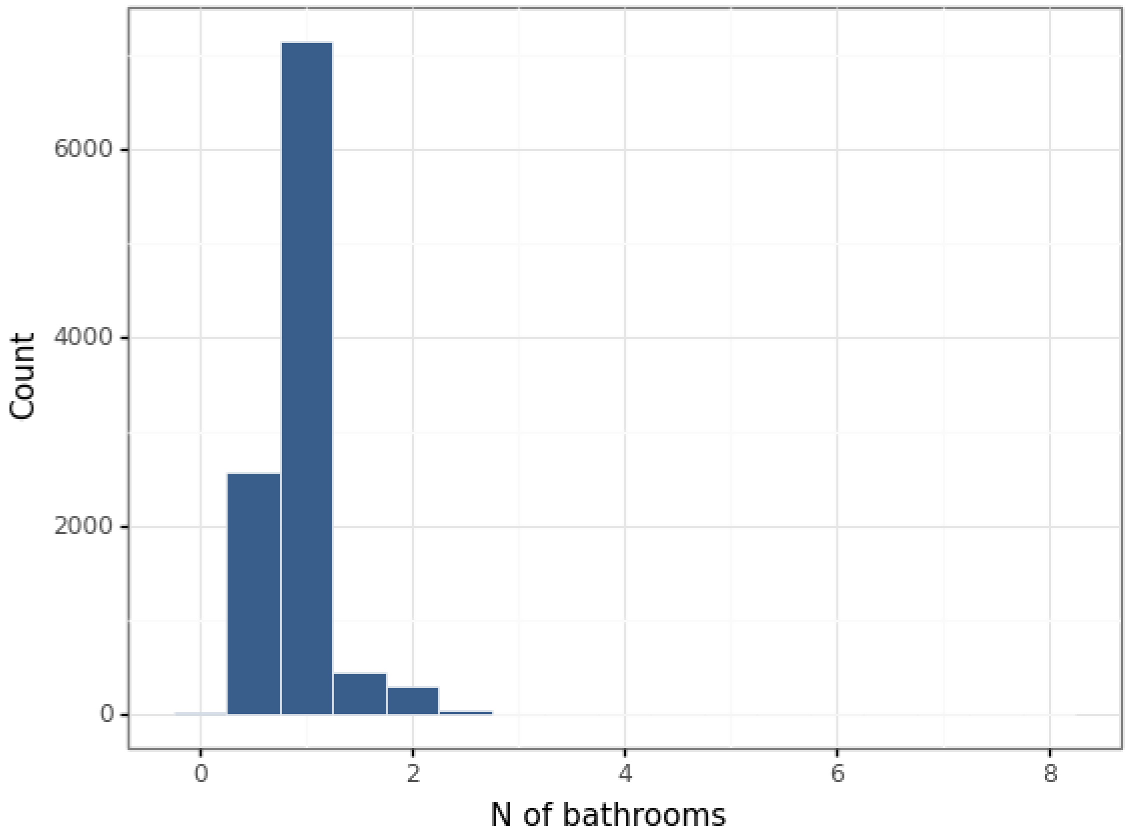
Out[29]:

	mean_price
n_accommodates	
2.0	51.712230
3.0	65.236636
4.0	89.119913
5.0	111.515075
6.0	135.908397

Find out the distribution of bathrooms

In [30]:

```
## bathrooms
(
    ggplot(data, aes('n_bathrooms'))
    + geom_histogram(
        binwidth=0.5, closed='left', fill=color[0], color='white', alpha=0.8, size=0
    )
    + ylab('Count')
    + xlab('N of bathrooms')
    + theme_bw()
)
```



Out[30]:

```
<ggplot: (8764241733720)>
```

In [31]:

```
# Pool accomodations with 0,1,[2~10) bathrooms
bins = pd.IntervalIndex.from_tuples([(0, 1), (1, 2), (2, 10)], closed='left')
f_bath = pd.cut(data['n_bathrooms'].to_list(), bins, labels=['0', '1', '2'])
f_bath.categories = [0, 1, 2]
data['f_bathroom'] = f_bath
```

In [32]:

```
data.groupby('f_bathroom').agg(mean_price=('price', np.mean), n=('price', 'size'))
```

Out[32]:

f_bathroom	mean_price	n
0	39.615027	2795
1	71.936936	7421
2	132.310734	354

In [33]:

```
data.groupby('n_beds').agg(
    mean_price=('price', np.mean),
    min_price=('price', np.min),
    max_price=('price', np.max),
    n=('price', 'size'),
)
```

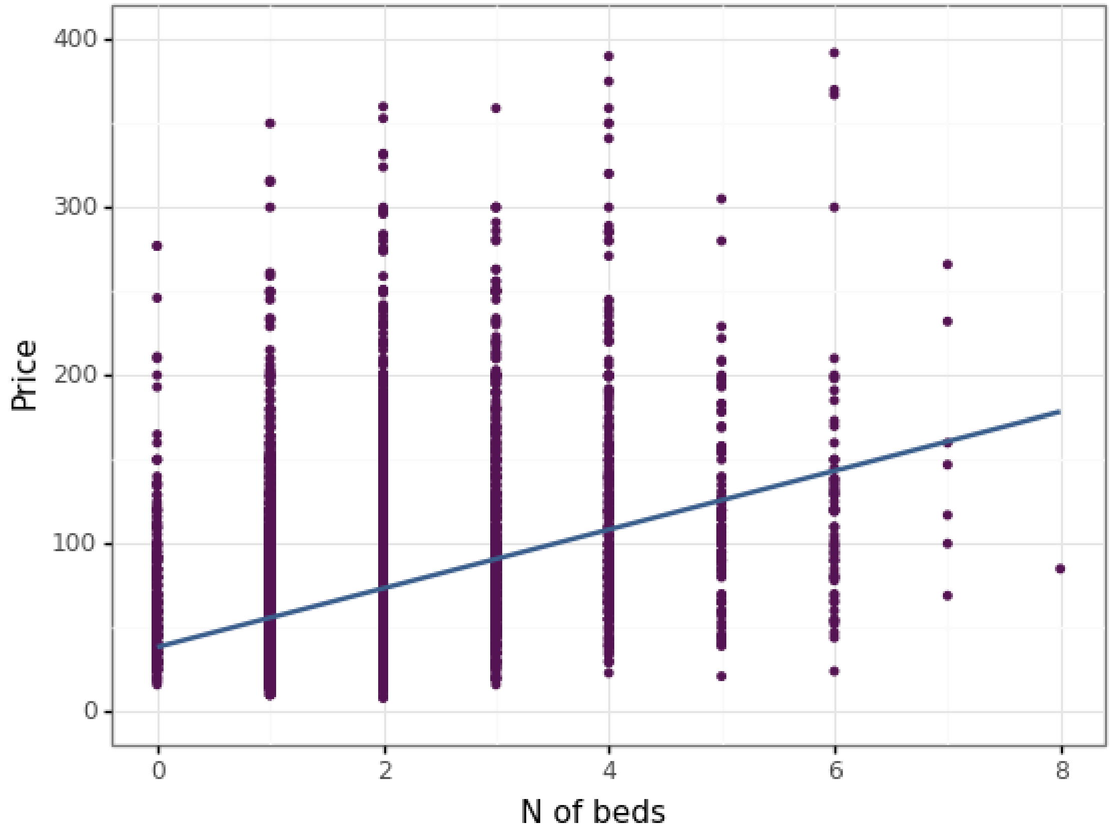
Out[33]:

n_beds	mean_price	min_price	max_price	n
0.0	64.596306	16.0	277.0	379
1.0	53.140251	10.0	350.0	6139
2.0	73.506385	8.0	360.0	2741
3.0	98.515228	16.0	359.0	788
4.0	115.537791	23.0	390.0	344
5.0	116.352381	21.0	305.0	105
6.0	127.984848	24.0	392.0	66
7.0	155.857143	69.0	266.0	7
8.0	85.000000	85.0	85.0	1

Find out the relation bewteen bathroom and beds in graph and table

In [34]:

```
(
    ggplot(data, aes(x='n_beds', y='price'))
    + geom_point(size=1, colour=color[2])
    + ylim(0, 400)
    + xlim(0, 8)
    + labs(x='N of beds', y='Price')
    + geom_smooth(method='lm', colour=color[0], se=False)
    + theme_bw()
)
```



Out[34]:

```
<ggplot: (8764279219405)>
```

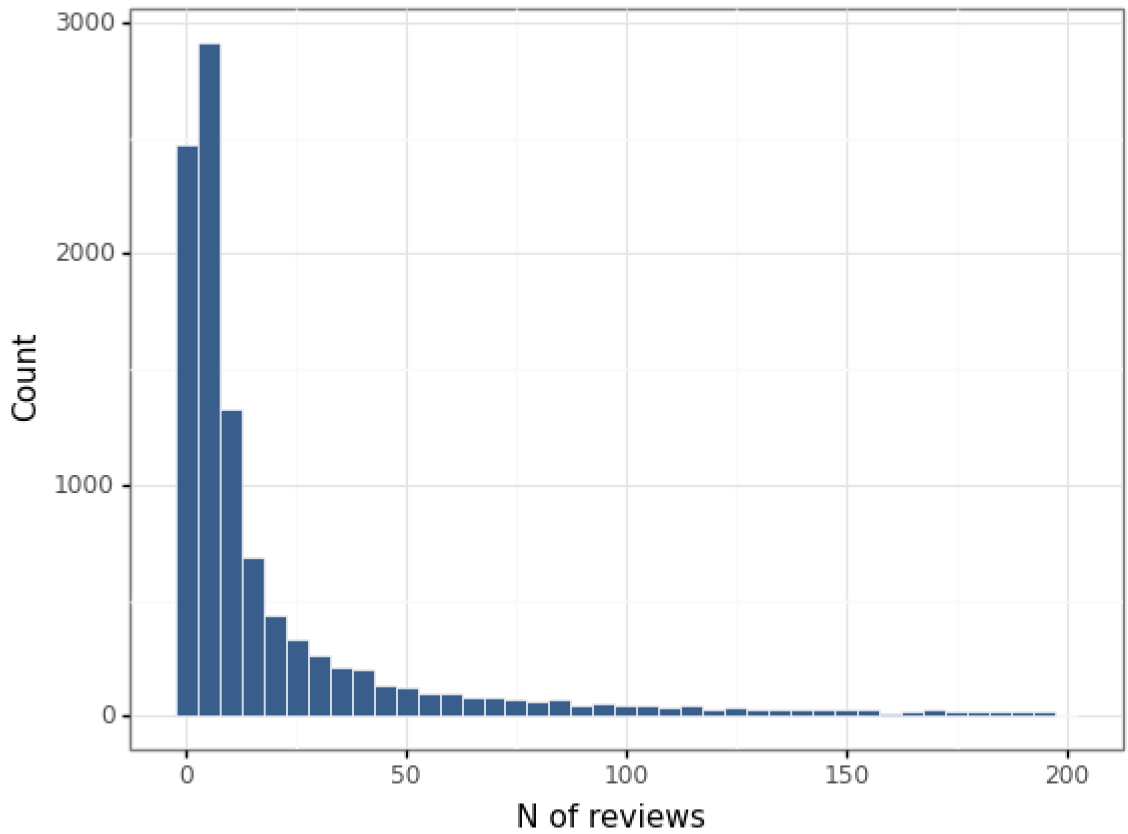
Find out the reviews bewteen bathroom and beds in graph and table

In [35]:

```
## Number of reviews
nreview_plot = data.loc[data.n_number_of_reviews <200]
```

In [36]:

```
(
    ggplot(nreview_plot, aes('n_number_of_reviews'))
    + geom_histogram(binwidth=5, fill=color[0], color='white', alpha=0.8, size=0.25)
    + ylab('Count')
    + xlab('N of reviews')
    + theme_bw()
)
```



Out[36]:

```
<ggplot: (8764278955867)>
```

In [37]:

```
bins = pd.IntervalIndex.from_tuples([(0, 2), (2, 51), (51, max(data.n_number_of_revi
f_number_of_reviews = pd.cut(data['n_number_of_reviews'].to_list(), bins, labels=['0
f_number_of_reviews.categories = [0, 1, 2]
data['f_number_of_reviews'] = f_number_of_reviews
```

In [38]:

```
data.groupby('f_number_of_reviews').agg(median_price=('price', np.median), mean_pric
```

Out[38]:

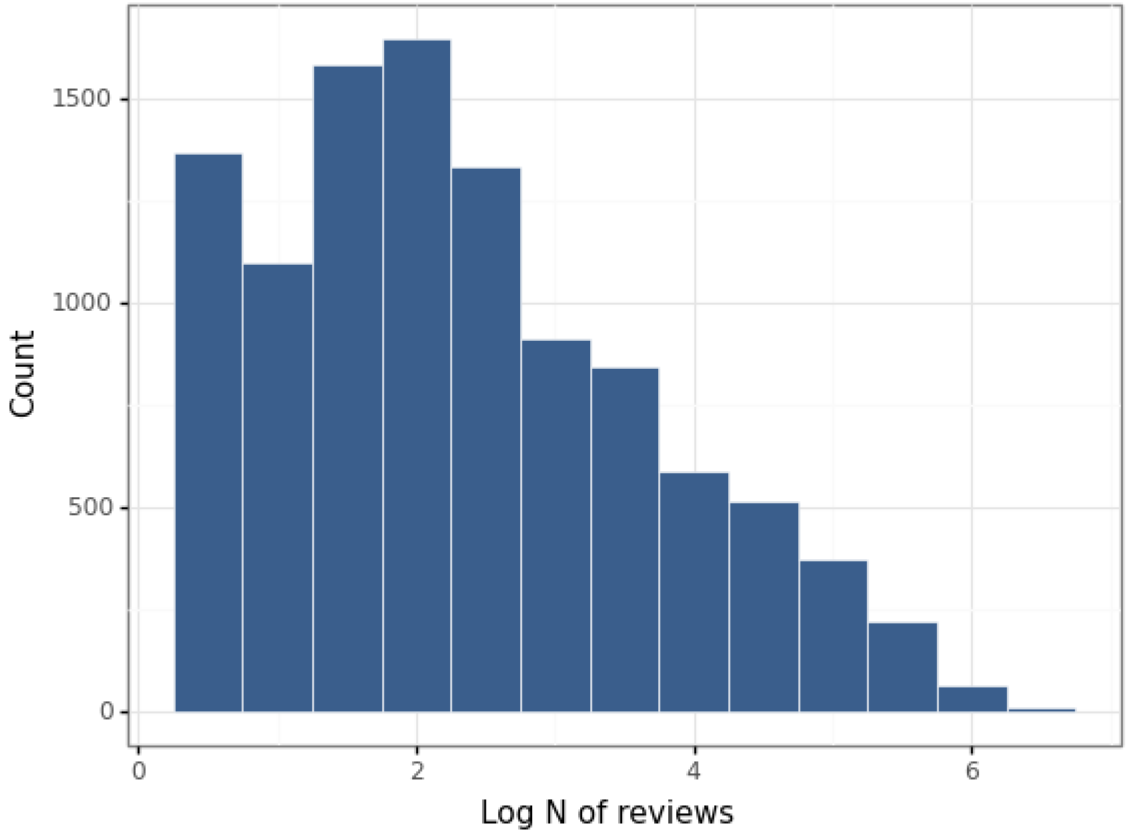
	median_price	mean_price	n
f_number_of_reviews			
0	50.0	59.757487	1369
1	54.0	63.947526	7661
2	65.0	77.755036	1539

In [39]:

```
# number of reviews: use logs as well
data['ln_number_of_reviews']=np.log(data.n_number_of_reviews+1)
```

In [40]:

```
(
    ggplot(data, aes('ln_number_of_reviews'))
    + geom_histogram(binwidth=0.5, fill=color[0], color="white", alpha=0.8, size=0.2
    + ylab('Count')
    + xlab('Log N of reviews')
    + theme_bw()
)
```



Out[40]:

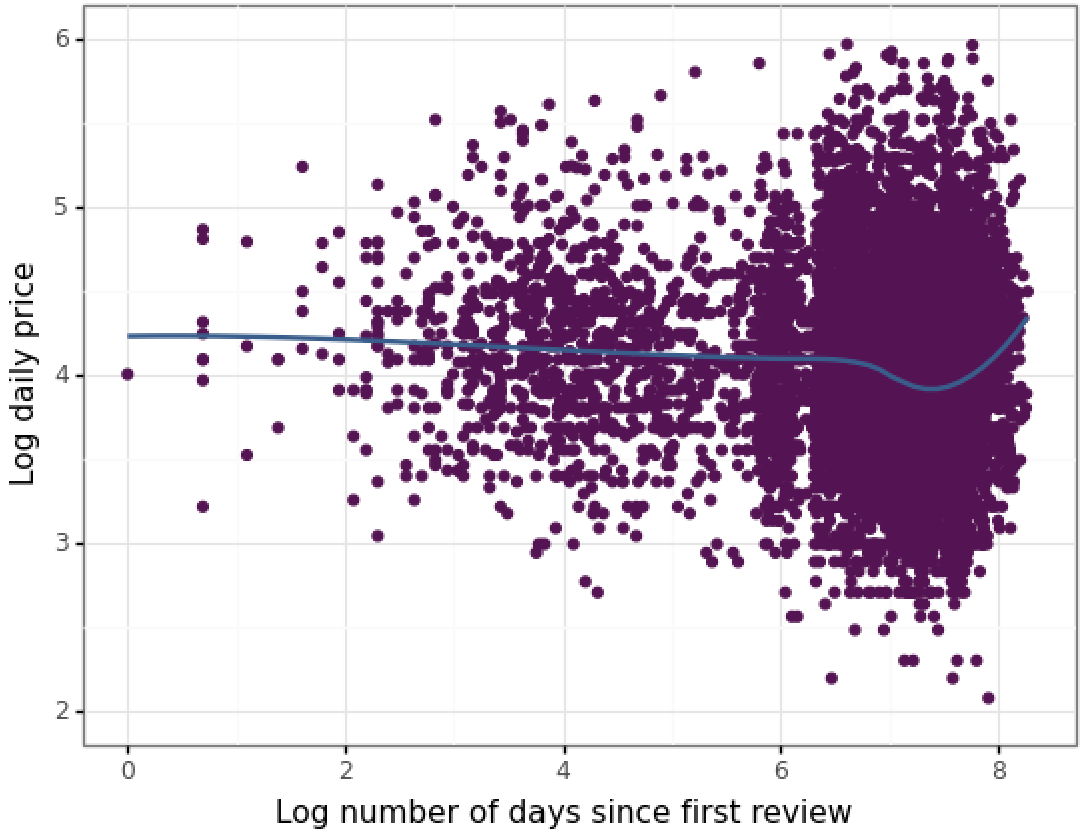
```
<ggplot: (8764241616893)>
```

In [41]:

```
data['ln_days_since'] = np.log(data['n_days_since'])
```

In [42]:

```
(
    ggplot(data, aes(x='ln_days_since', y='ln_price'))
    + geom_point(size=1.5, colour=color[2])
    + ylim(2, 6)
    + xlim(0, 8.3)
    + geom_smooth(method='loess', colour=color[0], se=False)
    + labs(x='Log number of days since first review', y='Log daily price')
    + theme_bw()
)
```

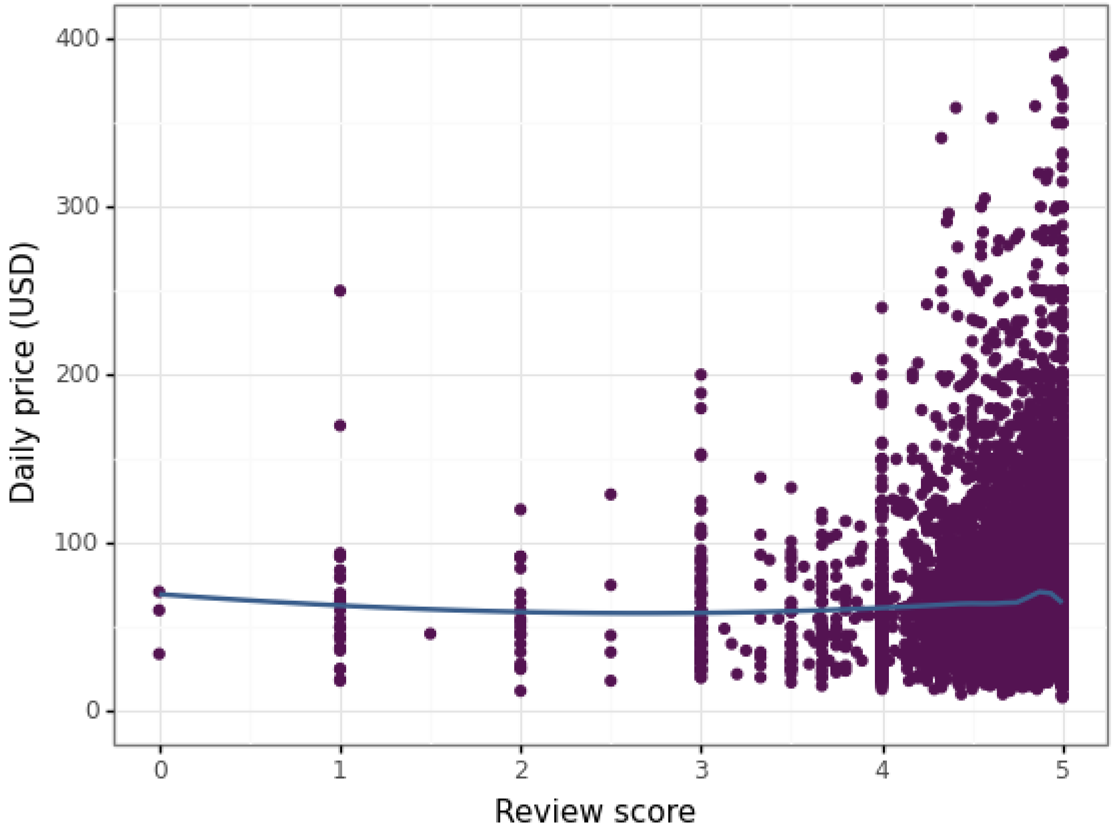


Out[42]:

```
<ggplot: (8764241630145)>
```

In [43]:

```
## review score effect
(
    ggplot(data, aes(x='n_review_scores_rating', y='price'))
    + geom_point(size=1.5, colour=color[2])
    + ylim(0, 400)
    + xlim(0, 5)
    + geom_smooth(method="loess", colour=color[0], se=False)
    + labs(x='Review score', y='Daily price (USD)')
    + theme_bw()
)
```



Out[43]:

```
<ggplot: (8764279111048)>
```

Data further analysis

Price distribution in absolute and logs values

In [44]:

```
# where do we have missing variables now?
na_filter=data.isna().sum()
na_filter[na_filter>0].index
```

Out[44]:

```
Index(['f_number_of_reviews'], dtype='object')
```

In [45]:

```
data['f_number_of_reviews']=data['f_number_of_reviews'].fillna(1)
```

In [46]:

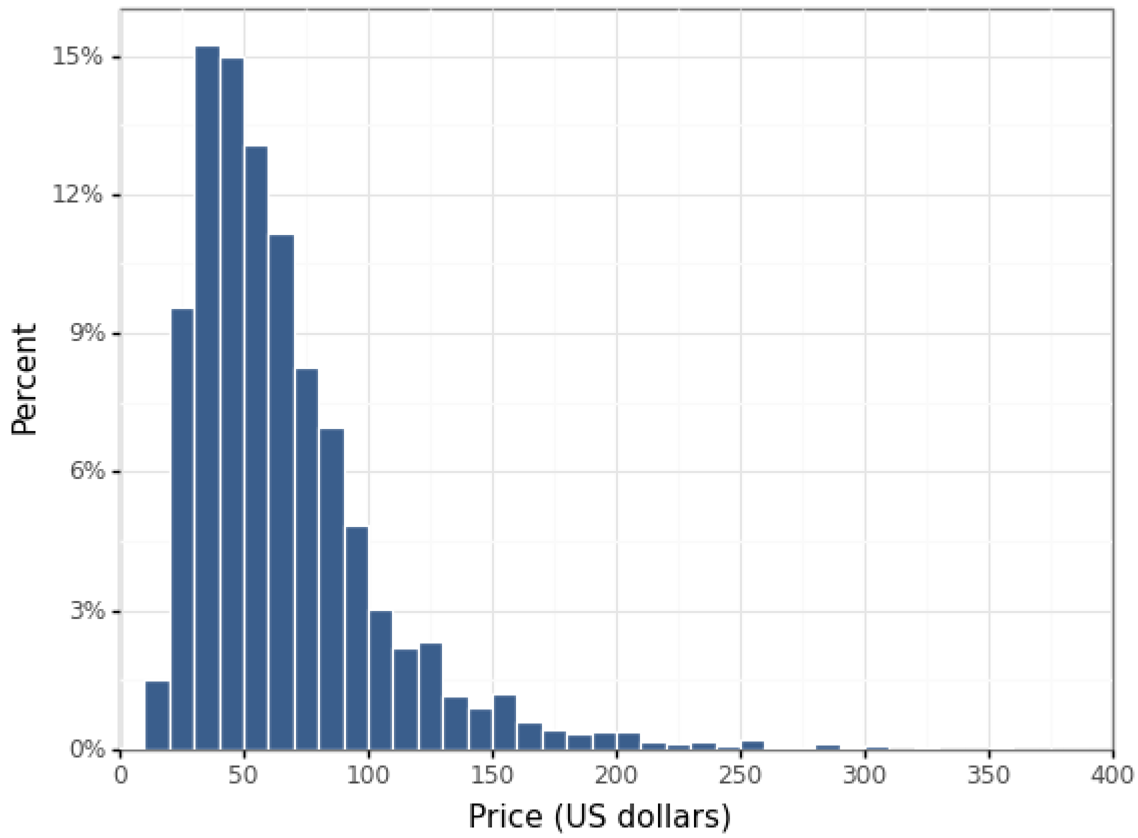
```
data.groupby('f_property_type').agg(mean_price=('price', np.mean))
```

Out[46]:

	mean_price
f_property_type	
entire uint	80.656145
private room	40.812067

In [47]:

```
# Distribution of price by type below 400# Histograms# price
(
    ggplot(data, aes(x='price'))
    + geom_histogram(
        aes(y='stat(count)/sum(stat(count))'),
        binwidth=10,
        fill=color[0],
        color='white',
        alpha=0.8,
        boundary=0,
        closed='left',
    )
    + labs(x='Price (US dollars)', y='Percent')
    + scale_y_continuous(
        expand=(0.00, 0.00),
        limits=(0, 0.16),
        breaks=seq(0, 0.16, by=0.03),
        labels=percent_format(),
    )
    + scale_x_continuous(expand=(0.00, 0.00), limits=(0, 400), breaks=seq(0, 401, 50
    + theme_bw()
)
```

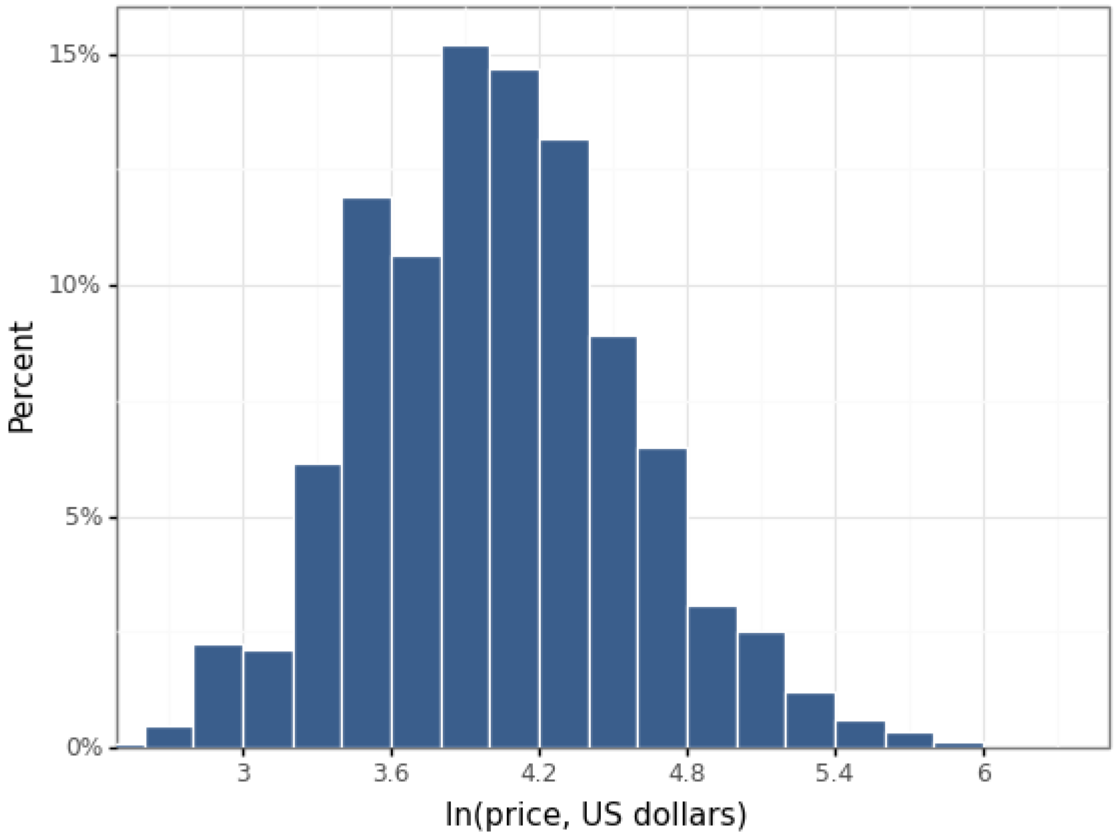


Out[47]:

```
<ggplot: (8764279291868)>
```

In [48]:

```
(
    ggplot(data, aes(x='ln_price'))
    + geom_histogram(
        aes(y='stat(count)/sum(stat(count))'),
        binwidth=0.2,
        fill=color[0],
        color='white',
        alpha=0.8,
        boundary=0,
        closed='left',
    )
    + coord_cartesian(xlim=(2.5, 6.5))
    + scale_y_continuous(
        expand=(0.00, 0.00),
        limits=(0, 0.16),
        breaks=seq(0, 0.16, by=0.05),
        labels=percent_format(),
    )
    + scale_x_continuous(expand=(0.00, 0.01), breaks=seq(2.4, 6.7, 0.6))
    + labs(x='ln(price, US dollars)', y='Percent')
    + theme_bw()
)
```



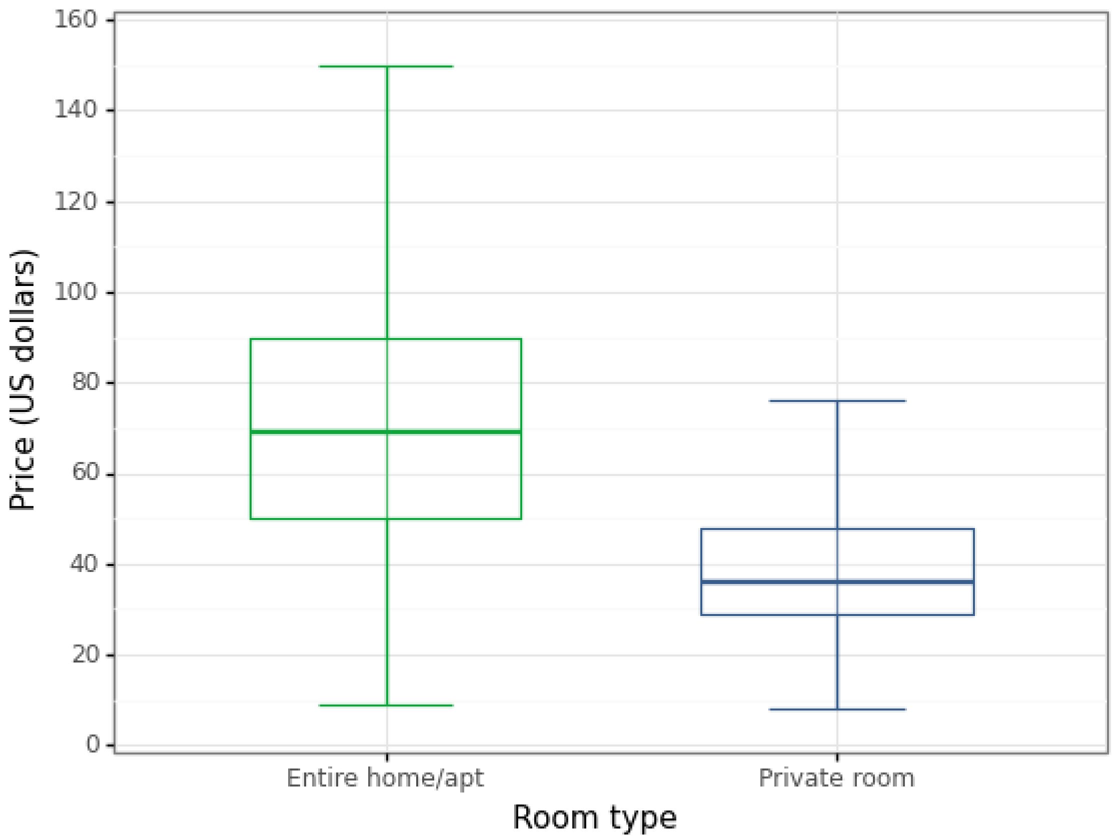
Out[48]:

```
<ggplot: (8764284789282)>
```

Analyse the room type with Box Plot, and accomodated people number are also included

In [49]:

```
## Boxplot of price by room type
(
    ggplot(data, aes(x='f_room_type', y='price'))
    + stat_boxplot(
        aes(group='f_room_type'),
        geom='errorbar',
        width=0.3,
        color=(color[1], color[0]),
        size=0.5,
        na_rm=True,
    )
    + geom_boxplot(
        aes(group='f_room_type'),
        color=(color[1], color[0]),
        size=0.5,
        width=0.6,
        alpha=0.3,
        na_rm=True,
        outlier_shape='',
    )
    + scale_y_continuous(expand=(0.01, 0.01), limits=(0, 160), breaks=seq(0, 201, 20
    + labs(x='Room type', y='Price (US dollars)')
    + theme_bw()
)
```

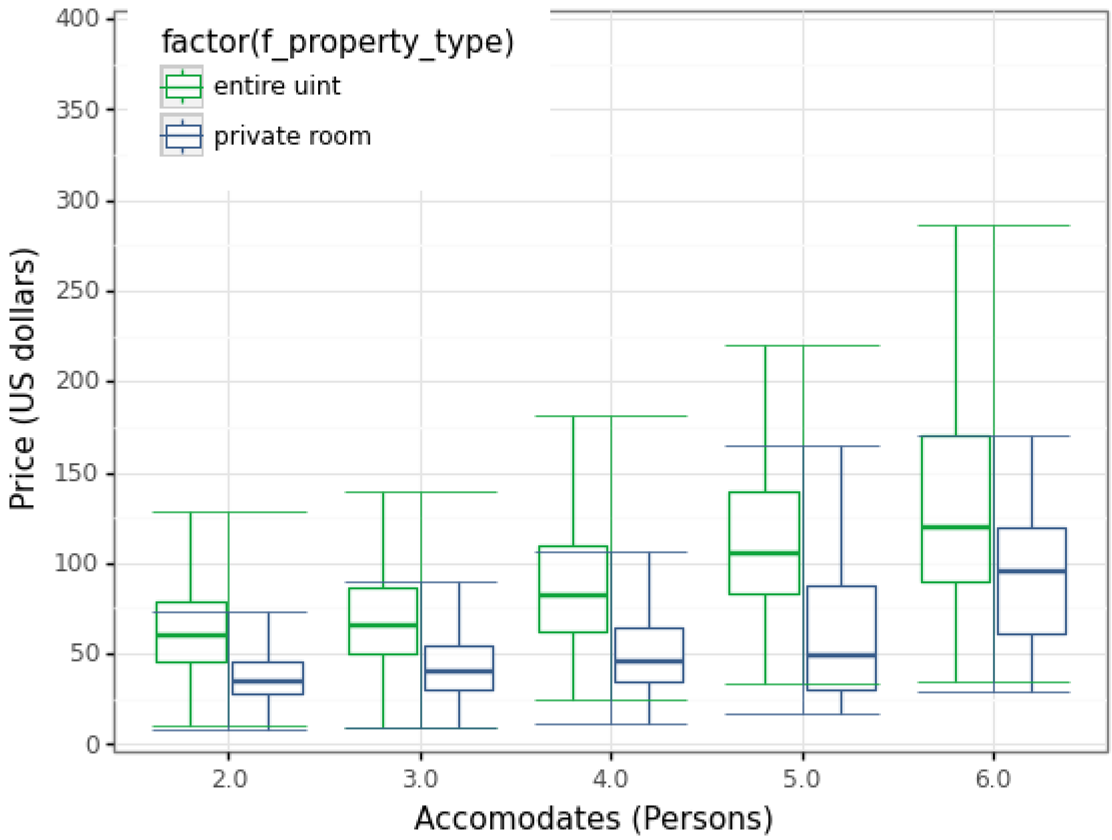


Out[49]:

```
<ggplot: (8764279141545)>
```

In [50]:

```
(
    ggplot(
        data,
        aes(
            x='factor(n_accommodates)',
            y='price',
            color='factor(f_property_type)',
        ),
    )
    + geom_boxplot(alpha=0.8, na_rm=True, outlier_shape='', width=0.8, stat='boxplot
    + stat_boxplot(geom='errorbar', width=0.8, size=0.3, na_rm=True)
    + scale_color_manual(name='', values=(color[1], color[0]))
    + scale_fill_manual(name='', values=(color[1], color[0]))
    + labs(x='Accomodates (Persons)', y='Price (US dollars)')
    + scale_y_continuous(expand=(0.01, 0.01), limits=(0, 400), breaks=seq(0, 401, 50
    + theme_bw()
    + theme(legend_position=(0.3, 0.8))
)
```



Out[50]:

```
<ggplot: (8764285187560)>
```

Amenities should be also considered in predication, elevator and TV are used combined with type of room or number of people accomodates for anaysis

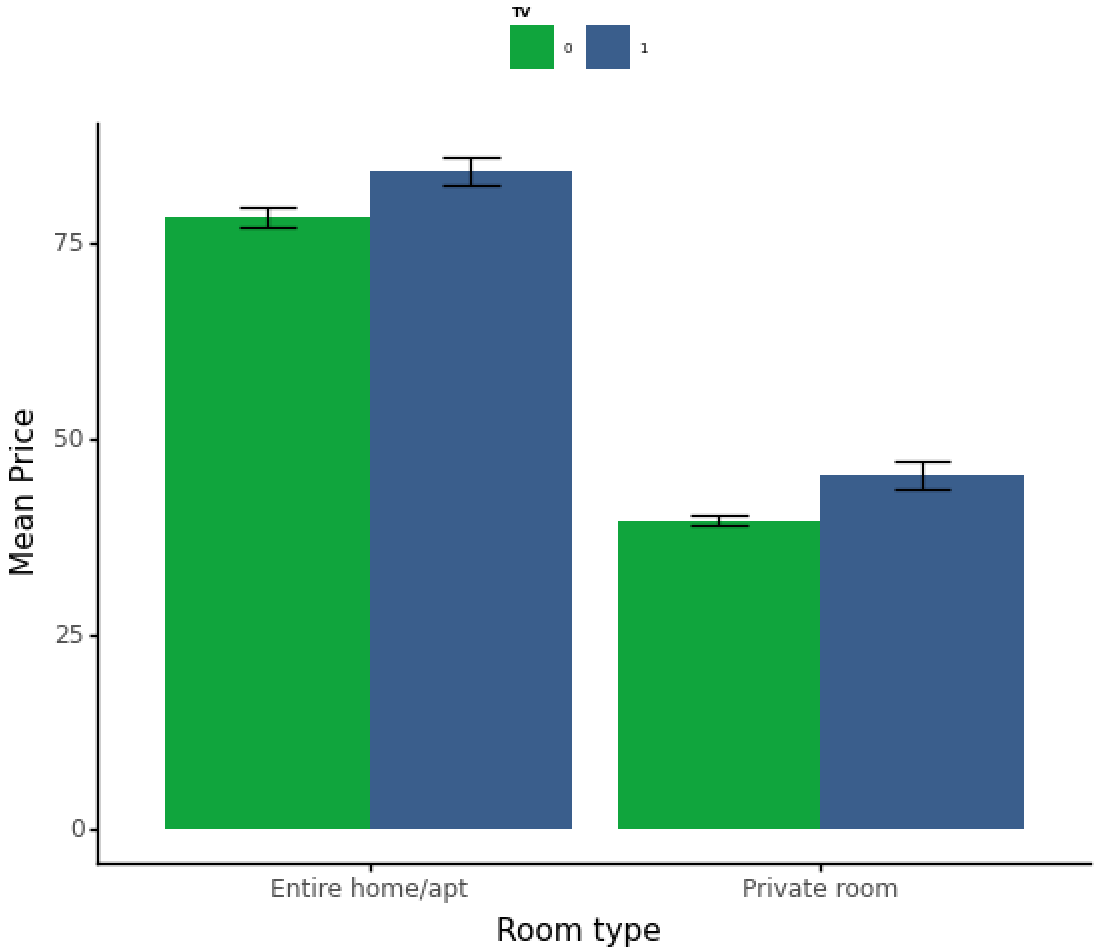
In [51]:

```
## Helper functions
def price_diff_by_variables2(df, factor_var, dummy_var, factor_lab, dummy_lab):
    stats = df.groupby([factor_var, dummy_var]).agg(
        Mean=('price', np.mean), sd=('price', np.std), size=('price', 'size')
    )
    stats['se'] = stats['sd'] / stats['size'] ** (1 / 2)
    stats['Mean_l'] = stats['Mean'] - (1.96 * stats['se'])
    stats['Mean_u'] = stats['Mean'] + (1.96 * stats['se'])
    stats = stats.drop(['sd', 'size'], axis=1).reset_index()
    plot = (
        ggplot(
            stats,
            aes(
                stats.columns[0],
                stats.columns[2],
                fill='factor(' + stats.columns[1] + ')',
            ),
        )
        + geom_bar(stat='identity', position=position_dodge(width=0.9))
        + geom_errorbar(
            aes(ymin='Mean_l', ymax='Mean_u'),
            position=position_dodge(width=0.9),
            width=0.25,
        )
        + scale_color_manual(name=dummy_lab, values=(color[1], color[0]))
        + scale_fill_manual(name=dummy_lab, values=(color[1], color[0]))
        + ylab('Mean Price')
        + xlab(factor_lab)
        + theme_bw()
        + theme(
            panel_grid_major=element_blank(),
            panel_grid_minor=element_blank(),
            panel_border=element_blank(),
            axis_line=element_line(),
            legend_position='top',
            legend_box='vertical',
            legend_text=element_text(size=5),
            legend_title=element_text(size=5, face='bold'),
        )
    )

    return plot
```

In [52]:

```
price_diff_by_variables2(data,'f_room_type','d_TV','Room type', 'TV')
```

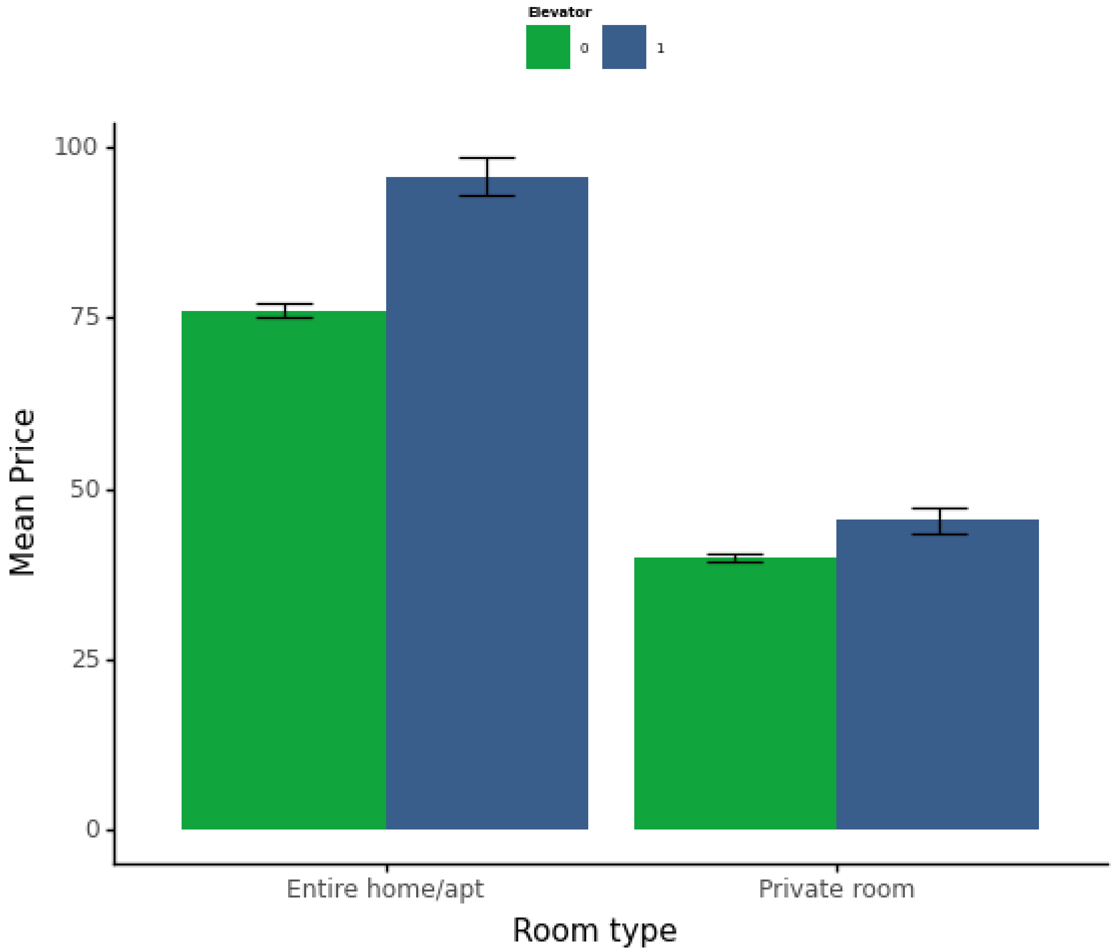


Out[52]:

```
<ggplot: (8764285730178)>
```

In [53]:

```
price_diff_by_variables2(data,'f_room_type','d_Elevator','Room type', 'Elevator')
```

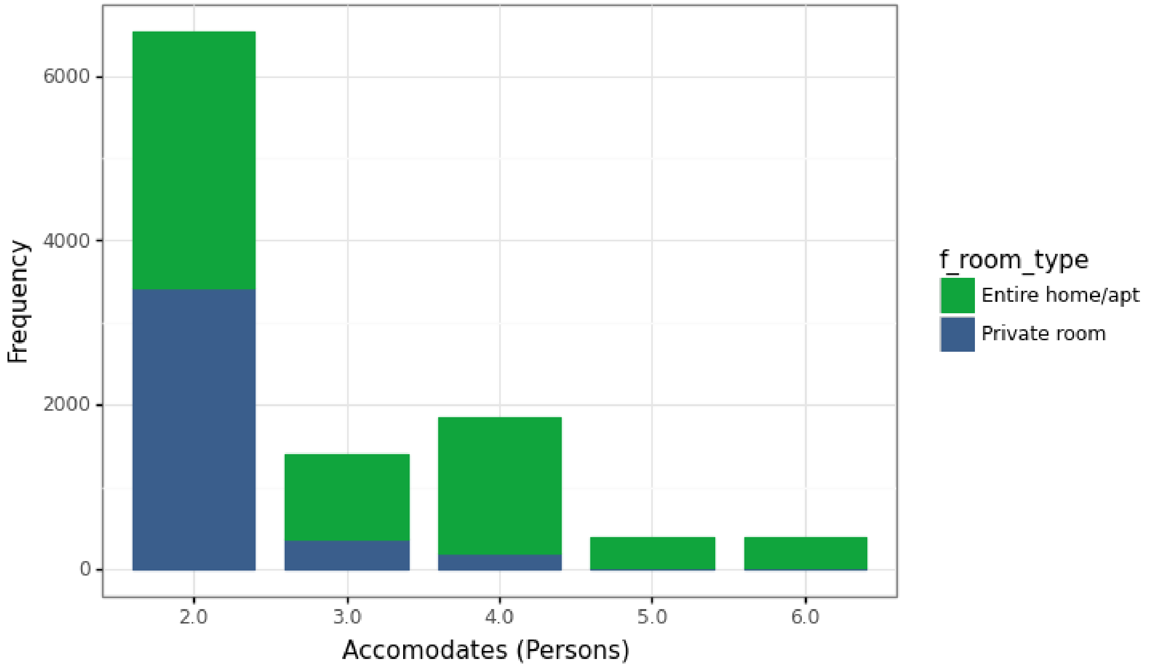


Out[53]:

```
<ggplot: (8764280057643)>
```

In [54]:

```
# Barchart
(
    ggplot(
        data, aes(x='factor(n_accommodates)', color='f_room_type', fill='f_room_type
    )
    + geom_bar(alpha=0.8, na_rm=True, width=0.8)
    + scale_color_manual(name='', values=(color[1], color[0], color[2]))
    + scale_fill_manual(name='', values=(color[1], color[0], color[2]))
    + labs(x='Accomodates (Persons)', y='Frequency')
    + theme_bw()
    + theme(legend_position='right')
)
```



Out[54]:

```
<ggplot: (8764279291685)>
```

Model Prediction and Selection

OLS, LASSO, CART and GBM are use for predication

The reason of choosing

OLS: traditional regression;
LASSO: Shrinkage of the coefficients
CART: Simple decision tree algorithm
GBM: ensemble learning with decision trees

StandardScaler( ) is used for standardization

In [55]:

```
data.drop(columns=['neighbourhood_cleansed', 'room_type', 'property_type', 'f_proper
                   'f_room_type2', 'f_neighbourhood_cleansed', 'f_neighbourhood_group
                   'ln_price', 'id'], axis=1, inplace=True)
```

In [56]:

```
data['f_room_type'] = (data['f_room_type'] == 'Entire home/apt').astype(int)
```

In [57]:

```
X = data.drop(['price'], axis=1)  # X
y = data['price']  # target
# data standard
ss = StandardScaler()
X_std = ss.fit_transform(X)

88# train test split
X_train, X_test, y_train, y_test = train_test_split(X_std, y, test_size=0.2, random_
```

OLS model

Coefficients and their importance are draw for the easy comparison

In [58]:

```
ols_model = LinearRegression().fit(X_train, y_train)
y_hat = ols_model.predict(X_test)
ols_rmse = mean_squared_error(y_test, y_hat, squared=False)
```

In [59]:

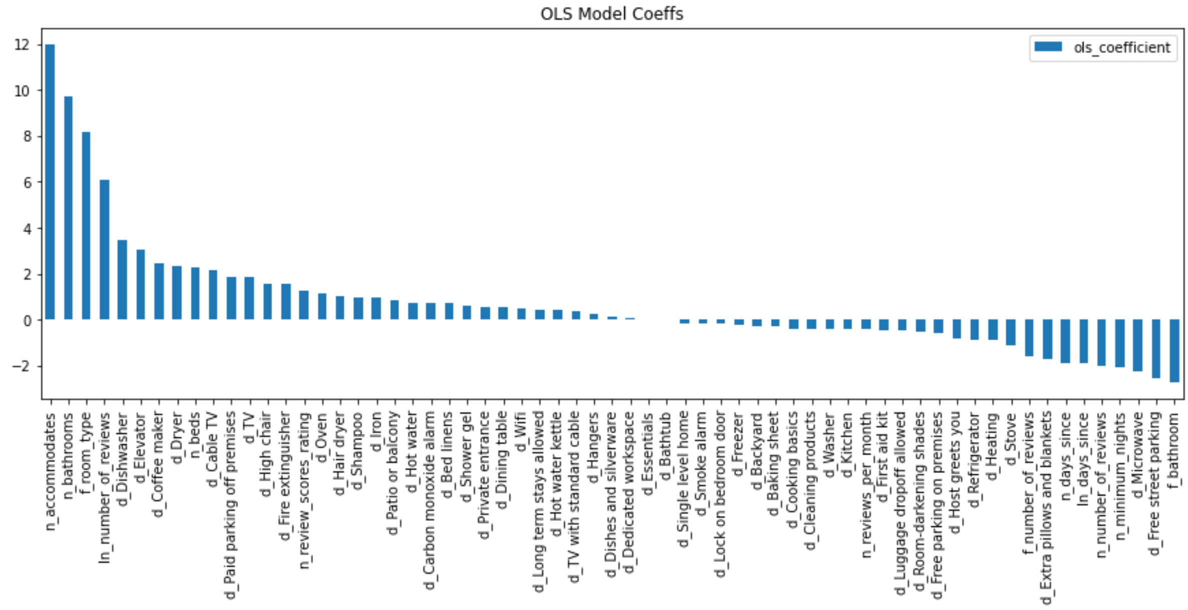
```
ols_model_coeffs_df = pd.DataFrame(
    ols_model.coef_.tolist(),
    index=X.columns,
    columns=['ols_coefficient'],
).assign(ols_coefficient=lambda x: x.ols_coefficient.round(3))
ols_model_coeffs_df.sort_values('ols_coefficient', inplace=True, ascending=False)
```

In [60]:

```
ols_model_coeffs_df.plot.bar(y='ols_coefficient', rot=90, figsize=(15, 5), title='OL
```

Out[60]:

```
<AxesSubplot:title={'center':'OLS Model Coeffs'}>
```

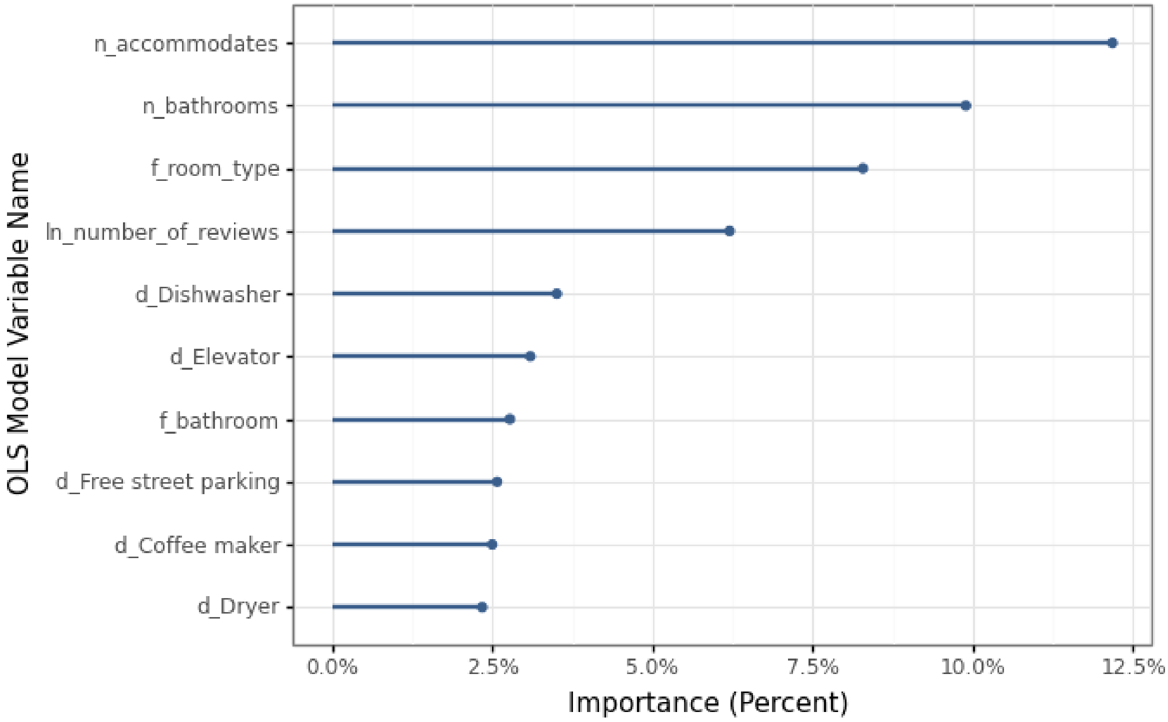


In [61]:

```
ols_model_coeffs_var_imp_df = (
    pd.DataFrame(
        abs(ols_model.coef_), X.columns
    )
    .reset_index()
    .rename({'index': 'varname',0: 'imp'}, axis=1)
    .assign(imp_percentage=lambda x: x['imp'] / x['imp'].sum())
    .sort_values(by=['imp'], ascending=False)
)
```

In [62]:

```
ggplot(
    ols_model_coeffs_var_imp_df.iloc[:10, :],
    aes(x='reorder(varname, imp)', y='imp_percentage'),
) + geom_point(color=color[0], size=1.5) + geom_segment(
    aes(x='varname', xend='varname', y=0, yend='imp_percentage'), color=color[0], si
) + ylab(
    'Importance (Percent)'
) + xlab(
    'OLS Model Variable Name'
) + coord_flip() + scale_y_continuous(
    labels=percent_format()
) + theme_bw()
```



Out[62]:

```
<ggplot: (8764285680818)>
```

Use cross validation and calulate RMSE for the futher RMSE comparison

In [63]:

```
# cross validation
ols_model = LinearRegression()
ols_cv_mse = cross_val_score(ols_model, X_std, y, cv=5, scoring='neg_mean_squared_er
ols_cv_rmse = [np.sqrt(-x) for x in ols_cv_mse]
```

In [64]:

```
ols_cv_rmse
```

Out[64]:

```
[29.28412078893475,
 32.53828249431209,
 29.392151995967893,
 31.241236658150154,
 31.157206101331965]
```

LASSO model

Coefficients and their importance are draw for the easy comparison

In [65]:

```
lasso_model = Lasso(alpha=0.5).fit(X_train, y_train)
y_hat = lasso_model.predict(X_test)
lasso_rmse = mean_squared_error(y_test, y_hat, squared=False)
```

In [66]:

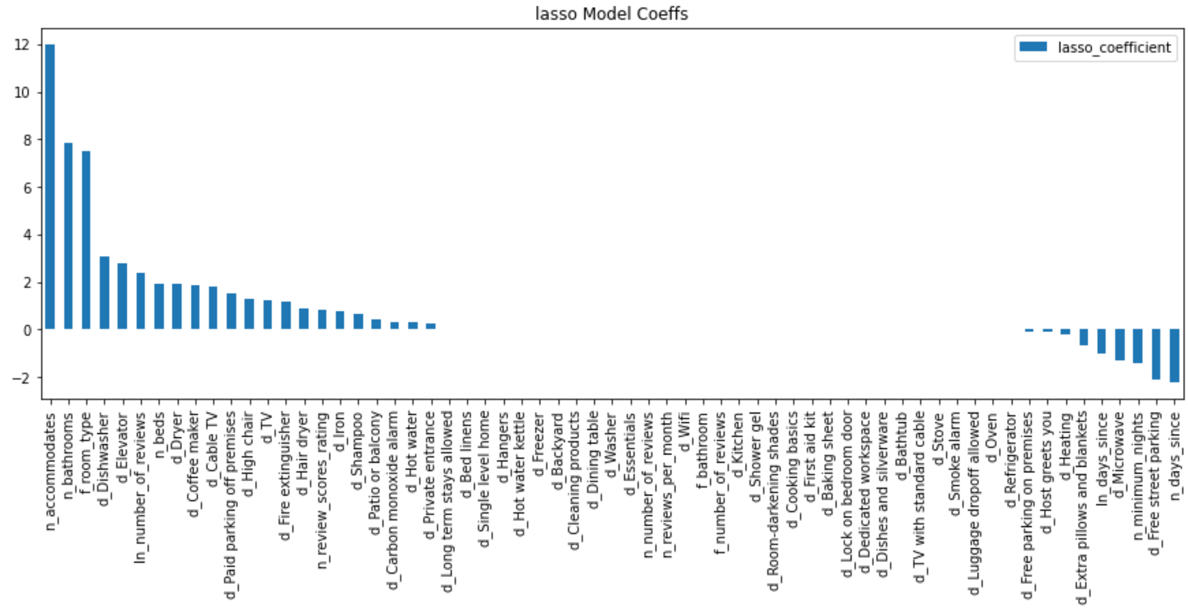
```
lasso_model_coeffs_df = pd.DataFrame(
    lasso_model.coef_.tolist(),
    index=X.columns,
    columns=['lasso_coefficient'],
).assign(lasso_coefficient=lambda x: x.lasso_coefficient.round(3))
lasso_model_coeffs_df.sort_values('lasso_coefficient', inplace=True, ascending=False
```

In [67]:

```
lasso_model_coeffs_df.plot.bar(y='lasso_coefficient', rot=90, figsize=(15, 5), title
```

Out[67]:

```
<AxesSubplot:title={'center':'lasso Model Coeffs'}>
```

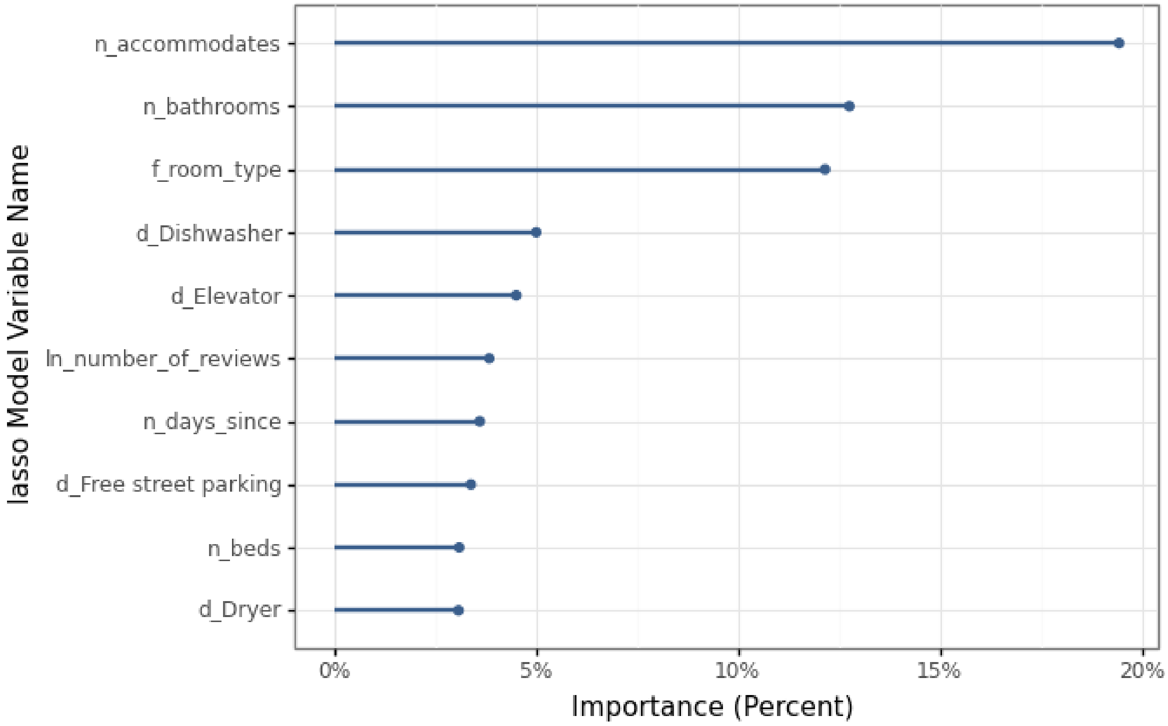


In [68]:

```
lasso_model_coeffs_var_imp_df = (
    pd.DataFrame(
        abs(lasso_model.coef_), X.columns
    )
    .reset_index()
    .rename({'index': 'varname',0: 'imp'}, axis=1)
    .assign(imp_percentage=lambda x: x['imp'] / x['imp'].sum())
    .sort_values(by=['imp'], ascending=False)
)
```

In [69]:

```
ggplot(
    lasso_model_coeffs_var_imp_df.iloc[:10, :],
    aes(x='reorder(varname, imp)', y='imp_percentage'),
) + geom_point(color=color[0], size=1.5) + geom_segment(
    aes(x='varname', xend='varname', y=0, yend='imp_percentage'), color=color[0], si
) + ylab(
    'Importance (Percent)'
) + xlab(
    'lasso Model Variable Name'
) + coord_flip() + scale_y_continuous(
    labels=percent_format()
) + theme_bw()
```



Out[69]:

<ggplot: (8764284936126)>

Use cross validation and calulate RMSE for the futher RMSE comparison

In [70]:

```
# cross validation
lasso_model = Lasso(alpha=0.5)
lasso_cv_mse = cross_val_score(lasso_model, X_std, y, cv=5, scoring='neg_mean_square
lasso_cv_rmse = [np.sqrt(-x) for x in lasso_cv_mse]
```

In [71]:

```
lasso_cv_rmse
```

Out[71]:

```
[29.038324229640647,
 32.84099823915201,
 29.473791861809993,
 31.274808005783054,
 30.921404013044636]
```

CART Model

Coefficients and their importance are draw for the easy comparison

In [72]:

```
cart_model = DecisionTreeRegressor().fit(X_train, y_train)
y_hat = cart_model.predict(X_test)
cart_rmse = mean_squared_error(y_test, y_hat, squared=False)
```

In [73]:

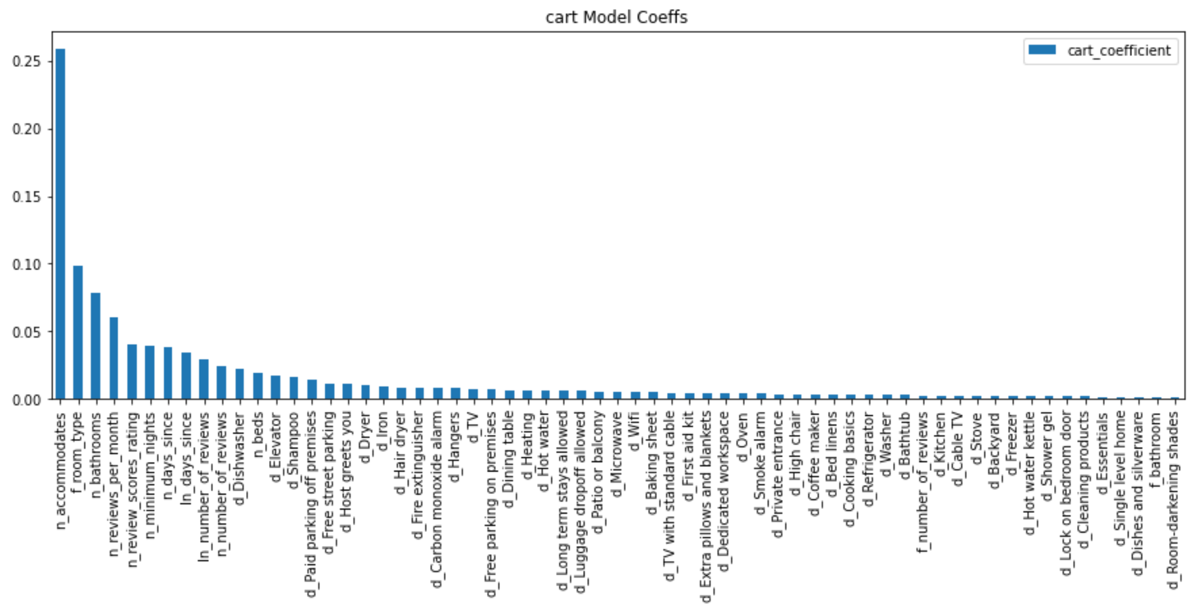
```
cart_model_coeffs_df = pd.DataFrame(
    cart_model.feature_importances_.tolist(),
    index=X.columns,
    columns=['cart_coefficient'],
).assign(cart_coefficient=lambda x: x.cart_coefficient.round(3))
cart_model_coeffs_df.sort_values('cart_coefficient', inplace=True, ascending=False)
```

In [74]:

```
cart_model_coeffs_df.plot.bar(y='cart_coefficient', rot=90, figsize=(15, 5), title='
```

Out[74]:

```
<AxesSubplot:title={'center':'cart Model Coeffs'}>
```

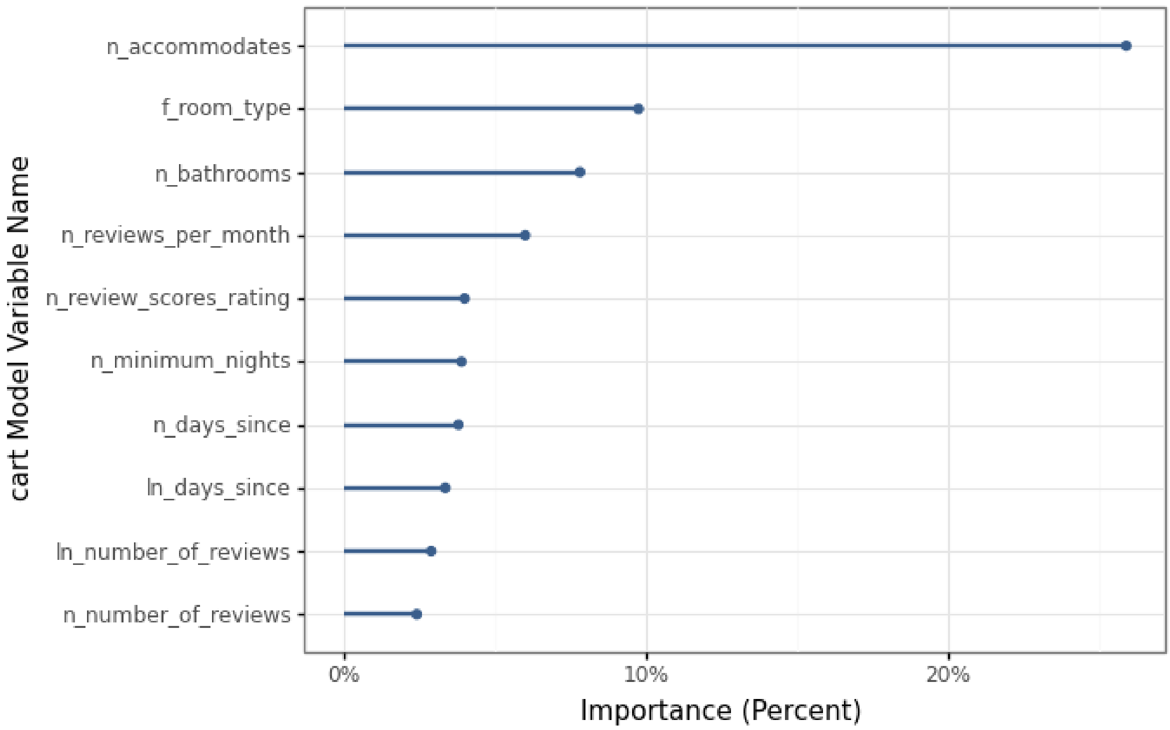


In [75]:

```
cart_model_coeffs_var_imp_df = (
    pd.DataFrame(
        abs(cart_model.feature_importances_), X.columns
    )
    .reset_index()
    .rename({'index': 'varname',0: 'imp'}, axis=1)
    .assign(imp_percentage=lambda x: x['imp'] / x['imp'].sum())
    .sort_values(by=['imp'], ascending=False)
)
```

In [76]:

```
ggplot(
    cart_model_coeffs_var_imp_df.iloc[:10, :],
    aes(x='reorder(varname, imp)', y='imp_percentage'),
) + geom_point(color=color[0], size=1.5) + geom_segment(
    aes(x='varname', xend='varname', y=0, yend='imp_percentage'), color=color[0], si
) + ylab(
    'Importance (Percent)'
) + xlab(
    'cart Model Variable Name'
) + coord_flip() + scale_y_continuous(
    labels=percent_format()
) + theme_bw()
```



Out[76]:

```
<ggplot: (8764242184662)>
```

Use cross validation and calulate RMSE for the futher RMSE comparison

In [77]:

```
# cross validation
cart_model = DecisionTreeRegressor()
cart_cv_mse = cross_val_score(cart_model, X_std, y, cv=5, scoring='neg_mean_squared_
cart_cv_rmse = [np.sqrt(-x) for x in cart_cv_mse]
```

In [78]:

```
cart_cv_rmse
```

Out[78]:

```
[49.4165150367036,
 40.99427123832549,
 41.633833168866616,
 42.627742242627384,
 45.8753452705229]
```

GBM Model

Coefficients and their importance are draw for the easy comparison

In [79]:

```
gbm_model = GradientBoostingRegressor().fit(X_train, y_train)
y_hat = gbm_model.predict(X_test)
gbm_rmse = mean_squared_error(y_test, y_hat, squared=False)
```

In [80]:

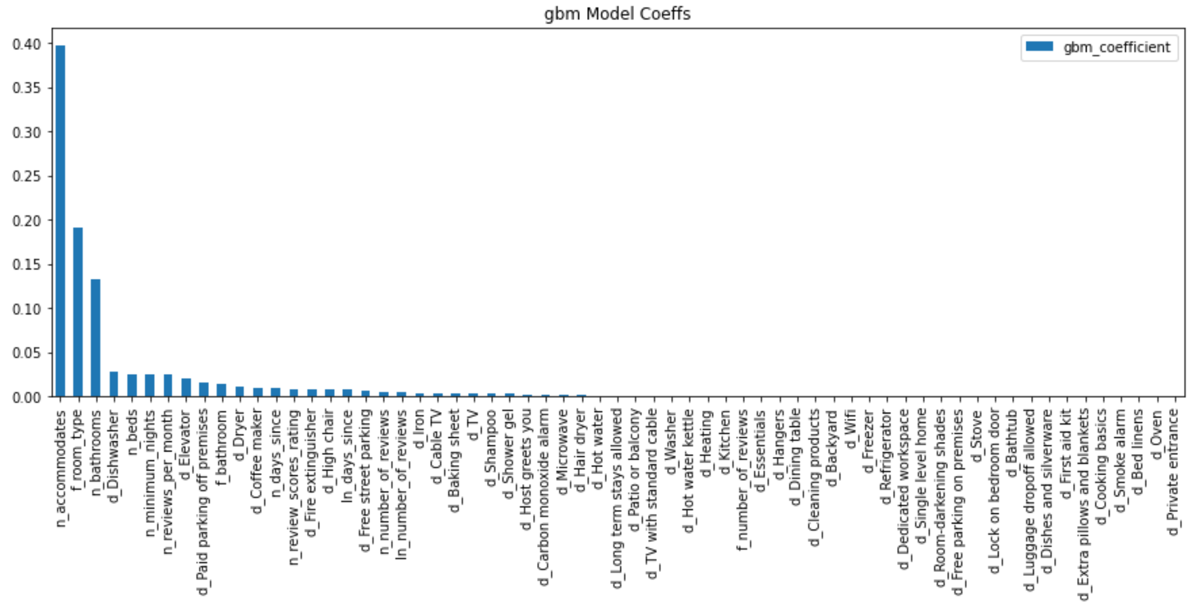
```
gbm_model_coeffs_df = pd.DataFrame(
    gbm_model.feature_importances_.tolist(),
    index=X.columns,
    columns=['gbm_coefficient'],
).assign(gbm_coefficient=lambda x: x.gbm_coefficient.round(3))
gbm_model_coeffs_df.sort_values('gbm_coefficient', inplace=True, ascending=False)
```

In [81]:

```
gbm_model_coeffs_df.plot.bar(y='gbm_coefficient', rot=90, figsize=(15, 5), title='gb
```

Out[81]:

```
<AxesSubplot:title={'center':'gbm Model Coeffs'}>
```

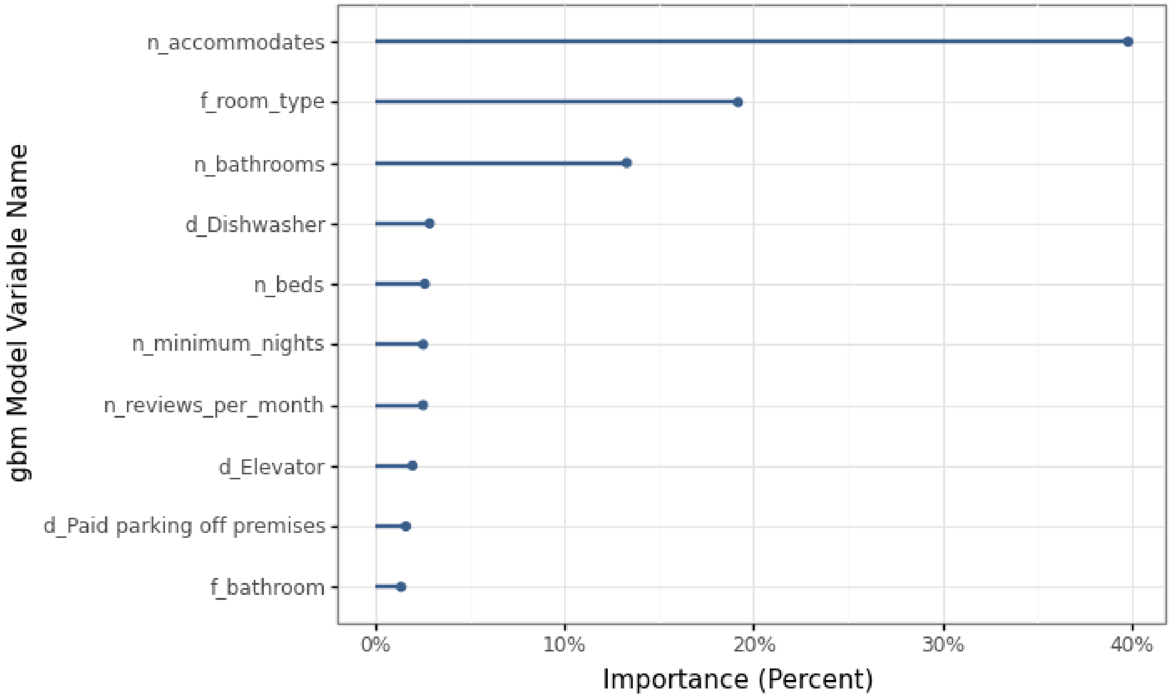


In [82]:

```
gbm_model_coeffs_var_imp_df = (
    pd.DataFrame(
        abs(gbm_model.feature_importances_), X.columns
    )
    .reset_index()
    .rename({'index': 'varname',0: 'imp'}, axis=1)
    .assign(imp_percentage=lambda x: x['imp'] / x['imp'].sum())
    .sort_values(by=['imp'], ascending=False)
)
```

In [83]:

```
ggplot(
    gbm_model_coeffs_var_imp_df.iloc[:10, :],
    aes(x='reorder(varname, imp)', y='imp_percentage'),
) + geom_point(color=color[0], size=1.5) + geom_segment(
    aes(x='varname', xend='varname', y=0, yend='imp_percentage'), color=color[0], si
) + ylab(
    'Importance (Percent)'
) + xlab(
    'gbm Model Variable Name'
) + coord_flip() + scale_y_continuous(
    labels=percent_format()
) + theme_bw()
```



Out[83]:

```
<ggplot: (8764286608505)>
```

Use cross validation and calulate RMSE for the futher RMSE comparison

In [84]:

```
# cross validation
gbm_model = GradientBoostingRegressor()
gbm_cv_mse = cross_val_score(gbm_model, X_std, y, cv=5, scoring='neg_mean_squared_er
gbm_cv_rmse = [np.sqrt(-x) for x in gbm_cv_mse]
```

In [85]:

```
gbm_cv_rmse
```

Out[85]:

```
[28.50590767722782,
 31.12869709066846,
 28.587405488743435,
 30.24569382069324,
 30.27422987026081]
```

In [86]:

```
def combine(type_, rmse):
    res = []
    index = 1
    for r in rmse:
        res.append([index, type_, r])
        index += 1
    return res
```

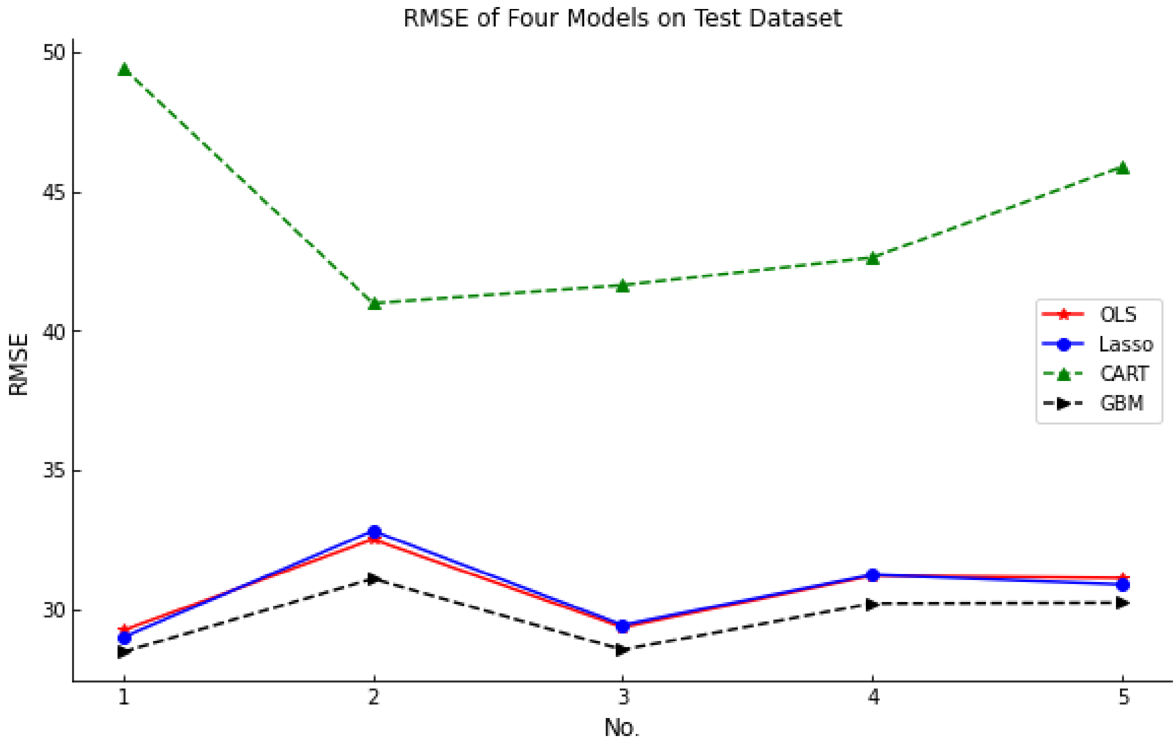
Visual model prediction results

Results of RMSE for different test times with four models

Average of RMSE for different test times with four models

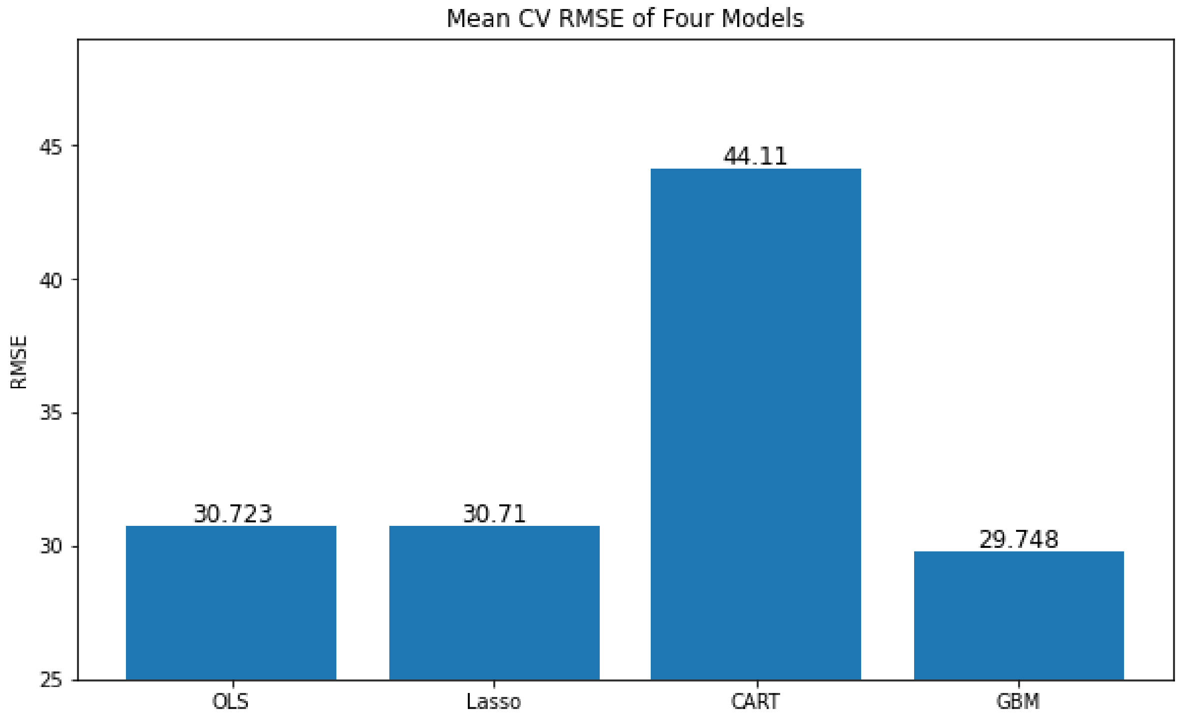
In [87]:

```
# cv RMSE compare
plt.figure(figsize=(10, 6))
plt.xlabel('No.', fontsize=12)
plt.ylabel('RMSE', fontsize=12)
ax = plt.gca()
ax.tick_params(axis='both', which='both', direction='in')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
serial = [1, 2, 3, 4, 5]
plt.plot(serial, ols_cv_rmse, 'r-*', label='OLS')
plt.plot(serial, lasso_cv_rmse, 'b-o', label='Lasso')
plt.plot(serial, cart_cv_rmse, 'g--^', label='CART')
plt.plot(serial, gbm_cv_rmse, 'k-->', label='GBM')
plt.title('RMSE of Four Models on Test Dataset')
plt.xticks(serial)
plt.legend()
plt.show()
```



In [88]:

```
plt.figure(figsize=(10, 6))
x_list = ['OLS', 'Lasso', 'CART', 'GBM']
y_list = [round(np.mean(ols_cv_rmse), 3),
          round(np.mean(lasso_cv_rmse), 3),
          round(np.mean(cart_cv_rmse), 3),
          round(np.mean(gbm_cv_rmse), 3)]
plt.bar(x_list, y_list)
plt.title('Mean CV RMSE of Four Models')
plt.ylabel('RMSE')
plt.ylim([25, 49])
for a, b in zip(x_list, y_list):
    plt.text(a, b, b, ha='center', va='bottom', fontsize=12)
plt.show()
```



With the help of the two graphs, we can easily judge GBM and lowest RMSE, which has the best predication result and is the best model. OLS and LASS

O results are alomost the same, which seem not so bad. CART is the worst reu slt and has much higher RMSE than the other three.