# Где дешевле жить? Предсказание цен в Airbnb

Опробованные техники.

- Была сделана стандартная предобработка признаков
- построены различные визуализации
- опробован ohe через dummies
- применены различные типы шкалирования (MinMax, StandartScaller, Robust)
- для переменной neibohood применено частотное кодирование, чтобы не перегружать число признаков
- применена помимо линейных моделей - random forest

Итоги:

- фича превращения long и lat в расстояние от центра манхетена до недвижимости на удивление не помогла
- заметно улучшиело модель шкалирование данных, лучше всего сработало robust шкалирование
- в целом линейные модели показали примерно одинаковый результат
- random forest оказался немного лучше линейных моделей

Все итоговые метрики расположены в конце ноутбука в dataframe measured_metrics

# Часть 1. EDA

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

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
pd.set_option('display.max_columns', None)


from scipy import stats
from scipy.stats import norm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
from sklearn.linear_model import LinearRegression, RidgeCV, LassoCV, ElasticNe
tCV, Lasso


%matplotlib inline
plt.rcParams["figure.figsize"] = (12,8)


np.random.seed(49)
```

для отображения графиков без скроллов

In [2]:
```
%%javascript
IPython.OutputArea.auto_scroll_threshold = 9999;
```

In [3]:
```
data = pd.read_csv('AB_NYC_2019.csv')
```

In [4]:
```
data.head()
```

Out[4]:

| | id | name | host_id | host_name | neighbourhood_group | neighbourhood | latitude |
|---|---|---|---|---|---|---|---|
| **0** | 2539 | Clean & quiet apt home by the park | 2787 | John | Brooklyn | Kensington | 40.64749 |
| **1** | 2595 | Skylit Midtown Castle | 2845 | Jennifer | Manhattan | Midtown | 40.75362 |
| **2** | 3647 | THE VILLAGE OF HARLEM....NEW YORK ! | 4632 | Elisabeth | Manhattan | Harlem | 40.80902 |
| **3** | 3831 | Cozy Entire Floor of Brownstone | 4869 | LisaRoxanne | Brooklyn | Clinton Hill | 40.68514 |
| **4** | 5022 | Entire Apt: Spacious Studio/Loft by central park | 7192 | Laura | Manhattan | East Harlem | 40.79851 |

In [5]:
```
data.columns
```

Out[5]:
```
Index(['id', 'name', 'host_id', 'host_name', 'neighbourhood_group',
       'neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'last_review',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365'],
      dtype='object')
```

In [6]:
```
use_cols = data.columns[4:12].to_list() + data.columns[13:].to_list()
```

In [7]:
```
use_cols
```

Out[7]:
```
['neighbourhood_group',
 'neighbourhood',
 'latitude',
 'longitude',
 'room_type',
 'price',
 'minimum_nights',
 'number_of_reviews',
 'reviews_per_month',
 'calculated_host_listings_count',
 'availability_365']
```

In [8]:
```
data = pd.read_csv('AB_NYC_2019.csv', usecols=use_cols)
```

In [9]:
```
data.head()
```

Out[9]:

| | neighbourhood_group | neighbourhood | latitude | longitude | room_type | price | minimum_nights |
|---|---|---|---|---|---|---|---|
| **0** | Brooklyn | Kensington | 40.64749 | -73.97237 | Private room | 149 | 1 |
| **1** | Manhattan | Midtown | 40.75362 | -73.98377 | Entire home/apt | 225 | 1 |
| **2** | Manhattan | Harlem | 40.80902 | -73.94190 | Private room | 150 | 3 |
| **3** | Brooklyn | Clinton Hill | 40.68514 | -73.95976 | Entire home/apt | 89 | 1 |
| **4** | Manhattan | East Harlem | 40.79851 | -73.94399 | Entire home/apt | 80 | 10 |

In [10]:
```
data.describe()
```

Out[10]:

| | latitude | longitude | price | minimum_nights | number_of_reviews | reviews_ |
|---|---|---|---|---|---|---|
| **count** | 48895.000000 | 48895.000000 | 48895.000000 | 48895.000000 | 48895.000000 | 388 |
| **mean** | 40.728949 | -73.952170 | 152.720687 | 7.029962 | 23.274466 | |
| **std** | 0.054530 | 0.046157 | 240.154170 | 20.510550 | 44.550582 | |
| **min** | 40.499790 | -74.244420 | 0.000000 | 1.000000 | 0.000000 | |
| **25%** | 40.690100 | -73.983070 | 69.000000 | 1.000000 | 1.000000 | |
| **50%** | 40.723070 | -73.955680 | 106.000000 | 3.000000 | 5.000000 | |
| **75%** | 40.763115 | -73.936275 | 175.000000 | 5.000000 | 24.000000 | |
| **max** | 40.913060 | -73.712990 | 10000.000000 | 1250.000000 | 629.000000 | |

In [11]:
```
data.info()
```

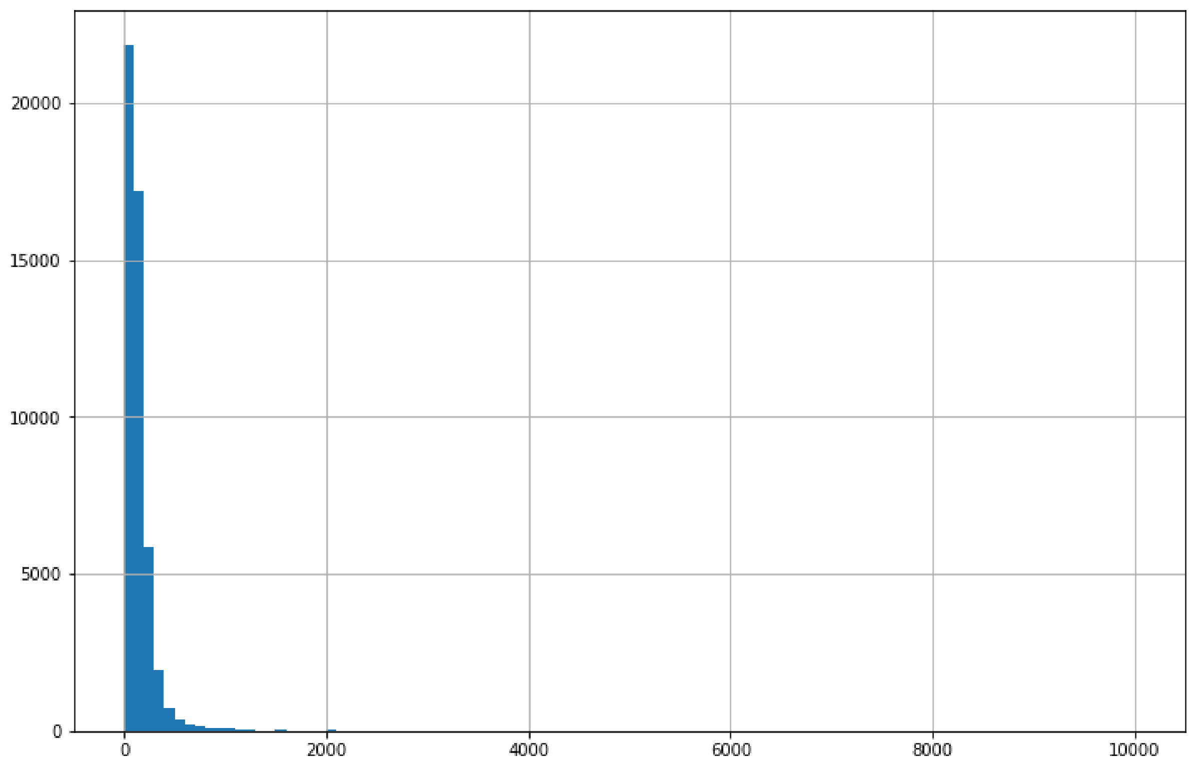
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 11 columns):
neighbourhood_group               48895 non-null object
neighbourhood                     48895 non-null object
latitude                          48895 non-null float64
longitude                         48895 non-null float64
room_type                         48895 non-null object
price                             48895 non-null int64
minimum_nights                    48895 non-null int64
number_of_reviews                 48895 non-null int64
reviews_per_month                 38843 non-null float64
calculated_host_listings_count    48895 non-null int64
availability_365                  48895 non-null int64
dtypes: float64(3), int64(5), object(3)
memory usage: 4.1+ MB
```

In [12]:
```
data.dtypes
```

Out[12]:
```
neighbourhood_group                object
neighbourhood                      object
latitude                          float64
longitude                         float64
room_type                          object
price                               int64
minimum_nights                      int64
number_of_reviews                   int64
reviews_per_month                 float64
calculated_host_listings_count      int64
availability_365                    int64
dtype: object
```

In [13]:
```
data.price.hist(bins = 100)
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20273c26088>
```

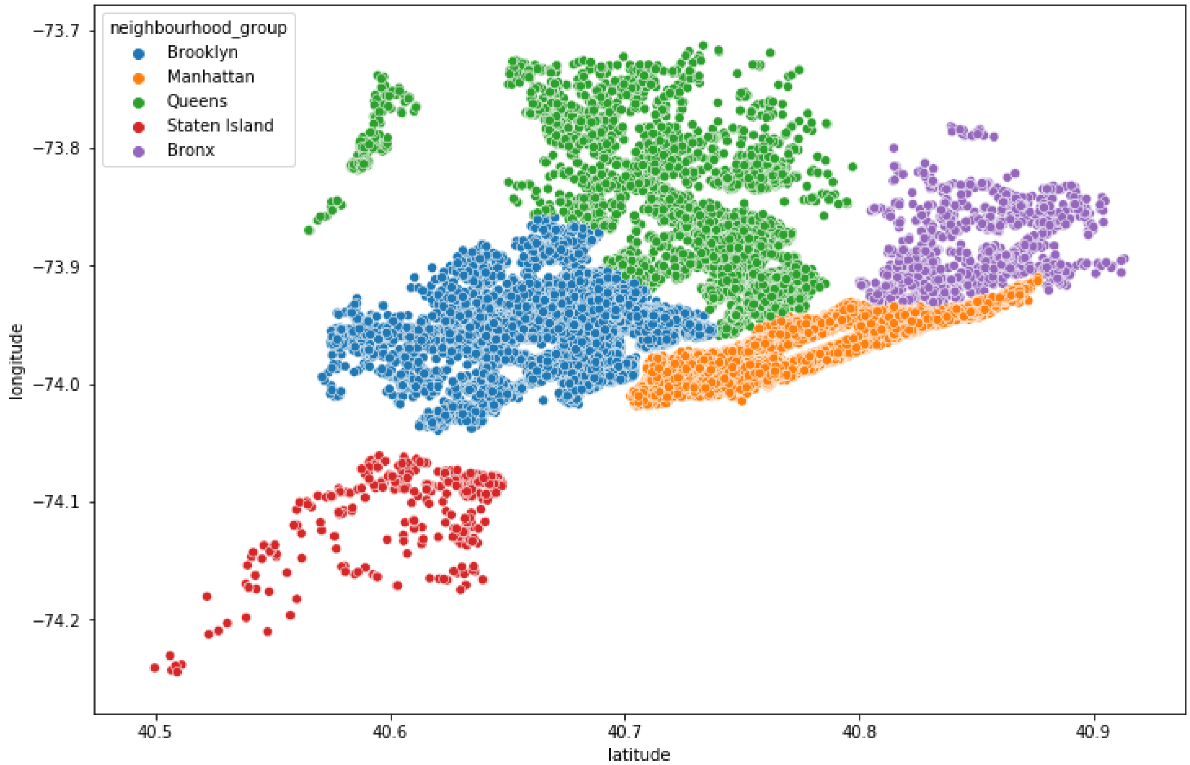



целевая переменная распределена ненормально, пока осавим ее как есть, чтобы в дальнейшем сравнить метрики до и после предобработки.

карта района:

In [14]:
```
sns.scatterplot(data.latitude, data.longitude, hue=data.neighbourhood_group)
```

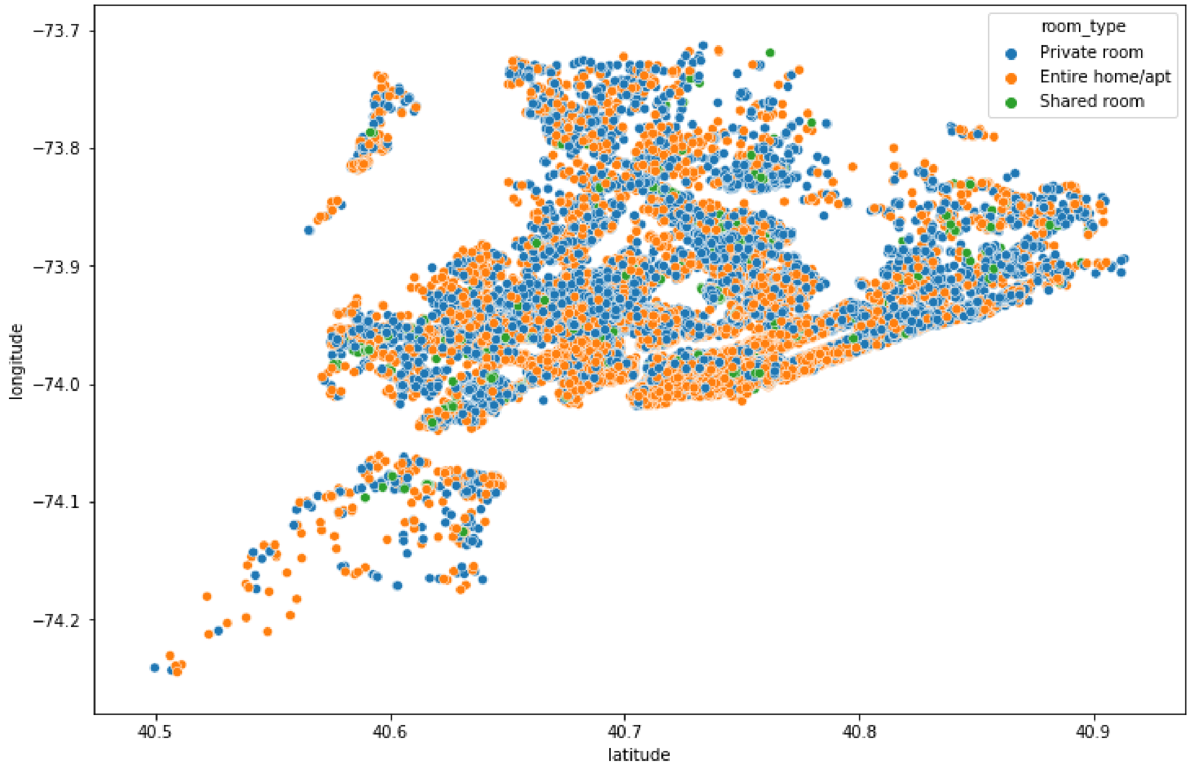
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x202746101c8>




тип комнаты в зависимости от района

In [15]:
```
sns.scatterplot(data.latitude, data.longitude, hue=data.room_type)
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20274f36a88>
```

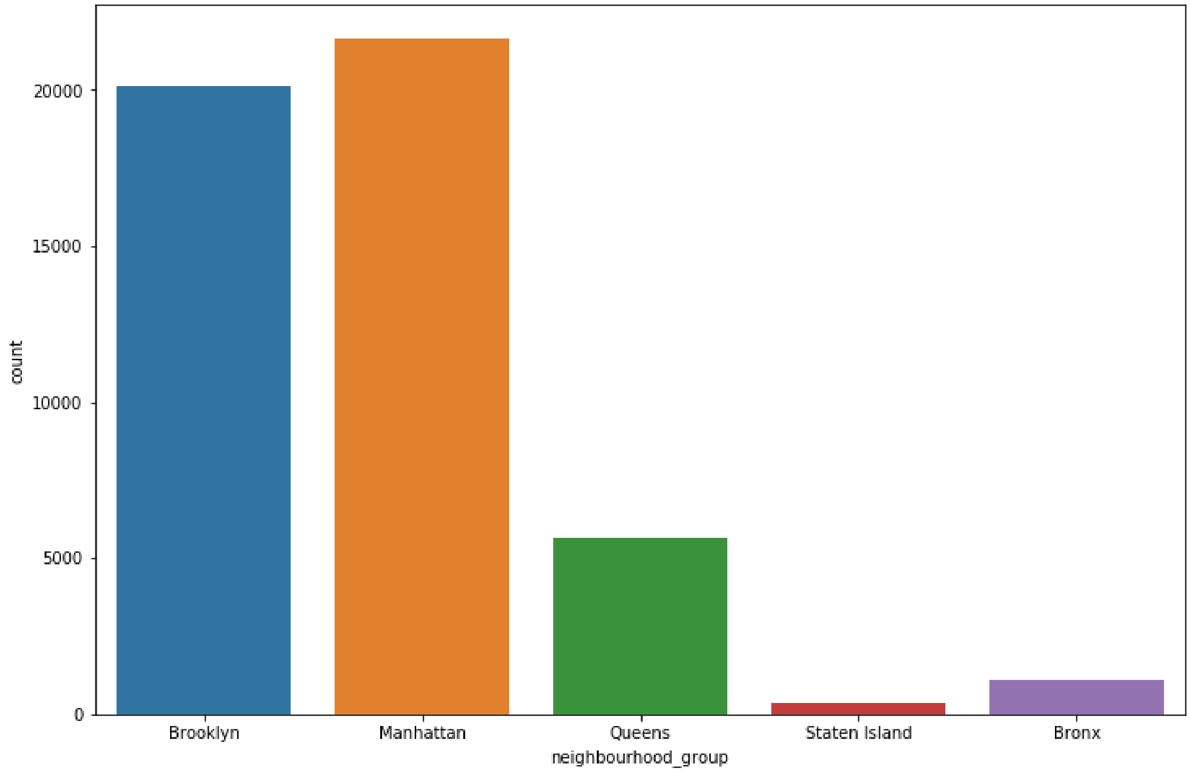



In [16]:
```
data.neighbourhood_group.value_counts()
```

Out[16]:
```
Manhattan        21661
Brooklyn         20104
Queens            5666
Bronx             1091
Staten Island      373
Name: neighbourhood_group, dtype: int64
```

In [17]:
```
sns.countplot(x = data.neighbourhood_group)
```

Out[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20274598688>
```




проверка на дубликаты

In [18]:
```
data.duplicated().sum()
```

Out[18]:
```
0
```

проверка на пропуски

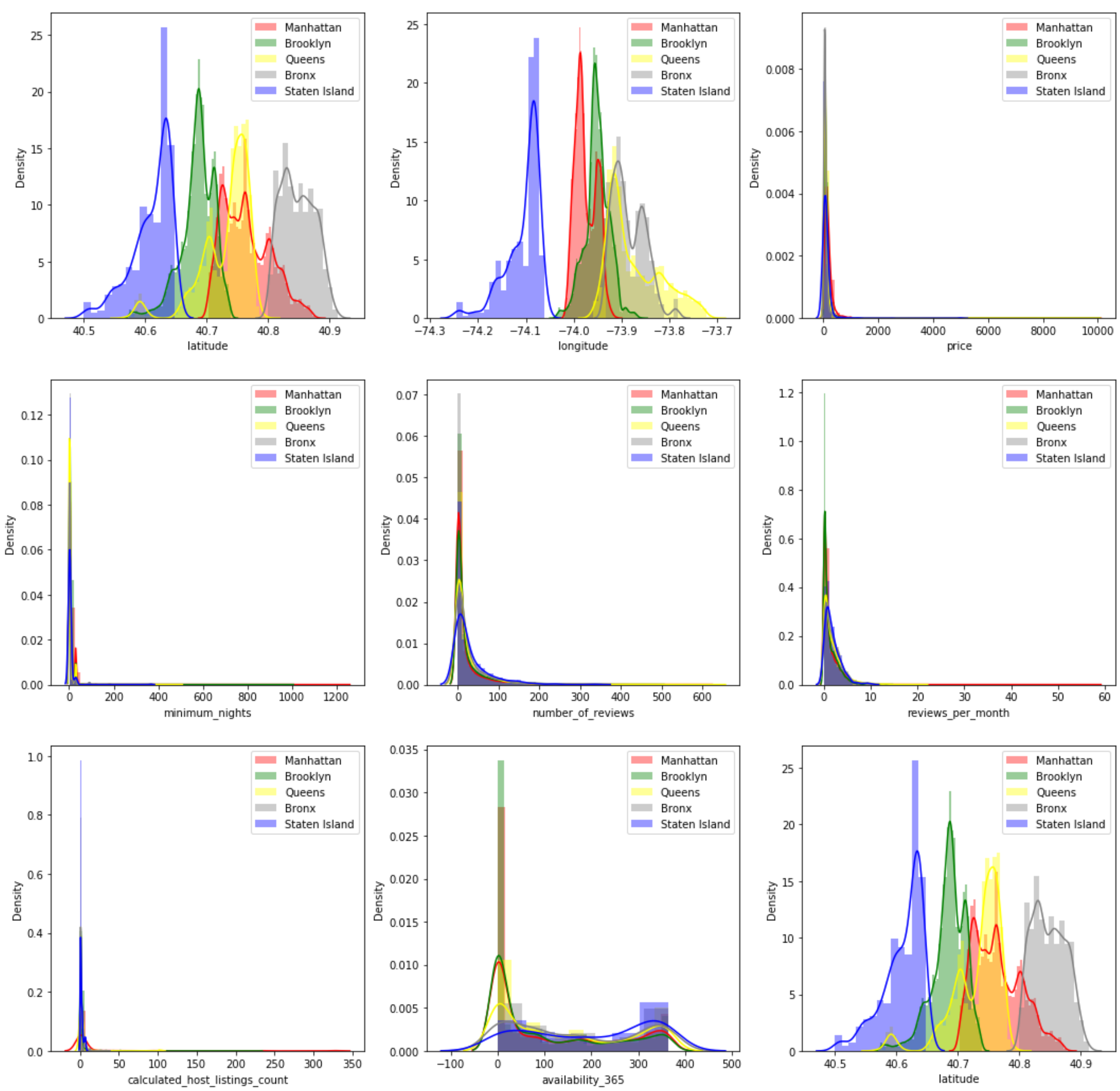
In [19]:
```
data.isnull().sum()
```

Out[19]:
```
neighbourhood_group                0
neighbourhood                      0
latitude                           0
longitude                          0
room_type                          0
price                              0
minimum_nights                     0
number_of_reviews                  0
reviews_per_month              10052
calculated_host_listings_count     0
availability_365                   0
dtype: int64
```

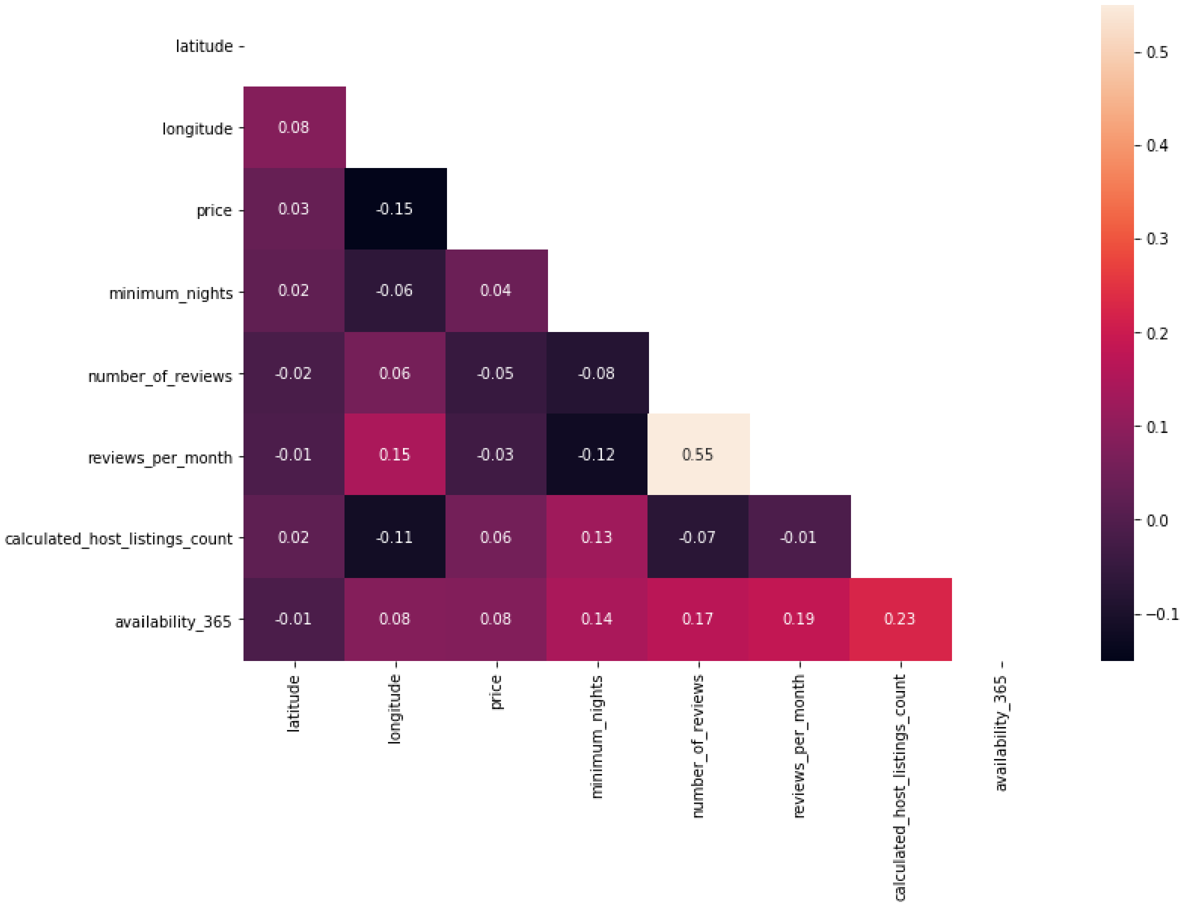
гистограммы распределения признаков

In [20]:
```
int_colums = ['latitude', 'longitude','price','minimum_nights','number_of_reviews','reviews_per_month','calculated_host_listings_count','availability_365']
```

In [21]:
```
nrows = 3
ncols = 3
fig, ax = plt.subplots(nrows, ncols, figsize=(ncols*6, nrows*6))
a = -8
for i in range(nrows):
    for j in range(ncols):
      ax1 = sns.distplot(data[data['neighbourhood_group'] == 'Manhattan'][int_
colums[a]], ax = ax[i,j], color = 'red', label = 'Manhattan').legend()
      ax2 = sns.distplot(data[data['neighbourhood_group'] == 'Brooklyn'][int_c
olums[a]], ax = ax[i,j], color = 'green', label = 'Brooklyn').legend()
      ax3 = sns.distplot(data[data['neighbourhood_group'] == 'Queens'][int_col
ums[a]], ax = ax[i,j], color = 'yellow', label = 'Queens').legend()
      ax4 = sns.distplot(data[data['neighbourhood_group'] == 'Bronx'][int_colu
ms[a]], ax = ax[i,j], color = 'gray', label = 'Bronx').legend()
      ax5 = sns.distplot(data[data['neighbourhood_group'] == 'Staten Island'][
int_colums[a]], ax = ax[i,j], color = 'blue', label = 'Staten Island').legend
()
      a +=1
plt.show()
```

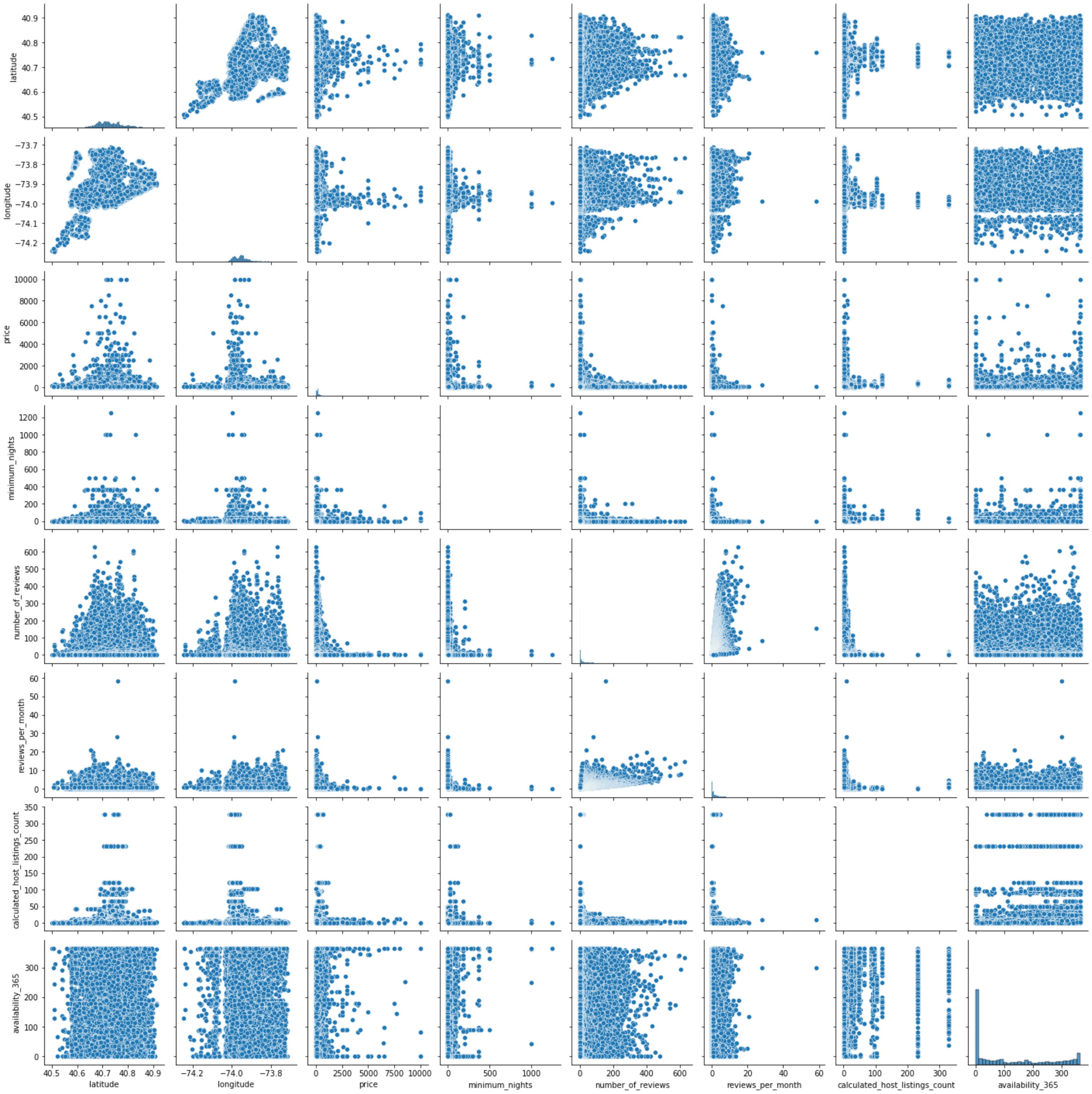


In [22]:
```
corr = data.corr()
sns.heatmap(corr, annot=True, fmt='.2f',  mask = np.triu(np.ones_like(corr, dtype=bool)));
```



In [23]:
```
sns.pairplot(data)
```

Out[23]: <seaborn.axisgrid.PairGrid at 0x2027443c608>




# Часть 2. Preprocessing & Feature Engineering

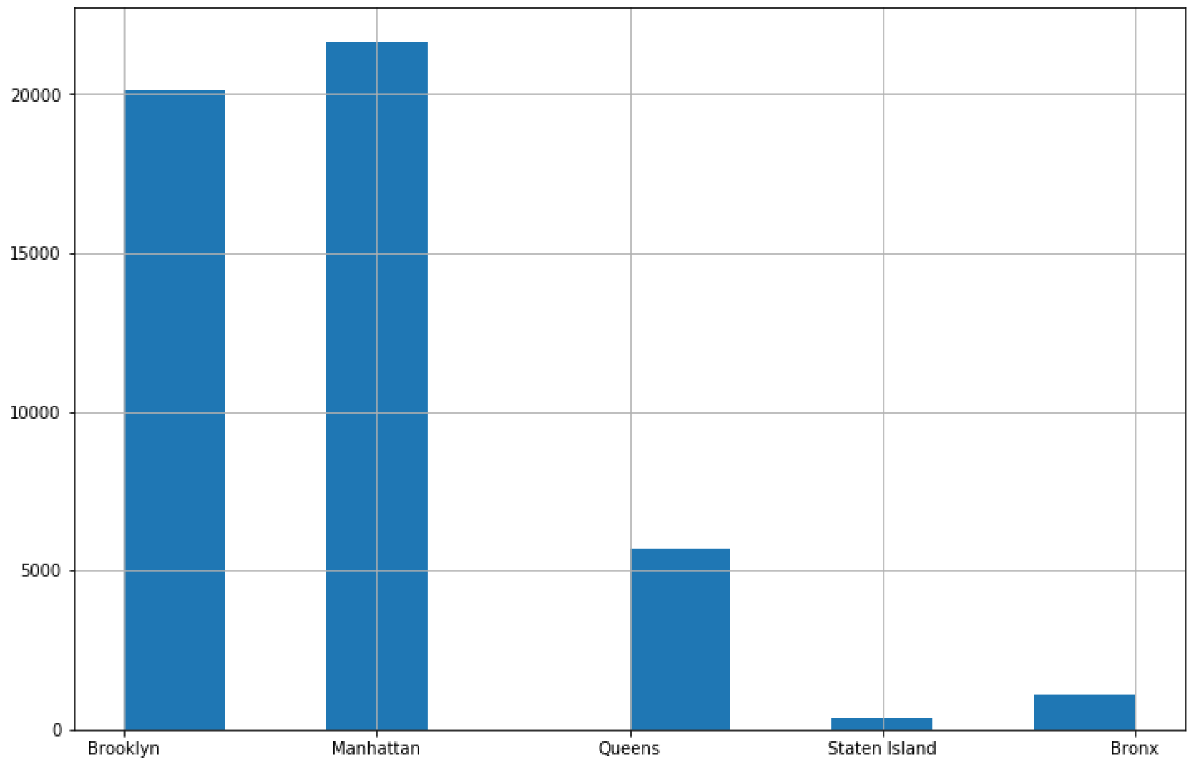
### neighbourhood_group

In [24]:
```
data.neighbourhood_group.value_counts()
```

Out[24]:
```
Manhattan        21661
Brooklyn         20104
Queens            5666
Bronx             1091
Staten Island      373
Name: neighbourhood_group, dtype: int64
```

In [25]:
```
data.neighbourhood_group.hist()
```

Out[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2020150e208>
```




применим one-hot encoding

In [26]:
```
data = pd.get_dummies(data, columns=['neighbourhood_group'],  prefix='neighbou
rhood_group', drop_first=True)
```

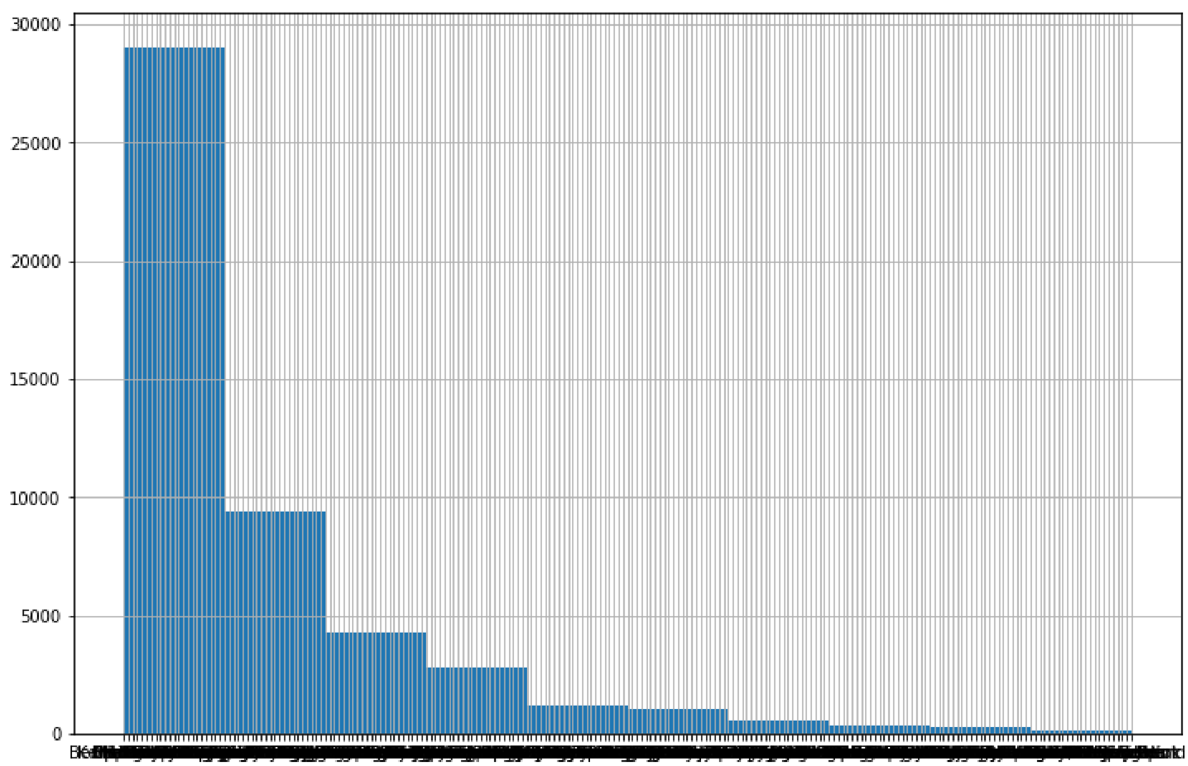
## neighbourhood

In [27]:
```
data.neighbourhood.value_counts()
```

Out[27]:
```
Williamsburg          3920
Bedford-Stuyvesant    3714
Harlem                2658
Bushwick              2465
Upper West Side       1971
                      ... 
Willowbrook              1
Fort Wadsworth           1
Richmondtown             1
Woodrow                  1
New Dorp                 1
Name: neighbourhood, Length: 221, dtype: int64
```

In [28]:
```
data.neighbourhood.hist()
```

Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20206d18508>
```




применим частнотное кодирование

In [29]:
```
data['neighbourhood_freq'] = data['neighbourhood'].map(data['neighbourhood'].v
alue_counts(normalize=True))
```

## root_type

In [30]:
```
data.room_type.value_counts()
```

Out[30]:
```
Entire home/apt    25409
Private room       22326
Shared room         1160
Name: room_type, dtype: int64
```

применим one_hot_encoding

In [31]:
```
data = pd.get_dummies(data, columns=['room_type'],  prefix='room_type', drop_f
irst=True)
```

## reviews_per_month

In [32]:
```
data[data.reviews_per_month.isnull()].shape
```

Out[32]:
```
(10052, 16)
```

заменим null на 0 в первом случае, предположив, что null означает 0, на среднее значение, и на случайное, чтобы в последующем сравнить результаты.

In [33]:
```
def impute_NA_with_random(data, NA_col=None, random_state=0):
    """Заполняем пропуски случайными значениями из этой колонки."""
    NA_col = NA_col or []
    data_copy = data.copy(deep=True)
    for i in NA_col:
        if data_copy[i].isnull().sum() > 0:
            data_copy[f'{i}_random'] = data_copy[i]
            random_sample = data_copy[i].dropna().sample(data_copy[i].isnull()
.sum(), random_state=random_state)
            random_sample.index = data_copy[data_copy[i].isnull()].index
            data_copy.loc[data_copy[i].isnull(), f'{i}_random'] = random_sampl
e
        else:
            warn("Нет пропущенных значений" % i)
    return data_copy
```

In [34]:
```
data = impute_NA_with_random(data=data, NA_col=['reviews_per_month'])
```

In [35]:
```
data['reviews_per_month_mean'] = data['reviews_per_month'].fillna(data['review
s_per_month'].mean())
```

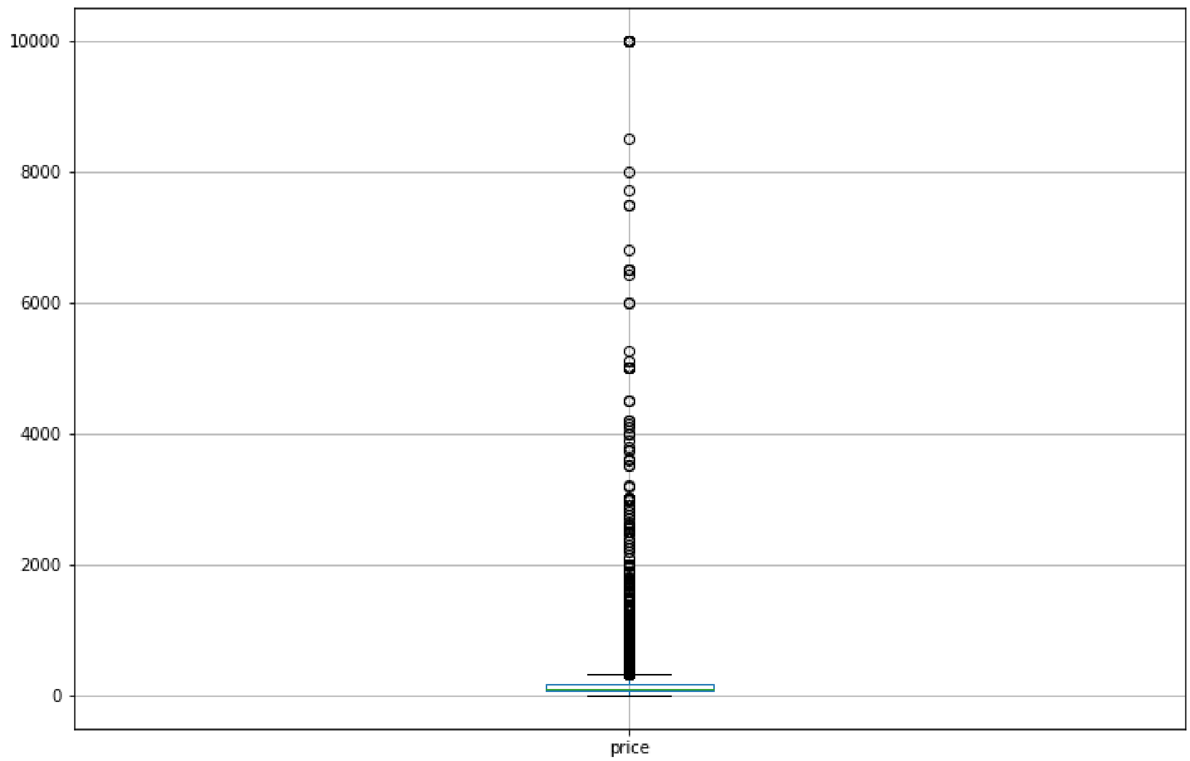
In [36]:
```
data['reviews_per_month_zero'] = data['reviews_per_month'].fillna(0)
```

In [ ]:

## price

In [37]:
```
data.boxplot(['price'])
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x2020dc87a48>

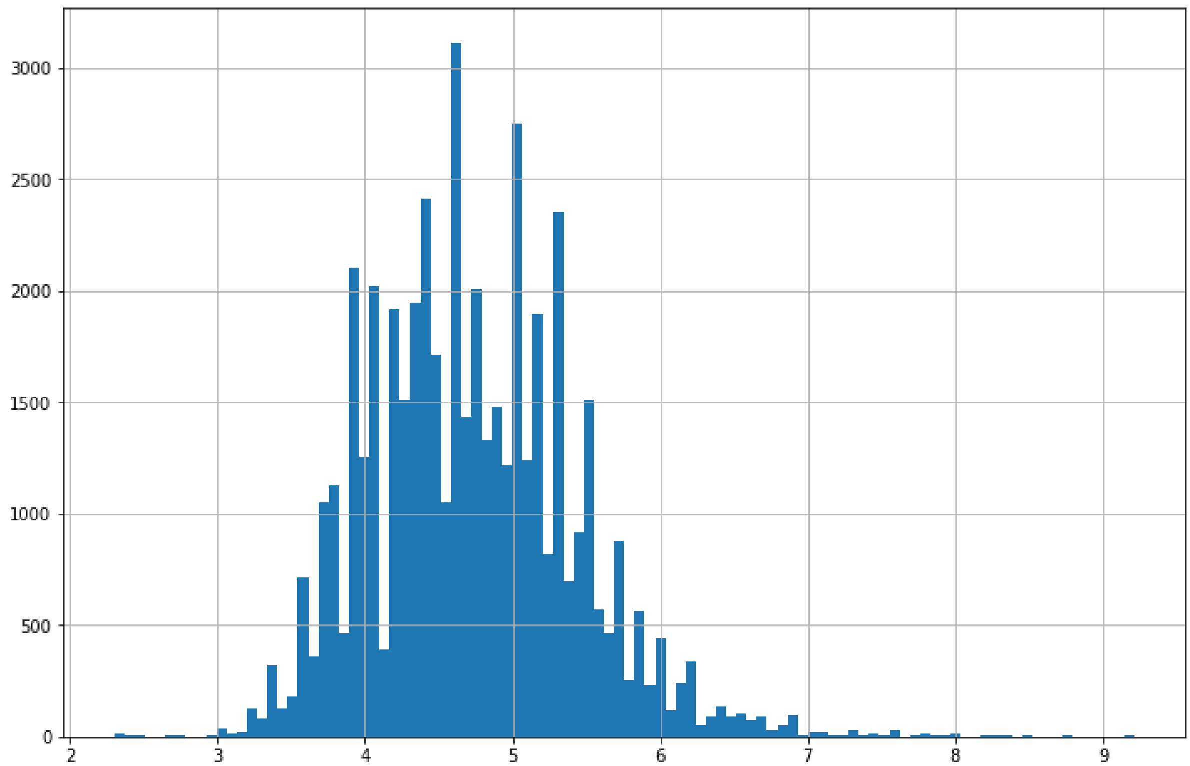



переменная имеет выбросы и 0 значения, а так же распределена ненормально. предлагаю удалить значения = 0, а также прологарифмировать целевую переменную чтобы распределение стало норм - проверим это.

In [38]:
```
data = data[data.price > 0]
```

In [39]:
```
np.log(data['price']).hist(bins = 100)
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x2020dc9f1c8>

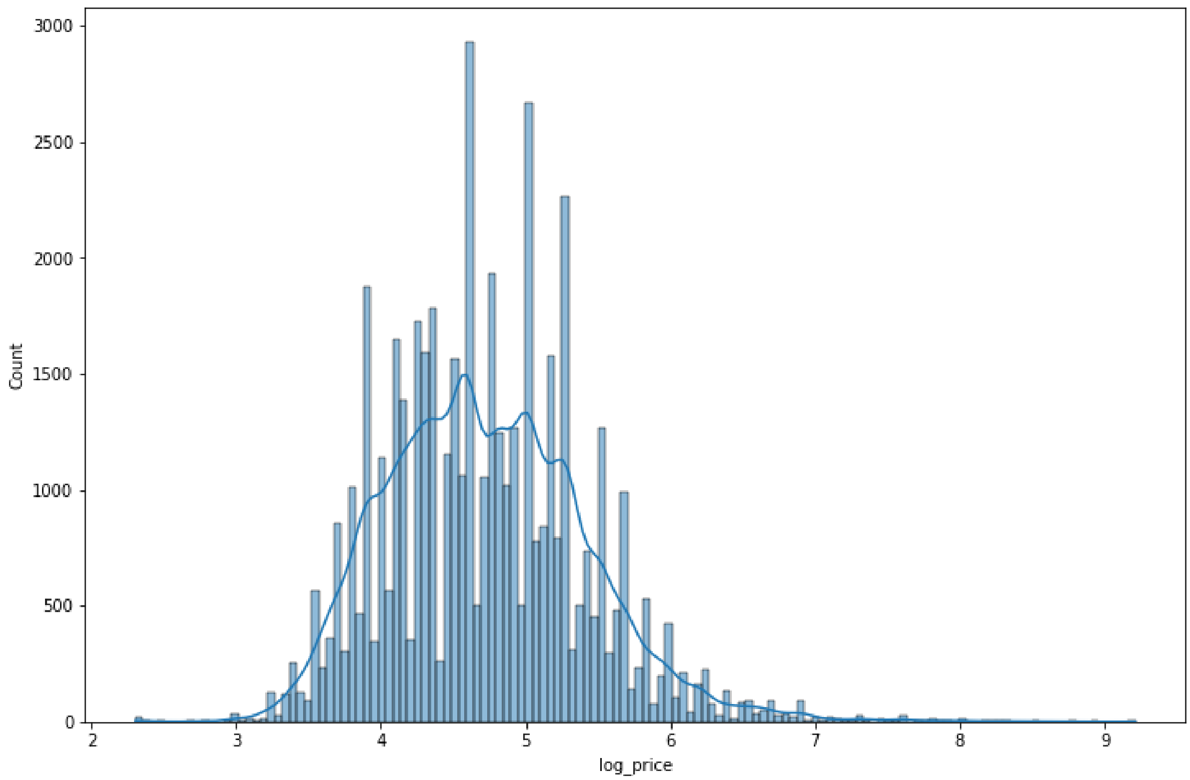



уже похоже на нормальное распределение

In [40]:
```
data['log_price'] = np.log(data['price'])
```

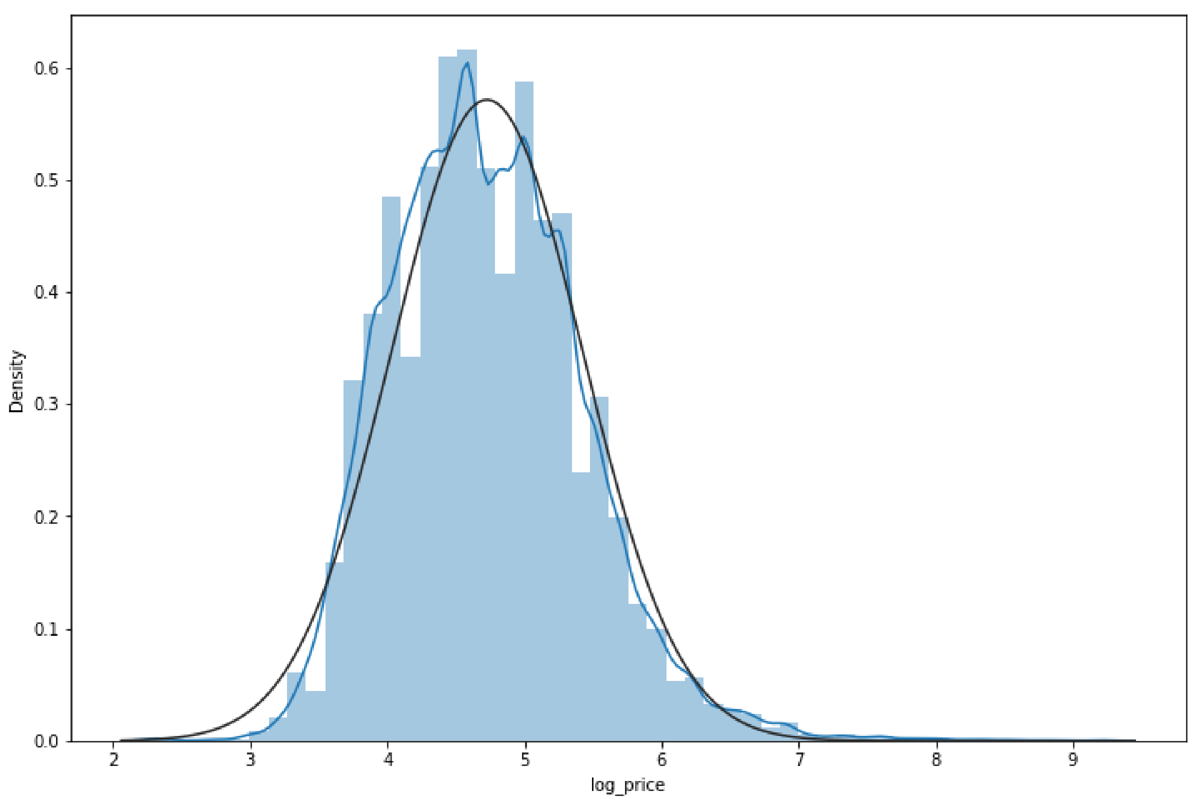
In [41]:
```
sns.histplot(data=data, x="log_price", kde=True)
```

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x2020de95d88>

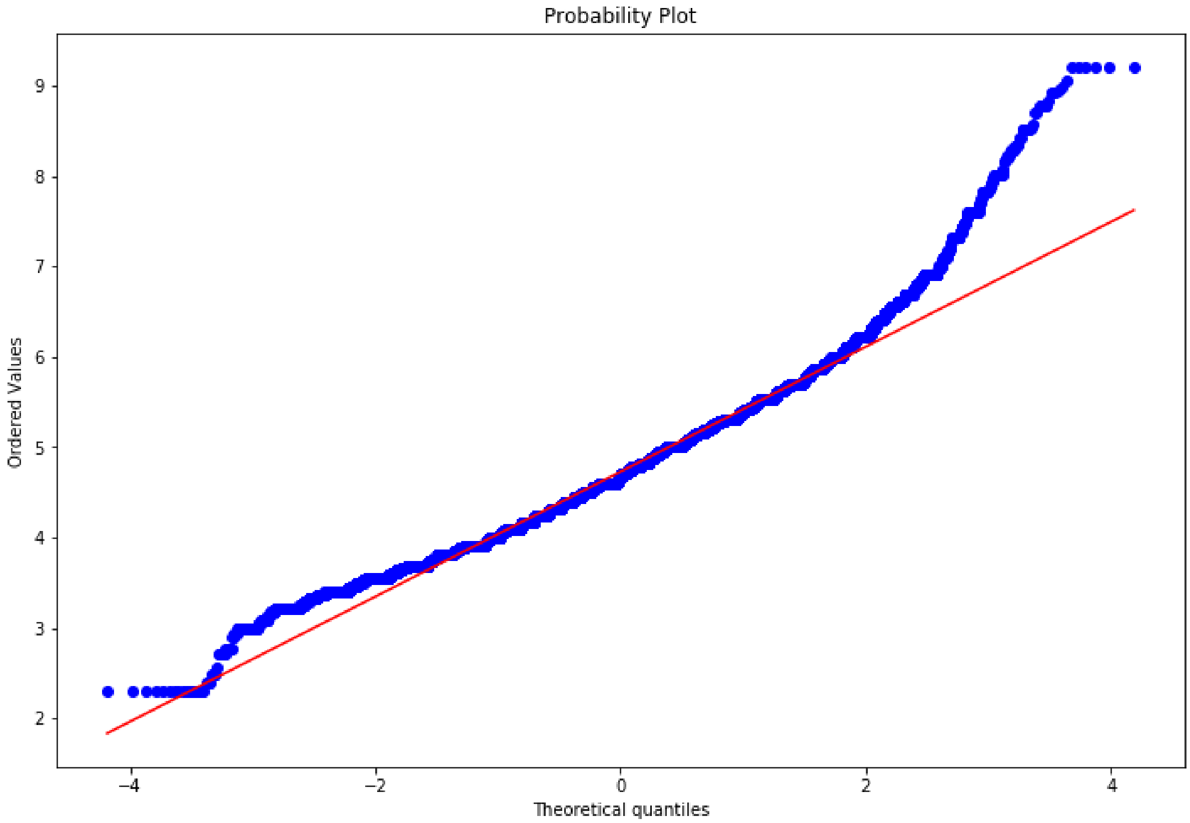



In [42]:
```
sns.distplot(data['log_price'], fit=norm)
```

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x2020e38f548>



In [43]:
```
stats.probplot(data['log_price'], plot=plt)
plt.show()
```




видим, что целевая переменная после логарифмирования распределена нормалоьно

# Часть 3. Моделирование и улучшение качества модели с помощью future ingenering (baseline, доп фичи)

функция для записи метрик качества

In [44]:
```
def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

def dataframe_metrics(y_test,y_pred):
    stats = [
       metrics.mean_absolute_error(y_test, y_pred),
       np.sqrt(metrics.mean_squared_error(y_test, y_pred)),
       metrics.r2_score(y_test, y_pred),
       mean_absolute_percentage_error(y_test, y_pred)
    ]
    return stats

measured_metrics = pd.DataFrame({"error_type":["MAE", "RMSE", "R2", "MAPE"]})
measured_metrics.set_index("error_type")
```

Out[44]:

| error_type |
|---|
| MAE |
| RMSE |
| R2 |
| MAPE |

## baseline (предсказания = median, mean)

In [45]:
```
data.columns.to_list()
```

Out[45]:
```
['neighbourhood',
 'latitude',
 'longitude',
 'price',
 'minimum_nights',
 'number_of_reviews',
 'reviews_per_month',
 'calculated_host_listings_count',
 'availability_365',
 'neighbourhood_group_Brooklyn',
 'neighbourhood_group_Manhattan',
 'neighbourhood_group_Queens',
 'neighbourhood_group_Staten Island',
 'neighbourhood_freq',
 'room_type_Private room',
 'room_type_Shared room',
 'reviews_per_month_random',
 'reviews_per_month_mean',
 'reviews_per_month_zero',
 'log_price']
```

In [46]:
```
X_train, X_test, y_train, y_test = train_test_split(
    data.drop(['price','log_price','neighbourhood','reviews_per_month','review
s_per_month_random','reviews_per_month_mean'], axis=1),
    data['log_price'],
    test_size=0.3
)
```

In [47]:
```
X_train.shape, X_test.shape
```

Out[47]: ((34218, 14), (14666, 14))

In [48]:
```
median_train = y_train.median()
mean_train = y_train.mean()
```

In [49]:
```
y_test_baseline_median = np.array([median_train]*len(y_test))
y_test_baseline_mean = np.array([mean_train]*len(y_test))
```

In [50]:
```
measured_metrics["baseline_median"] = dataframe_metrics(y_test, y_test_baselin
e_median)
measured_metrics["baseline_mean"] = dataframe_metrics(y_test, y_test_baseline_
mean)
measured_metrics
```

Out[50]:

| | error_type | baseline_median | baseline_mean |
|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 |
| **1** | RMSE | 0.701938 | 0.697842 |
| **2** | R2 | -0.011807 | -0.000032 |
| **3** | MAPE | 11.739620 | 11.942985 |

## baseline log_reg, lassoCV, rigeCV, elasticnet_CV

In [51]:
```
continuous_vars = [
  'latitude',
  'longitude',
  'minimum_nights',
 'number_of_reviews',
 'reviews_per_month_zero',
 'calculated_host_listings_count',
 'availability_365',
]
```

In [52]:
```
scaler = StandardScaler()
```

In [53]:
```
X_train[continuous_vars] = scaler.fit_transform(X_train[continuous_vars])
X_test[continuous_vars] = scaler.transform(X_test[continuous_vars])
```

In [54]:
```
X_train.head()
```

Out[54]:

| | latitude | longitude | minimum_nights | number_of_reviews | calculated_host_listings_count |
|---|---|---|---|---|---|
| **2610** | -0.743979 | 1.651368 | 1.041079 | 1.518163 | -0.094473 |
| **24625** | 0.182619 | -0.979271 | -0.250245 | 0.016914 | -0.186170 |
| **37480** | 1.704114 | -0.037515 | 1.140412 | -0.520847 | -0.155604 |
| **16803** | 0.455341 | 0.439858 | -0.200578 | 0.375421 | -0.155604 |
| **22886** | -0.619431 | 0.267095 | -0.250245 | 0.532268 | -0.186170 |

In [55]:
```
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
```

Out[55]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

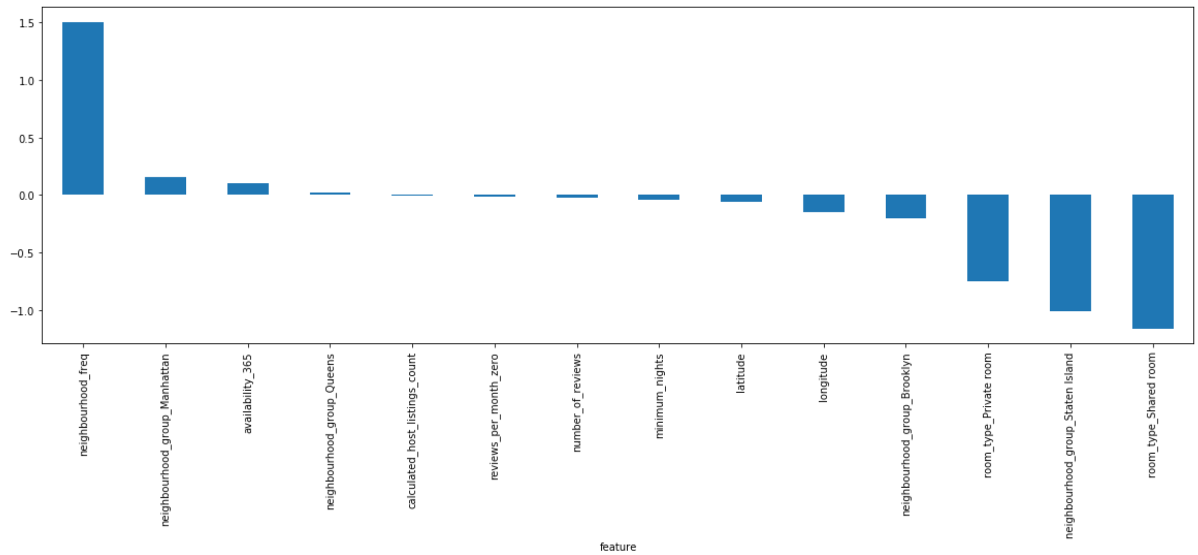
In [56]:
```
measured_metrics["lin_reg"] = dataframe_metrics(y_test, lin_reg.predict(X_test
))
measured_metrics
```

Out[56]:

| | error_type | baseline_median | baseline_mean | lin_reg |
|---|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 | 0.360964 |
| **1** | RMSE | 0.701938 | 0.697842 | 0.495772 |
| **2** | R2 | -0.011807 | -0.000032 | 0.495265 |
| **3** | MAPE | 11.739620 | 11.942985 | 7.628493 |

In [57]:
```
featureImportance = pd.DataFrame({"feature": X_train.columns,
                                  "importance": lin_reg.coef_})

featureImportance.set_index('feature', inplace=True)
featureImportance.sort_values(["importance"], ascending=False, inplace=True)
featureImportance["importance"].plot(kind = 'bar', figsize=(20, 6));
```



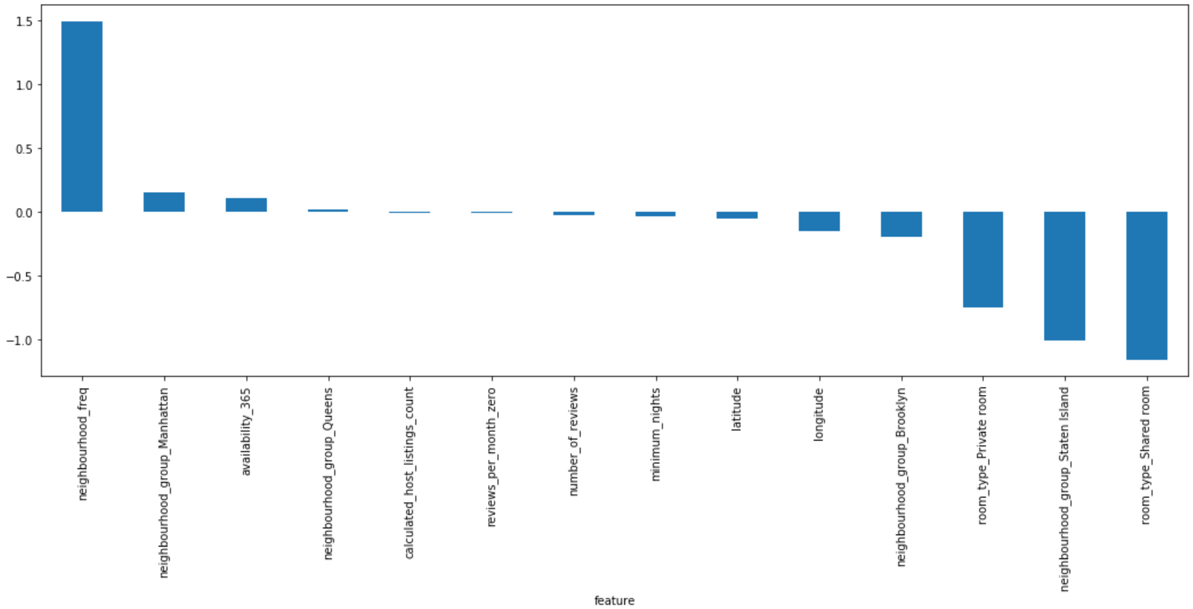

## Ridge CV

In [58]:
```
ridge_cv = RidgeCV()
ridge_cv.fit(X_train, y_train)
```

Out[58]:
```
RidgeCV(alphas=array([ 0.1,  1. , 10. ]), cv=None, fit_intercept=True,
        gcv_mode=None, normalize=False, scoring=None, store_cv_values=False)
```

In [59]:
```
featureImportance = pd.DataFrame({"feature": X_train.columns,
                                  "importance": ridge_cv.coef_})

featureImportance.set_index('feature', inplace=True)
featureImportance.sort_values(["importance"], ascending=False, inplace=True)
featureImportance["importance"].plot(kind = 'bar', figsize=(18, 6));
```




In [60]:
```
measured_metrics["ridge_cv"] = dataframe_metrics(y_test, ridge_cv.predict(X_te
st))
measured_metrics
```

Out[60]:

| | error_type | baseline_median | baseline_mean | lin_reg | ridge_cv |
|---|---|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 | 0.360964 | 0.360964 |
| **1** | RMSE | 0.701938 | 0.697842 | 0.495772 | 0.495773 |
| **2** | R2 | -0.011807 | -0.000032 | 0.495265 | 0.495262 |
| **3** | MAPE | 11.739620 | 11.942985 | 7.628493 | 7.628503 |

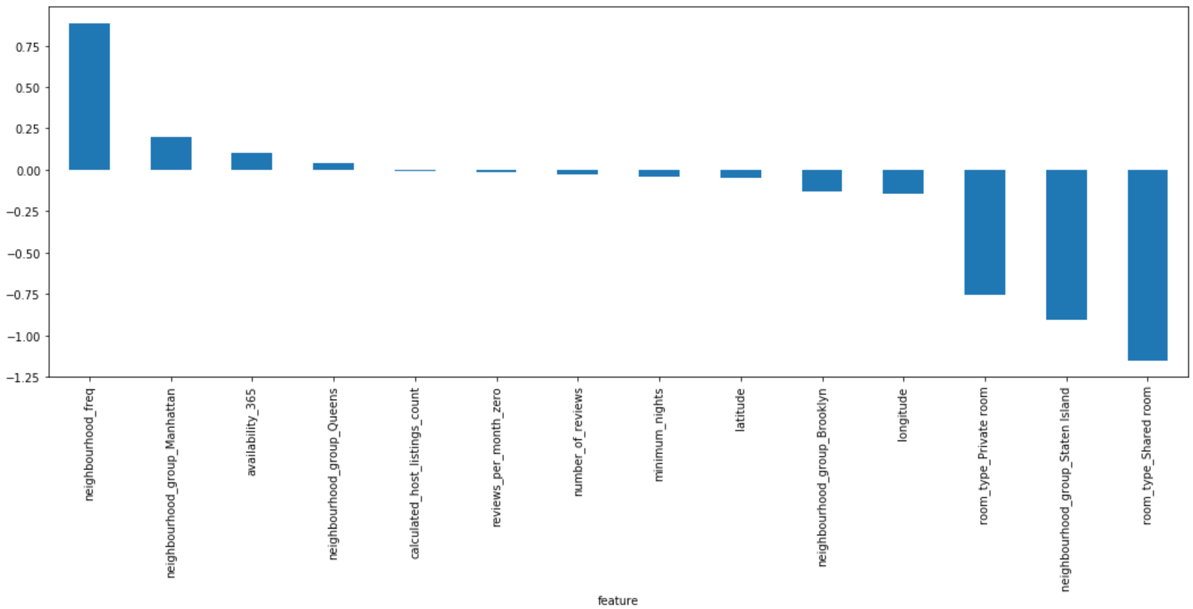
## Lasso CV

In [61]:
```
lasso_cv = LassoCV()
lasso_cv.fit(X_train, y_train)
```

Out[61]:
```
LassoCV(alphas=None, copy_X=True, cv='warn', eps=0.001, fit_intercept=True,
        max_iter=1000, n_alphas=100, n_jobs=None, normalize=False,
        positive=False, precompute='auto', random_state=None,
        selection='cyclic', tol=0.0001, verbose=False)
```

In [62]:
```
featureImportance = pd.DataFrame({"feature": X_train.columns[lasso_cv.coef_!=0
],
                                  "importance": lasso_cv.coef_[lasso_cv.coef_!
=0]})

featureImportance.set_index('feature', inplace=True)
featureImportance.sort_values(["importance"], ascending=False, inplace=True)
featureImportance["importance"].plot(kind = 'bar', figsize=(18, 6));
```




In [63]:
```
measured_metrics["lasso_cv"] = dataframe_metrics(y_test, lasso_cv.predict(X_te
st))
measured_metrics
```

Out[63]:

| | error_type | baseline_median | baseline_mean | lin_reg | ridge_cv | lasso_cv |
|---|---|---|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 | 0.360964 | 0.360964 | 0.361060 |
| **1** | RMSE | 0.701938 | 0.697842 | 0.495772 | 0.495773 | 0.495993 |
| **2** | R2 | -0.011807 | -0.000032 | 0.495265 | 0.495262 | 0.494815 |
| **3** | MAPE | 11.739620 | 11.942985 | 7.628493 | 7.628503 | 7.631662 |

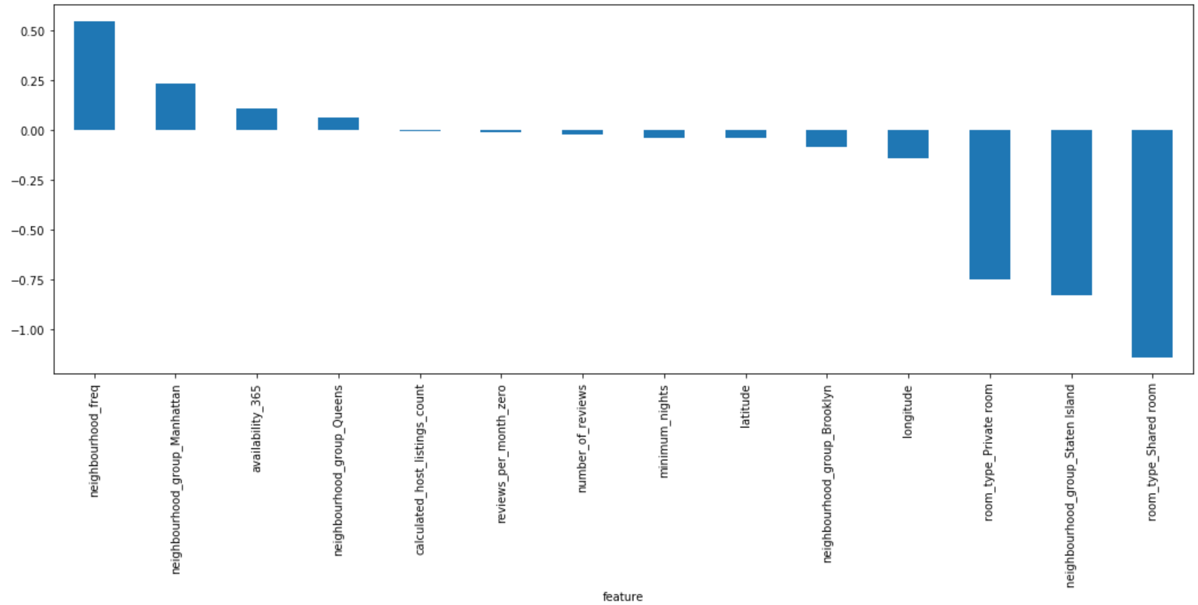
## ElasticNet CV

In [64]:
```
elastic_cv = ElasticNetCV()
elastic_cv.fit(X_train, y_train)
```

Out[64]:
```
ElasticNetCV(alphas=None, copy_X=True, cv='warn', eps=0.001, fit_intercept=Tr
ue,
             l1_ratio=0.5, max_iter=1000, n_alphas=100, n_jobs=None,
             normalize=False, positive=False, precompute='auto',
             random_state=None, selection='cyclic', tol=0.0001, verbose=0)
```

In [65]:
```
featureImportance = pd.DataFrame({"feature": X_train.columns[elastic_cv.coef_!
=0],
                                  "importance": elastic_cv.coef_[elastic_cv.co
ef_!=0]})

featureImportance.set_index('feature', inplace=True)
featureImportance.sort_values(["importance"], ascending=False, inplace=True)
featureImportance["importance"].plot(kind = 'bar', figsize=(18, 6));
```




In [66]:
```
measured_metrics["elastic_cv"] = dataframe_metrics(y_test, elastic_cv.predict(
X_test))
measured_metrics
```

Out[66]:

| | error_type | baseline_median | baseline_mean | lin_reg | ridge_cv | lasso_cv | elastic_cv |
|---|---|---|---|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 | 0.360964 | 0.360964 | 0.361060 | 0.361257 |
| **1** | RMSE | 0.701938 | 0.697842 | 0.495772 | 0.495773 | 0.495993 | 0.496253 |
| **2** | R2 | -0.011807 | -0.000032 | 0.495265 | 0.495262 | 0.494815 | 0.494284 |
| **3** | MAPE | 11.739620 | 11.942985 | 7.628493 | 7.628503 | 7.631662 | 7.636934 |

## улучшение модели (обработка latitude, longitude)

возьмем за центh нью-йорка - центр Central Park (40.782748, -73.965743), создадим новую фичу - расстояние от недвижимости до центра Central Park

In [67]:
```
data['dist_manh'] = np.sqrt((data['latitude']  - 40.782748)**2 + (data['longit
ude']-(-73.965743))**2)
```

In [68]:
```
data.head()
```

Out[68]:

| | neighbourhood | latitude | longitude | price | minimum_nights | number_of_reviews | reviews_per_ |
|---|---|---|---|---|---|---|---|
| **0** | Kensington | 40.64749 | -73.97237 | 149 | 1 | 9 | |
| **1** | Midtown | 40.75362 | -73.98377 | 225 | 1 | 45 | |
| **2** | Harlem | 40.80902 | -73.94190 | 150 | 3 | 0 | |
| **3** | Clinton Hill | 40.68514 | -73.95976 | 89 | 1 | 270 | |
| **4** | East Harlem | 40.79851 | -73.94399 | 80 | 10 | 9 | |

In [69]:
```
X_train, X_test, y_train, y_test = train_test_split(
    data.drop(['price','log_price','neighbourhood','latitude','longitude','rev
iews_per_month','reviews_per_month_random','reviews_per_month_mean'], axis=1),
    data['log_price'],
    test_size=0.3
)
continuous_vars = [
  'dist_manh',
  'minimum_nights',
 'number_of_reviews',
 'reviews_per_month_zero',
 'calculated_host_listings_count',
 'availability_365',
]
scaler = StandardScaler()
X_train[continuous_vars] = scaler.fit_transform(X_train[continuous_vars])
X_test[continuous_vars] = scaler.transform(X_test[continuous_vars])
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
ridge_cv = RidgeCV()
ridge_cv.fit(X_train, y_train)
lasso_cv = LassoCV()
lasso_cv.fit(X_train, y_train)
elastic_cv = ElasticNetCV()
elastic_cv.fit(X_train, y_train)
measured_metrics["lin_reg_manh_dist"] = dataframe_metrics(y_test, lin_reg.pred
ict(X_test))
measured_metrics["ridge_cv_manh_dist"] = dataframe_metrics(y_test, ridge_cv.pr
edict(X_test))
measured_metrics["lasso_cv_manh_dist"] = dataframe_metrics(y_test, lasso_cv.pr
edict(X_test))
measured_metrics
```

Out[69]:

| | error_type | baseline_median | baseline_mean | lin_reg | ridge_cv | lasso_cv | elastic_cv | lin_reg |
|---|---|---|---|---|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 | 0.360964 | 0.360964 | 0.361060 | 0.361257 | |
| **1** | RMSE | 0.701938 | 0.697842 | 0.495772 | 0.495773 | 0.495993 | 0.496253 | |
| **2** | R2 | -0.011807 | -0.000032 | 0.495265 | 0.495262 | 0.494815 | 0.494284 | |
| **3** | MAPE | 11.739620 | 11.942985 | 7.628493 | 7.628503 | 7.631662 | 7.636934 | |

новая фича не улучшила модель

## улучшение модели (обработка min_max_scaller)

In [70]:
```
X_train, X_test, y_train, y_test = train_test_split(
    data.drop(['price','log_price','neighbourhood','dist_manh','reviews_per_mo
nth','reviews_per_month_random','reviews_per_month_mean'], axis=1),
    data['log_price'],
    test_size=0.3
)
continuous_vars = [
  'latitude',
  'longitude',
  'minimum_nights',
 'number_of_reviews',
 'reviews_per_month_zero',
 'calculated_host_listings_count',
 'availability_365',
]
scaler = MinMaxScaler()
X_train[continuous_vars] = scaler.fit_transform(X_train[continuous_vars])
X_test[continuous_vars] = scaler.transform(X_test[continuous_vars])
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
ridge_cv = RidgeCV()
ridge_cv.fit(X_train, y_train)
lasso_cv = LassoCV()
lasso_cv.fit(X_train, y_train)
elastic_cv = ElasticNetCV()
elastic_cv.fit(X_train, y_train)
measured_metrics["lin_reg_minmax"] = dataframe_metrics(y_test, lin_reg.predict
(X_test))
measured_metrics["ridge_cv_minmax"] = dataframe_metrics(y_test, ridge_cv.predi
ct(X_test))
measured_metrics["lasso_cv_minmax"] = dataframe_metrics(y_test, lasso_cv.predi
ct(X_test))
measured_metrics
```

Out[70]:

| | error_type | baseline_median | baseline_mean | lin_reg | ridge_cv | lasso_cv | elastic_cv | lin_reg |
|---|---|---|---|---|---|---|---|---|
| 0 | MAE | 0.552621 | 0.553657 | 0.360964 | 0.360964 | 0.361060 | 0.361257 | |
| 1 | RMSE | 0.701938 | 0.697842 | 0.495772 | 0.495773 | 0.495993 | 0.496253 | |
| 2 | R2 | -0.011807 | -0.000032 | 0.495265 | 0.495262 | 0.494815 | 0.494284 | |
| 3 | MAPE | 11.739620 | 11.942985 | 7.628493 | 7.628503 | 7.631662 | 7.636934 | |

## улучшение модели robustscaller

In [71]:
```
X_train, X_test, y_train, y_test = train_test_split(
    data.drop(['price','log_price','neighbourhood','dist_manh','reviews_per_mo
nth','reviews_per_month_random','reviews_per_month_mean'], axis=1),
    data['log_price'],
    test_size=0.3
)
continuous_vars = [
  'latitude',
  'longitude',
  'minimum_nights',
 'number_of_reviews',
 'reviews_per_month_zero',
 'calculated_host_listings_count',
 'availability_365',
]
scaler = RobustScaler()
X_train[continuous_vars] = scaler.fit_transform(X_train[continuous_vars])
X_test[continuous_vars] = scaler.transform(X_test[continuous_vars])
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
ridge_cv = RidgeCV()
ridge_cv.fit(X_train, y_train)
lasso_cv = LassoCV()
lasso_cv.fit(X_train, y_train)
elastic_cv = ElasticNetCV()
elastic_cv.fit(X_train, y_train)
measured_metrics["lin_reg_robust"] = dataframe_metrics(y_test, lin_reg.predict
(X_test))
measured_metrics["ridge_cv_robust"] = dataframe_metrics(y_test, ridge_cv.predi
ct(X_test))
measured_metrics["lasso_cv_robust"] = dataframe_metrics(y_test, lasso_cv.predi
ct(X_test))
measured_metrics
```

Out[71]:

| | error_type | baseline_median | baseline_mean | lin_reg | ridge_cv | lasso_cv | elastic_cv | lin_reg |
|---|---|---|---|---|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 | 0.360964 | 0.360964 | 0.361060 | 0.361257 | |
| **1** | RMSE | 0.701938 | 0.697842 | 0.495772 | 0.495773 | 0.495993 | 0.496253 | |
| **2** | R2 | -0.011807 | -0.000032 | 0.495265 | 0.495262 | 0.494815 | 0.494284 | |
| **3** | MAPE | 11.739620 | 11.942985 | 7.628493 | 7.628503 | 7.631662 | 7.636934 | |

## улучшение модели (убираем фичу avaible_365)

In [72]:
```
X_train, X_test, y_train, y_test = train_test_split(
    data.drop(['availability_365','price','log_price','neighbourhood','dist_ma
nh','reviews_per_month','reviews_per_month_random','reviews_per_month_mean'],
axis=1),
    data['log_price'],
    test_size=0.3
)
continuous_vars = [
  'latitude',
  'longitude',
  'minimum_nights',
 'number_of_reviews',
 'reviews_per_month_zero',
 'calculated_host_listings_count',
]
scaler = RobustScaler()
X_train[continuous_vars] = scaler.fit_transform(X_train[continuous_vars])
X_test[continuous_vars] = scaler.transform(X_test[continuous_vars])
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
ridge_cv = RidgeCV()
ridge_cv.fit(X_train, y_train)
lasso_cv = LassoCV()
lasso_cv.fit(X_train, y_train)
elastic_cv = ElasticNetCV()
elastic_cv.fit(X_train, y_train)
measured_metrics["lin_reg_no_365"] = dataframe_metrics(y_test, lin_reg.predict
(X_test))
measured_metrics["ridge_cv_no_365"] = dataframe_metrics(y_test, ridge_cv.predi
ct(X_test))
measured_metrics["lasso_cv_no_365"] = dataframe_metrics(y_test, lasso_cv.predi
ct(X_test))
measured_metrics
```

Out[72]:

| | error_type | baseline_median | baseline_mean | lin_reg | ridge_cv | lasso_cv | elastic_cv | lin_reg |
|---|---|---|---|---|---|---|---|---|
| **0** | MAE | 0.552621 | 0.553657 | 0.360964 | 0.360964 | 0.361060 | 0.361257 | |
| **1** | RMSE | 0.701938 | 0.697842 | 0.495772 | 0.495773 | 0.495993 | 0.496253 | |
| **2** | R2 | -0.011807 | -0.000032 | 0.495265 | 0.495262 | 0.494815 | 0.494284 | |
| **3** | MAPE | 11.739620 | 11.942985 | 7.628493 | 7.628503 | 7.631662 | 7.636934 | |

## пробы random_forest

In [73]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [74]:
```
rf_reg = RandomForestRegressor(n_jobs=-1)
rf_reg.fit(X_train, y_train)

measured_metrics["rf_reg"] = dataframe_metrics(y_test, rf_reg.predict(X_test))
measured_metrics
```

Out[74]:

| :v_minmax | lin_reg_robust | ridge_cv_robust | lasso_cv_robust | lin_reg_no_365 | ridge_cv_no_365 | las: |
|---|---|---|---|---|---|---|
| 0.362994 | 0.360272 | 0.360274 | 0.363005 | 0.368039 | 0.368037 | |
| 0.499830 | 0.495004 | 0.495002 | 0.498898 | 0.510643 | 0.510640 | |
| 0.483971 | 0.495907 | 0.495912 | 0.487944 | 0.472819 | 0.472826 | |
| 7.677352 | 7.594587 | 7.594647 | 7.667996 | 7.689093 | 7.689060 | |

In [ ]: