

lnlzljliv

January 22, 2025

1 Projet Airbnb - WU Kylie

But du projet : prédire le logarithme du prix de location d'un Airbnb à partir d'un ensemble de caractéristiques.

1.0.1 Importation des bibliothèques

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

```
[2]: import plotly.express as px
import folium
import json

#from pandas.plotting import register_matplotlib_converters
#register_matplotlib_converters()
```

2 I. Partie exploration qualitative des données

2.0.1 1. Présentation de la base

```
[3]: # Chargement des données dans un dataframe Pandas
dataset = pd.read_csv("airbnb_train.csv", sep=",")

# Aperçu des données :
dataset.head()
```

```
[3]:      id  log_price property_type room_type \
0   5708593    4.317488         House  Private room
1  14483613    4.007333         House  Private room
2  10412649    7.090077    Apartment  Entire home/apt
3  17954362    3.555348         House  Private room
4   9969781    5.480639         House  Entire home/apt
```

	amenities	accommodates	bathrooms	\
0	{TV,"Wireless Internet",Kitchen,"Free parking ...	3	1.0	
1	{"Wireless Internet","Air conditioning",Kitche...	4	2.0	
2	{TV,"Wireless Internet","Air conditioning",Kit...	6	2.0	
3	{TV,"Cable TV",Internet,"Wireless Internet","A...	1	1.0	
4	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4	1.0	

	bed_type	cancellation_policy	cleaning_fee	...	last_review	latitude	\
0	Real Bed	flexible	False	...	NaN	33.782712	
1	Real Bed	strict	False	...	2017-09-17	40.705468	
2	Real Bed	flexible	False	...	NaN	38.917537	
3	Real Bed	flexible	True	...	2017-09-29	40.736001	
4	Real Bed	moderate	True	...	2017-08-28	37.744896	

	longitude	name	\
0	-118.134410	Island style Spa Studio	
1	-73.909439	Beautiful and Simple Room W/2 Beds, 25 Mins to...	
2	-77.031651	2br/2ba luxury condo perfect for infant / toddler	
3	-73.924248	Manhattan view from Queens. Lovely single room .	
4	-122.430665	Zen Captured Noe Valley House	

	neighbourhood	number_of_reviews	review_scores_rating	zipcode	bedrooms	\
0	Long Beach	0	NaN	90804	0.0	
1	Ridgewood	38	86.0	11385	1.0	
2	U Street Corridor	0	NaN	20009	2.0	
3	Sunnyside	19	96.0	11104	1.0	
4	Noe Valley	15	96.0	94131	2.0	

	beds
0	2.0
1	2.0
2	2.0
3	1.0
4	2.0

[5 rows x 28 columns]

```
[4]: # Informations supplémentaires :
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22234 entries, 0 to 22233
Data columns (total 28 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    22234 non-null  int64
1   log_price             22234 non-null  float64
```

```

2  property_type      22234 non-null object
3  room_type         22234 non-null object
4  amenities         22234 non-null object
5  accommodates      22234 non-null int64
6  bathrooms         22183 non-null float64
7  bed_type          22234 non-null object
8  cancellation_policy 22234 non-null object
9  cleaning_fee      22234 non-null bool
10 city              22234 non-null object
11 description        22234 non-null object
12 first_review       17509 non-null object
13 host_has_profile_pic 22178 non-null object
14 host_identity_verified 22178 non-null object
15 host_response_rate 16759 non-null object
16 host_since         22178 non-null object
17 instant_bookable   22234 non-null object
18 last_review        17518 non-null object
19 latitude           22234 non-null float64
20 longitude          22234 non-null float64
21 name              22234 non-null object
22 neighbourhood      20148 non-null object
23 number_of_reviews  22234 non-null int64
24 review_scores_rating 17256 non-null float64
25 zipcode            21931 non-null object
26 bedrooms           22208 non-null float64
27 beds              22199 non-null float64
dtypes: bool(1), float64(7), int64(3), object(17)
memory usage: 4.6+ MB

```

```
[5]: dataset.shape
```

```
[5]: (22234, 28)
```

Donc il y a 22233 offres étudiées et 28 caractéristiques initiales.

Les caractéristiques étudiées (intitulés des colonnes) :

```
[6]: print(dataset.columns)
```

```

Index(['id', 'log_price', 'property_type', 'room_type', 'amenities',
      'accommodates', 'bathrooms', 'bed_type', 'cancellation_policy',
      'cleaning_fee', 'city', 'description', 'first_review',
      'host_has_profile_pic', 'host_identity_verified', 'host_response_rate',
      'host_since', 'instant_bookable', 'last_review', 'latitude',
      'longitude', 'name', 'neighbourhood', 'number_of_reviews',
      'review_scores_rating', 'zipcode', 'bedrooms', 'beds'],
      dtype='object')

```

Je choisis de supprimer les colonnes suivantes : description, first_review, first_review,

host_has_profile_pic, host_identity_verified, host_response_rate, host_since, instant_bookable, last_review, name, number_of_reviews, review_scores_rating

car je trouve qu'elles n'influent pas principalement le prix, donc sont moins intéressantes pour travailler sur un dataset ayant des informations plus essentielles.

```
[7]: # Nouveau dataset :
df = dataset.drop(['description', 'first_review', 'host_has_profile_pic',
                  'host_identity_verified', 'host_response_rate', 'host_since',
                  'instant_bookable', 'last_review', 'name', 'number_of_reviews',
                  'review_scores_rating'], axis=1)
# Et j'ai remarqué qu'il y avait quelques 'NaN' (Not a Number) dans la colonne
↳ des zipcode
# donc je supprime ces lignes
df = df.dropna(subset=['zipcode'])
```

```
[8]: # Aperçu :
df.head()
```

```
[8]:
```

	id	log_price	property_type	room_type	\
0	5708593	4.317488	House	Private room	
1	14483613	4.007333	House	Private room	
2	10412649	7.090077	Apartment	Entire home/apt	
3	17954362	3.555348	House	Private room	
4	9969781	5.480639	House	Entire home/apt	

	amenities	accommodates	bathrooms	\
0	{TV,"Wireless Internet",Kitchen,"Free parking ...	3	1.0	
1	{"Wireless Internet","Air conditioning",Kitche...	4	2.0	
2	{TV,"Wireless Internet","Air conditioning",Kit...	6	2.0	
3	{TV,"Cable TV",Internet,"Wireless Internet","A...	1	1.0	
4	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4	1.0	

	bed_type	cancellation_policy	cleaning_fee	city	latitude	longitude	\
0	Real Bed	flexible	False	LA	33.782712	-118.134410	
1	Real Bed	strict	False	NYC	40.705468	-73.909439	
2	Real Bed	flexible	False	DC	38.917537	-77.031651	
3	Real Bed	flexible	True	NYC	40.736001	-73.924248	
4	Real Bed	moderate	True	SF	37.744896	-122.430665	

	neighbourhood	zipcode	bedrooms	beds
0	Long Beach	90804	0.0	2.0
1	Ridgewood	11385	1.0	2.0
2	U Street Corridor	20009	2.0	2.0
3	Sunnyside	11104	1.0	1.0
4	Noe Valley	94131	2.0	2.0

Les intitulés des colonnes sont désormais :

```
[9]: print(df.columns)
```

```
Index(['id', 'log_price', 'property_type', 'room_type', 'amenities',  
      'accommodates', 'bathrooms', 'bed_type', 'cancellation_policy',  
      'cleaning_fee', 'city', 'latitude', 'longitude', 'neighbourhood',  
      'zipcode', 'bedrooms', 'beds'],  
      dtype='object')
```

2.0.2 2. Exploration qualitative de la base (distribution des données, répartition)

Pour chacune des colonnes intéressantes, voyons les possibilités d'éléments présents :

```
[10]: print(df['property_type'].unique())
```

```
['House' 'Apartment' 'Townhouse' 'Guest suite' 'Condominium' 'Timeshare'  
 'Chalet' 'Guesthouse' 'Bungalow' 'Loft' 'In-law' 'Boat' 'Dorm' 'Other'  
 'Bed & Breakfast' 'Camper/RV' 'Villa' 'Boutique hotel' 'Cabin' 'Hostel'  
 'Hut' 'Yurt' 'Serviced apartment' 'Castle' 'Vacation home' 'Tent' 'Cave'  
 'Tipi' 'Earth House' 'Island' 'Treehouse']
```

```
[11]: print(df['room_type'].unique())
```

```
['Private room' 'Entire home/apt' 'Shared room']
```

```
[12]: print(df['amenities'].unique())
```

```
['{TV,"Wireless Internet",Kitchen,"Free parking on premises","Pets  
allowed","Suitable for events",Washer,Dryer,"Smoke  
detector",Essentials,Shampoo,"Lock on bedroom door",Hangers,"Hair dryer",Iron}'  
 '{"Wireless Internet","Air conditioning",Kitchen,Heating,"Family/kid  
friendly","Smoke detector","Carbon monoxide detector","Fire  
extinguisher",Essentials,"Lock on bedroom door","24-hour check-in","Hair  
dryer",Iron,"translation missing: en.hosting_amenity_50","Self Check-  
In",Keypad,"Bed linens",Microwave,"Coffee maker",Refrigerator,"Dishes and  
silverware","Cooking basics",Oven,Stove,"Luggage dropoff allowed"}'  
 '{TV,"Wireless Internet","Air conditioning",Kitchen,"Free parking on  
premises","Pets allowed","Elevator in building",Heating,"Family/kid  
friendly",Washer,Dryer,"Smoke detector","Carbon monoxide detector","First aid  
kit","Safety card","Fire extinguisher",Essentials,Shampoo,"Lock on bedroom  
door","Laptop friendly workspace"}'  
 ...  
 '{TV,Internet,"Wireless Internet","Air  
conditioning",Kitchen,Gym,Elevator,"Buzzet/wireless  
intercom",Heating,"Family/kid friendly",Washer,Dryer,"Smoke detector","Carbon  
monoxide detector","First aid kit",Essentials,Shampoo,Hangers,"Hair  
dryer",Iron,"Laptop friendly workspace","Hot water","Bed  
linens",Microwave,"Coffee maker",Refrigerator,Dishwasher,"Dishes and  
silverware","Cooking basics",Oven,Stove}']
```

```
{TV,"Wireless Internet","Air conditioning",Kitchen,Heating,Washer,Dryer,"Smoke detector","Carbon monoxide detector",Essentials,Shampoo,Hangers,"Hair dryer",Iron,"Laptop friendly workspace"}
```

```
{TV,Internet,"Wireless Internet",Kitchen,"Free parking on premises",Heating,"Family/kid friendly","Smoke detector","Carbon monoxide detector","First aid kit","Safety card","Fire extinguisher",Essentials,Shampoo,"24-hour check-in",Hangers,"Hair dryer","Laptop friendly workspace"}
```

Il serait intéressant d'extraire des termes d'équipements, pour voir s'ils réapparaissent dans d'autres descriptions (a priori plus il y en a, plus le prix sera élevé) :

```
[13]: import re

# Fonction pour enlever les guillemets, accolades et crochets
def remove_caracteres(s):
    return re.sub(r'["'\{\}\[\]]', '', s)

# On applique remove_caracteres
amenities_separés = df['amenities'].apply(lambda x: [remove_caracteres(item.strip()) for item in str(x).split(',')])

# Garder les éléments uniques
amenities_bis = [item for sublist in amenities_separés for item in sublist]
uniques_amenities = list(set(amenities_bis))

print(uniques_amenities)
```

```
['Waterfront', '', 'Smoke detector', 'Luggage dropoff allowed', 'Cooking basics', 'Paid parking off premises', 'Iron', 'Path to entrance lit at night', 'Doorman', 'Ground floor access', 'Crib', 'Single level home', 'Private living room', 'Host greets you', 'Wheelchair accessible', 'Indoor fireplace', 'Air conditioning', 'Fixed grab bars for shower & toilet', 'Cleaning before checkout', 'Hot water kettle', 'Lake access', 'TV', 'Smart lock', 'Wide entryway', 'Extra pillows and blankets', 'Dryer', 'Other pet(s)', 'Family/kid friendly', 'Lock on bedroom door', 'Beachfront', 'Patio or balcony', 'Pets allowed', 'Kitchen', 'Shampoo', 'Pocket wifi', 'Buzzer/wireless intercom', 'Fireplace guards', 'Handheld shower head', 'Smartlock', 'Ski in/Ski out', 'Roll-in shower with chair', 'Wide doorway', 'Cable TV', 'Smoking allowed', 'Coffee maker', 'Pack 'n Play/travel crib', 'Carbon monoxide detector', 'Wide hallway clearance', 'Window guards', 'Washer / Dryer', 'Garden or backyard', 'Free parking on street', 'Hangers', 'Ethernet connection', 'Dog(s)', 'Pool', 'Laptop friendly workspace', 'EV charger', 'Cat(s)', 'Grab-rails for shower and toilet', 'Flat smooth pathway to front door', 'Children's dinnerware', 'smooth pathway to front door', 'Bathtub with shower chair', 'Hair dryer', 'Private bathroom', 'Suitable for events', 'Well-lit path to entrance', 'Baby bath', 'Microwave', 'Bathtub', 'Gym', 'Stove', 'Table corner guards', 'Washer', 'Wide clearance to bed', 'Free parking on premises', 'Pets live on this property',
```

```
'Hot tub', 'Stair gates', 'Flat', 'Essentials', 'BBQ grill', 'Private entrance',
'First aid kit', 'Safety card', 'Elevator in building', 'Self Check-In', 'Step-
free access', 'Doorman Entry', 'Changing table', 'Firm mattress', 'Dishwasher',
'translation missing: en.hosting_amenity_49', 'Lockbox', 'Accessible-height
bed', 'Keypad', '24-hour check-in', 'Heating', 'Refrigerator', 'Outlet covers',
'Wide clearance to shower & toilet', 'Hot water', 'Beach essentials', 'High
chair', 'Wireless Internet', 'Baby monitor', 'Fire extinguisher', 'Dishes and
silverware', 'Breakfast', 'translation missing: en.hosting_amenity_50', 'Room-
darkening shades', 'Disabled parking spot', 'Long term stays allowed', 'Game
console', 'Children's books and toys', 'Bed linens', 'Elevator', 'Oven', 'Air
purifier', 'Babysitter recommendations', 'Internet', 'Accessible-height toilet',
'Firm mattress', 'Other']
```

```
[14]: print(df['accommodates'].unique())
```

```
[ 3  4  6  1  2 10  7  5 16  8  9 14 12 15 13 11]
```

```
[15]: print(df['bathrooms'].unique())
```

```
[1.  2.  3.5 1.5 3.  2.5 0.  nan 5.  4.  6.5 0.5 5.5 6.  7.  4.5 8.  7.5]
```

A priori plus il y a de salles de bains, plus le prix sera élevé.

```
[16]: # Afficher les lignes où il y a 5 salles de bain.
lignes_avec_5_salles_de_bain = df.loc[df['bathrooms'] == 5., :]
print(lignes_avec_5_salles_de_bain)
```

	id	log_price	property_type	room_type \
503	17257473	6.907755	House	Entire home/apt
1696	18053971	6.678342	House	Entire home/apt
1972	20978478	6.476972	House	Entire home/apt
5237	20761244	4.488636	Apartment	Shared room
8293	15939618	5.796058	Apartment	Entire home/apt
8902	16618193	6.579251	House	Entire home/apt
11146	13216537	4.553877	Hostel	Private room
12698	386966	6.204558	House	Entire home/apt
13286	4092283	6.684612	House	Entire home/apt
15449	3293695	4.094345	Apartment	Private room
16000	19820146	6.212606	House	Entire home/apt
18246	14426987	6.652863	House	Entire home/apt
18254	2500560	6.745236	House	Entire home/apt
20839	20827821	6.476972	House	Entire home/apt
20967	13698365	6.684612	House	Entire home/apt
21171	19213967	6.023448	Apartment	Entire home/apt
21419	15484888	7.166266	House	Entire home/apt
22154	19296720	6.907755	Villa	Entire home/apt

	amenities	accommodates \
503	{TV,"Cable TV",Internet,"Wireless Internet","A...	10

1696	{TV,"Cable TV",Internet,"Wireless Internet","A...	16
1972	{TV,"Cable TV",Internet,"Wireless Internet",Po...	10
5237	{TV,Internet,"Wireless Internet","Air conditio...	2
8293	{TV,"Cable TV","Wireless Internet","Air condit...	14
8902	{TV,Internet,"Wireless Internet",Kitchen,"Free...	9
11146	{TV,"Cable TV",Internet,"Wireless Internet","A...	2
12698	{TV,"Cable TV",Internet,"Wireless Internet","A...	16
13286	{TV,"Cable TV",Internet,"Wireless Internet","A...	16
15449	{TV,"Wireless Internet","Air conditioning",Kit...	2
16000	{TV,"Cable TV",Internet,"Wireless Internet","A...	16
18246	{TV,"Wireless Internet","Air conditioning",Poo...	8
18254	{TV,"Cable TV",Internet,"Wireless Internet","A...	8
20839	{TV,Internet,"Wireless Internet","Air conditio...	15
20967	{TV,"Cable TV",Internet,"Wireless Internet","A...	6
21171	{TV,"Cable TV",Internet,"Wireless Internet","A...	9
21419	{TV,"Cable TV",Internet,"Wireless Internet","A...	16
22154	{TV,"Cable TV",Internet,"Wireless Internet","A...	8

	bathrooms	bed_type	cancellation_policy	cleaning_fee	city \
503	5.0	Real Bed	strict	True	LA
1696	5.0	Real Bed	strict	True	LA
1972	5.0	Real Bed	flexible	False	LA
5237	5.0	Real Bed	flexible	True	NYC
8293	5.0	Real Bed	flexible	True	LA
8902	5.0	Real Bed	strict	True	LA
11146	5.0	Real Bed	strict	False	Boston
12698	5.0	Real Bed	strict	True	DC
13286	5.0	Real Bed	strict	True	NYC
15449	5.0	Real Bed	strict	False	NYC
16000	5.0	Real Bed	strict	True	NYC
18246	5.0	Real Bed	strict	True	LA
18254	5.0	Real Bed	strict	True	LA
20839	5.0	Real Bed	strict	True	LA
20967	5.0	Real Bed	strict	True	NYC
21171	5.0	Real Bed	flexible	False	NYC
21419	5.0	Real Bed	strict	True	LA
22154	5.0	Real Bed	strict	True	LA

	latitude	longitude	neighbourhood	zipcode	bedrooms	beds
503	34.114527	-118.581026	Topanga	90290	5.0	10.0
1696	34.130161	-118.363875	NaN	90068	5.0	16.0
1972	33.879094	-118.391052	Manhattan Beach	90266	5.0	5.0
5237	40.853222	-73.935631	Washington Heights	10033	1.0	1.0
8293	34.067207	-118.449054	Westwood	90024	5.0	11.0
8902	33.992222	-118.456121	Venice	90291	5.0	5.0
11146	42.336059	-71.045924	South Boston	02127	1.0	1.0
12698	38.939301	-77.018718	Petworth	20011	4.0	4.0
13286	40.684922	-73.954891	Bedford-Stuyvesant	11216	8.0	18.0

15449	40.693242	-73.921260	Bushwick	11221	1.0	1.0
16000	40.715211	-73.946142	Williamsburg	11211.0	8.0	11.0
18246	34.013029	-118.446103	Mar Vista	90066	4.0	4.0
18254	34.129597	-118.341948	Hollywood Hills	90068	4.0	4.0
20839	34.078944	-118.374199	Mid-Wilshire	90048	4.0	4.0
20967	40.782690	-73.983902	Upper West Side	10023	4.0	6.0
21171	40.683663	-73.941006	Bedford-Stuyvesant	11216	5.0	5.0
21419	34.097976	-118.426247	Bel Air/Beverly Crest	90210	5.0	5.0
22154	34.115600	-118.296714	Hollywood Hills	90027	5.0	5.0

```
[17]: print(df['bed_type'].unique())
```

```
['Real Bed' 'Pull-out Sofa' 'Futon' 'Airbed' 'Couch']
```

```
[18]: print(df['cancellation_policy'].unique())
```

```
['flexible' 'strict' 'moderate' 'super_strict_30' 'super_strict_60']
```

```
[19]: print(df['cleaning_fee'].unique())
```

```
[False True]
```

S'il y a des frais de ménage, le prix sera plus élevé.

```
[20]: print(df['city'].unique())
```

```
['LA' 'NYC' 'DC' 'SF' 'Chicago' 'Boston']
```

```
[21]: print(df['latitude'].unique())
```

```
[33.78271155 40.70546839 38.91753651 ... 40.70674885 40.73853473
 33.76109645]
```

```
[22]: print(df['neighbourhood'].unique())
```

```
['Long Beach' 'Ridgewood' 'U Street Corridor' 'Sunnyside' 'Noe Valley'
 'West Village' 'Harlem' 'Flushing' 'Westside' 'Upper West Side'
 'Shepherd Park' 'Santa Monica' 'Mission District' 'Murray Hill' nan
 'Chinatown' 'Echo Park' 'Hamilton Heights' 'Mar Vista' 'Encino'
 'Kips Bay' 'Williamsburg' 'West Hollywood' 'Carroll Gardens' 'Downtown'
 'Bedford-Stuyvesant' 'Wicker Park' 'Hell's Kitchen' 'Upper East Side'
 'Pasadena' 'Shaw' 'Greenpoint' 'Jackson Heights' 'Clinton Hill'
 'Tompkinsville' 'Torrance' 'Beverly Hills' 'Midtown' 'Financial District'
 'Fort Greene' 'Pacific Heights' 'Mid-City' 'Chelsea' 'Venice'
 'Crown Heights' 'South LA' 'Bushwick' 'Parkchester' 'Glendale'
 'Columbia Street Waterfront' 'East Flatbush' 'Western Addition/NOPA'
 'Hollywood' 'East Village' 'Lower East Side' 'Nolita' 'East Elmhurst'
 'Soho' 'The Rockaways' 'Beacon Hill' 'Forest Hills' 'Chevy Chase'
 'Flatbush' 'Lefferts Garden' 'Park Slope' 'East Harlem' 'Compton']
```

'Glover Park' 'Cahuenga Pass' 'East Hollywood' 'Trinidad' 'Elmhurst'
 'Westwood' 'Astoria' 'Southwest Waterfront'
 'Near Northeast/H Street Corridor' 'Mount Vernon Square'
 'Downtown/Penn Quarter' 'Back Bay' 'Silver Lake' 'Nob Hill' 'Whittier'
 'Mid-Wilshire' 'Richmond District' 'Inglewood' 'Granada Hills North'
 'Coney Island' 'Russian Hill' 'Westlake' 'Jamaica Plain'
 'Ditmars / Steinway' 'Midtown East' 'Capitol Hill' 'Monterey Park'
 'East Boston' 'Westchester/Playa Del Rey' 'Sunset Park' 'Alphabet City'
 'Mattapan' 'Cole Valley' 'Charlestown' 'Fenway/Kenmore' 'Gramercy Park'
 'South Beach' 'West End' 'The Castro' 'Telegraph Hill' 'Sheepshead Bay'
 'Greenwich Village' 'Washington Heights' 'Toluca Lake' 'Bucktown'
 'Jamaica' 'Outer Sunset' 'Eastchester' 'Georgetown' '16th Street Heights'
 'Little Italy/UIC' 'Morningside Heights' 'South Boston' 'Adams Morgan'
 'Cleveland Park' 'Near North Side' 'Roscoe Village' 'Cathedral Heights'
 'South Loop/Printers Row' 'Humboldt Park' 'Studio City' 'North End'
 'Los Feliz' 'Malibu' 'Ukrainian Village' 'Hyde Park' 'Avondale'
 'North Hollywood' 'South Shore' 'Inner Sunset' 'Hermosa Beach' 'Cerritos'
 'Eckington' 'Roslindale' 'Lower Haight' 'Prospect Heights' 'South End'
 'Burbank' 'Hollywood Hills' 'Arcadia' 'Sherman Oaks' 'Bernal Heights'
 'St. Elizabeths' 'Palisades' 'Borough Park' 'Flatiron District'
 'Brighton Beach' 'Gowanus' 'Pilsen' 'Manhattan Beach' 'Duboce Triangle'
 'West Los Angeles' 'West Hills' 'El Segundo' 'Roxbury' 'Van Nuys'
 'Columbia Heights' 'Bloomington' 'Park View' 'Midwood' 'Lakeview'
 'Logan Circle' 'Pleasant Plains' 'West Adams' 'Brentwood' 'Kensington'
 'Arts District' 'Palms' 'Gardenia' 'Bayview' 'South Chicago'
 'Magnificent Mile' 'Woodridge' 'Haight-Ashbury' 'Redondo Beach' 'Topanga'
 'Lawndale' 'Loop' 'Edgewood' 'Dorchester' 'Dogpatch' 'Carson'
 'Windsor Terrace' 'Kingsbridge Heights' 'Corona' 'Downtown Brooklyn'
 'Irving Park' 'Rogers Park' 'Bronzeville' 'Glen Park' 'South Pasadena'
 'Fisherman's Wharf' 'SoMa' 'Hermosa' 'Valley Village' 'Woodside'
 'Altadena' 'River North' 'Logan Square' 'Judiciary Square'
 'Greenwood Heights' 'Allston-Brighton' 'South Street Seaport'
 'Manor Park' 'Marina Del Rey' 'Alhambra' 'Anacostia' 'Alamo Square'
 'Woodland Hills/Warner Center' 'Foggy Bottom' 'Twin Peaks'
 'Andersonville' 'Del Rey' 'Richmond Hill' 'Tarzana' 'Tottenville'
 'Truxton Circle' 'Bel Air/Beverly Crest' 'Congress Heights'
 'Mount Pleasant' 'Bayside' 'Lynwood' 'Barney Circle' 'Oakland'
 'Bridgeport' 'Reseda' 'Fresh Meadows' 'Morris Heights' 'Twining'
 'Boerum Hill' 'Monterey Hills' 'Fairlawn' 'Pacific Palisades'
 'San Gabriel' 'West Town/Noble Square' 'Harbor Gateway' 'Canarsie'
 'Dupont Circle' 'Crotona' 'West Farms' 'Old Town' 'West Loop/Greektown'
 'Brookland' 'Uptown' 'Brooklyn' 'Brooklyn Heights' 'Brooklyn Navy Yard'
 'Gravesend' 'Concourse Village' 'Woodley Park' 'Ingleside'
 'Times Square/Theatre District' 'Parkside' 'Atwater Village'
 'Boyle Heights' 'Laurel Canyon' 'Concourse' 'Fordham' 'Red Hook'
 'Kalorama' 'Arboretum' 'Roosevelt Island' 'Lomita' 'Temple City'
 'Montecito Heights' 'Hayes Valley' 'Crestwood' 'Mission Hill'
 'Cow Hollow' 'Sun Valley' 'Lake Balboa' 'Highland Park'

'Mount Washington' 'Petworth' 'Lindenwood' 'Takoma' 'Bensonhurst'
'South Robertson' 'West Ridge' 'Kenwood' 'Tribeca' 'Mission Terrace'
'Hawthorne' 'Potrero Hill' 'Castle Hill' 'Winnetka' 'Valley Glen'
'East New York' 'San Pedro' 'Inwood' 'Kent' 'Cobble Hill'
'Long Island City' 'Brownsville' 'Little Village' 'Wakefield'
'Buena Vista' 'North Cleveland Park' 'Lincoln Park' 'Kingsbridge'
'El Sereno' 'Park Versailles' 'Crocker Amazon' 'Union Square'
'Michigan Park' 'Morrisania' 'La Crescenta-Montrose' 'Noho' 'Culver City'
'Baldwin Hills' 'Lincoln Heights' 'Bay Ridge' 'Duarte' 'Panorama City'
'Forest Hill' 'Port Morris' 'Sunland/Tujunga'
'Central Northeast/Mahoning Heights' 'Middle Village' 'Van Nest'
'Meatpacking District' 'Burleith' 'Hillbrook' 'Benning Ridge' 'Woodland'
'LeDroit Park' 'Baychester' 'Oceanview' 'West Covina' 'Lakeshore'
'University Heights' 'Maspeth' 'Mott Haven' 'Belmont' 'Deanwood' 'Marina'
'North Beach' 'Tenderloin' 'Civic Center' 'Balboa Terrace'
'New Dorp Beach' 'Norwood Park' 'Skid Row' 'Flatlands' 'Northridge'
'West Portal' 'Glassell Park' 'Albany Park' 'North Hills West'
'West Brighton' 'Meiers Corners' 'Allerton' 'Azusa' 'Downtown Crossing'
'Rosemead' 'Canoga Park' 'Gold Coast' 'Edgewater' 'Takoma Park, MD'
'Mt Rainier/Brentwood, MD' 'North Park' 'Palos Verdes'
'Washington Highlands' 'Glendora' 'Fort Davis' 'Bedford Park'
'Colonial Village' 'Lakewood' 'American University Park'
'South Ozone Park' 'Diamond Heights' 'Battery Park City' 'Lamond Riggs'
'Portage Park' 'Hudson Square' 'Silver Spring, MD' 'Streeterville'
'Navy Yard' 'Co-op City' 'West Puente Valley' 'Rego Park' 'West Roxbury'
'City Island' 'Eagle Rock' 'Bellflower' 'Theater District' 'Downey'
'North Center' 'Riverdale' 'Pleasant Hill' 'Dyker Heights' 'Arleta'
'Cypress Park' 'Woodlawn' 'Excelsior' 'Visitacion Valley' 'Kingman Park'
'Monrovia' 'Great Kills' 'Williamsbridge' 'Norwood' 'Morgan Park'
'Portola' 'River West' 'Near Northeast' 'Mission Bay' 'Armour Square'
'South Whittier' 'Elysian Valley' 'Marine Park' 'Woodhaven'
'Harvard Square' 'The Bronx' 'Tremont' 'Sierra Madre' 'Jefferson Park'
'Dunning' 'East San Gabriel' 'Boystown' 'Presidio Heights' 'Howard Beach'
'La Mirada' 'Soundview' 'Beverly' 'Melrose' 'Carver Langston' 'El Monte'
'Bronxdale' 'Rancho Palos Verdes' 'Ozone Park' 'Garfield Park'
'Little Italy' 'Chatsworth' 'McKinley Park' 'Claremont' 'Naylor Gardens'
'Pico Rivera' 'Douglass' 'Montebello' 'Manhattan' 'Lincoln Square'
'Signal Hill' 'Watts' 'Florence-Graham' 'Brightwood' 'Midland Beach'
'Pelham Bay' 'Sylmar' 'Near West Side' 'Eltingville' 'College Point'
'Wrigleyville' 'Hermon' 'St. George' 'Randall Manor' 'Highbridge'
'Belmont Cragin' 'DUMBO' 'East Los Angeles' 'Kew Garden Hills'
'Santa Fe Springs' 'Huguenot' 'Dupont Park' 'Mount Eden' 'Englewood'
'Covina' 'Bergen Beach' 'New Brighton' 'Hunts Point' 'River Terrace'
'Foxhall' 'Benning' 'La Canada Flintridge' 'Hillcrest' 'Garfield Ridge'
'Stronghold' 'Norwalk' 'Westchester Village' 'San Marino' 'Daly City'
'East Corner' 'Presidio' 'Stapleton' 'Back of the Yards' 'Roseland'
'North Michigan Park' 'West Lawn' 'Ivy City' 'Chestnut Hill' 'Japantown'
'Sea Gate' 'Commerce' 'Throgs Neck' 'Fort Lincoln' 'North Lawndale'

'Austin' 'Wesley Heights' 'Randle Highlands' 'La Puente' 'Good Hope'
 'Somerville' 'Winthrop' 'Porter Ranch' 'Longwood' 'Berkley'
 'Fort Wadsworth' 'Elm Park' 'Marshall Heights' 'South El Monte'
 'Eastland Gardens' 'Vinegar Hill' 'Whitestone' 'Rosebank' 'Langdon'
 'Sea Cliff' 'Grymes Hill' 'Montclare' 'Marble Hill' 'Bath Beach'
 'Harbor City' 'Bell' 'Spuyten Duyvil' 'Brookline' 'Bellevue' 'Newton'
 'Watertown' 'West Athens' 'Huntington Park' 'O'Hare' 'Grasmere' 'Pacoima'
 'Edenwald' 'South San Gabriel' 'Gerritsen Beach' 'Rossville' 'Greenway'
 'Westmont' 'Port Richmond' 'La Habra' 'Leather District' 'Irwindale'
 'Rolling Hills' 'Grant City' 'Baldwin Park' 'South Gate'
 'Hawaiian Gardens' 'North Hills East' 'Friendship Heights' 'Paramount'
 'Bradbury' 'Spring Valley']

```
[23]: print(df['zipcode'].unique())
```

```
['90804' '11385' '20009' '11104' '94131' '10014' '10027' '11355' '90064'
 '10024' '20002' '90404' '94110' '10016' '60657' '02111' '90026' '10031'
 '90066' '90405' '10002' '90094' '91316' '11211.0' '90046' '11231.0'
 '94109' '11221' '91601' '60622' '11249.0' '10019' '10065' '60642' '91105'
 '20001' '11222' '11370.0' '11378' '11205.0' '11233' '10128' '10301'
 '90278' '11206.0' '90048' '10026' '10038' '11205' '90019' '90403'
 '10001.0' '90291' '11225.0' '90015' '11237' '90212' '94108' '10462'
 '91207' '11216' '11212.0' '94117' '90028' '60608' '90815' '11213.0'
 '10003.0' '11207' '10012' '11369.0' '10021' '11216.0' '11693' '10018'
 '02114' '90006' '20008' '20015' '11226' '11225' '11215' '10029.0' '90222'
 '20007' '90068' '90029' '11238.0' '11377' '91101' '90024' '11106' '20024'
 '90016' '11103' '90005' '20005' '02116' '10028' '10025' '91302' '91364'
 '20032' '90039' '11206' '94133' '11237.0' '90601' '60601' '90036' '94118'
 '91766' '10011.0' '90301' '94103' '91344' '94115' '11224' '10075' '20011'
 '90021' '02130' '11105' '90065' '90049' '10022' '20003' '90069' '91754'
 '02128' '90293' '11220' '10001' '10009.0' '02126' '11372' '10010'
 '10002.0' '10023' '02129' '02215' '60626' '10003' '90604' '10035.0'
 '94105' '90249' '94114' '11235' '91790' '10011' '10040' '10036' '91602'
 '11238' '90035' '11422' '94122' '10032' '10469' '60612' '11232' '90014'
 '02210' '90018' '60610' '10013.0' '60618' '60616' '60647' '91423' '02113'
 '02108' '90027' '90265' '60637' '11692' '94121' '91605' '60649' '90254'
 '90703' '11102' '02131' '11101' '02118' '91205' '90023' '10017' '91506'
 '91007' '20010' '20016' '11204' '90025' '91307' '90245' '90803' '02119'
 '91405' '10013' '11230' '02127' '91748' '91107' '91745' '11233.0' '60613'
 '90007' '11211' '11218' '90012' '90034' '10039' '94124' '60617' '90038'
 '60611' '90277' '20018' '90290' '60625' '90260' '60605' '90502' '60641'
 '02125' '90247' '10004' '94107' '90746' '11217' '10463' '91010' '11368'
 '60654' '90808' '90004' '60653' '91301' '90802' '91030' '91502' '90020'
 '90302' '94123' '90650' '91776' '91006' '02124' '91001' '90814' '02134'
 '94115.0' '60607' '90813' '90292' '91803' '20020' '11375' '20037' '60640'
 '11222.0' '11418' '91356' '10307.0' '91403' '90810' '90077' '91767'
 '11364' '94102' '10037.0' '90262' '60609' '91335' '11365' '10453' '90266'
 '10033' '91202' '20019' '90013' '11210.0' '11412' '11373.0' '94117.0']
```

'90505' '90032' '11207.0' '91765' '91204' '10027.0' '90272' '90402'
 '90501' '11236.0' '91604' '11229' '91606' '10459' '91367' '10460' '91436'
 '10037' '11203.0' '91106' '60661' '20017' '91789' '91201' '02109' '10304'
 '11201' '10030' '11223' '20012' '10451.0' '02135' '94112' '91321' '94116'
 '90043' '11379' '90033' '90713' '94127' '10468' '11231' '90062' '90232'
 '90057' '11432' '11434' '10044' '91504' '90717' '91780' '90031' '10009'
 '20036' '11370' '94109.0' '90045' '02115' '11691' '91755' '91104' '91352'
 '91325' '11249' '90042' '91411' '90805' '90303' '11414' '90250' '11236'
 '60633' '91505' '90210' '60645' '60615' '90503' '11219' '11226.0' '11203'
 '10473' '91203' '91306' '91401' '90732' '10034' '91801' '90017' '11214'
 '90220' '11201.0' '11212' '60631' '60623' '10466' '91746' '11435' '60614'
 '10472' '90008' '10006' '91387' '10456.0' '94130' '10005' '20268' '91214'
 '90806' '91711' '11210' '91208' '02121' '11209' '94102.0' '91331' '91792'
 '90061' '10451' '91040' '90230' '91311' '91355' '02120' '11213' '94132'
 '91042' '02199' '91791' '60602' '10456' '10458' '90504' '10038.0' '91501'
 '10306' '10035' '11109' '11234' '90056' '91343' '91304' '20006' '91206'
 '7302.0' '10314.0' '10467' '91702' '91770' '90731' '91607' '60660'
 '20912' '20712' '90274' '90401' '91354' '91741' '60805' '02110' '91361'
 '11420' '11368.0' '10280' '20052' '60634' '11208.0' '20910' '10007.0'
 '10007' '11224.0' '10475.0' '11374' '02132' '10464' '90041' '94111'
 '90706' '91103' '90242' '94104.0' '94104' '10459.0' '91390' '10014.0'
 '02136' '91324' '10471.0' '90211' '11228.0' '90280' '93550' '11433'
 '91768' '90241' '94134' '10475' '91786' '11358' '91016' '90010' '10308'
 '11416' '10307' '94114.0' '60643' '02122' '94158' '91108' '90605' '90715'
 '10279' '11234.0' '90807' '11421' '02138' '10704' '10457' '10305' '91024'
 '10452.0' '60630' '90067' '60651' '91775' '90631' '91802' '10310' '90712'
 '90638' '10473.0' '91406' '90044' '90403-2638' '93563' '91377' '91731'
 '90275' '90606' '60624' '91732' '90660' '91303' '90640' '11417' '90037'
 '1m' '90602' '90755' '90059' '90001' '10461' '91342' '10312' '11356.0'
 '91708' '11354' '90304' '10282' '91326' '91351' '91773' '10452' '90305'
 '60659' '90063' '10069' '10018.0' '11361' '11367' '90670' '91733'
 '10457.0' '60621' '10454' '91722' '90022' '94118.0' '90704' '91723'
 '11209.0' '10474' '10453.0' '91011' '11411.0' '94014' '11360' '90248'
 '60638' '90221' '90716' '90034-2203' '60639' '94014.0' '90035-4475'
 '94129' '60636' '10304.0' '11694' '60619' '11429' '91724' '11220.0'
 '11423' '20004' '60629' '91381' '11509.0' '93536' '02467' '90040' '10465'
 '11415' '60606' '60644' '93551' '91744' '11412.0' '11413' '02145' '11001'
 '10010.0' '60302' '11419' '02152' '91020' '93534' '10455' '91340'
 '11362.0' '11363.0' '11372.0' '10303' '11411' '60660-1448' '91750'
 '11221.0' '10471' '90745' '11357' '20816' '11373' '90036-2514' '10026.0'
 '11429.0' '60603' '10308.0' '94401' '60707' '11228' '91210' '90710'
 '90201' '91402' '02186' '02445' '10162' '02458' '02472' '90047' '90255'
 '11426' '11215.0' '60656' '90240' '10004.0' '10305.0' '91384' '90744'
 '93535' '90003' '10128.0' '93543' '11428' '10309' '10463.0' '10270'
 '9004' '10282.0' '11239.0' '93552' '91706' '90011' '90723' '91362'
 '91008' '11436' '10012.0']

```
[24]: print(df['bedrooms'].unique())
```

```
[ 0.  1.  2.  5.  3.  8.  4. nan  7. 10.  6.  9.]
```

```
[25]: print(df['beds'].unique())
```

```
[ 2.  1.  3.  8. 10.  4.  5.  6. nan  9.  7. 13. 16.  0. 12. 11. 18.]
```

2.0.3 3. Les corrélations entre le prix et des caractéristiques

Quelques statistiques (moyenne, médiane, écart-type, etc.) :

```
[26]: df.describe()
```

```
[26]:
```

	id	log_price	accommodates	bathrooms	latitude \
count	2.193100e+04	21931.000000	21931.000000	21880.000000	21931.000000
mean	1.122766e+07	4.783193	3.154348	1.235923	38.463441
std	6.077360e+06	0.718268	2.141682	0.586293	3.072646
min	3.362000e+03	2.302585	1.000000	0.000000	33.339002
25%	6.224753e+06	4.317488	2.000000	1.000000	34.135374
50%	1.218496e+07	4.700480	2.000000	1.000000	40.662703
75%	1.639510e+07	5.220356	4.000000	1.000000	40.746395
max	2.120450e+07	7.600402	16.000000	8.000000	42.390248

	longitude	bedrooms	beds
count	21931.000000	21907.000000	21900.000000
mean	-92.267719	1.263477	1.710502
std	21.669362	0.850969	1.251887
min	-122.510940	0.000000	0.000000
25%	-118.340398	1.000000	1.000000
50%	-76.994992	1.000000	1.000000
75%	-73.954573	1.000000	2.000000
max	-70.989359	10.000000	18.000000

Conversion des variables catégorielles du dataset en variables indicatrices binaires :

```
[27]: categories = ['property_type', 'room_type', 'accommodates', 'bathrooms',  
↳ 'bed_type', 'cancellation_policy', 'cleaning_fee', 'city', 'neighbourhood',  
↳ 'zipcode', 'bedrooms', 'beds']  
df_bin = pd.get_dummies(df, columns=categories)
```

Voici les variables converties en variables indicatrices binaires, qui à mon avis ont des impacts significatifs sur le prix :

- property_type : différents types de logements (appartement, maison...)
- room_type : indiquant si l'espace loué est un logement entier, une chambre privée ou partagée...
- accommodates et bathrooms pour voir

- `bed_type` : le type de lit peut aussi influencer les préférences des locataires et donc le prix
- `cancellation_policy` : peut affecter la flexibilité et la demande
- `cleaning_fee` pour voir
- `city` : la localisation géographique (ville) est un facteur pour les prix de location
- `neighbourhood` : certains quartiers peuvent être plus recherchés que d'autres
- `zipcode`, `bedrooms` et `beds` pour voir
- `amenities` : nécessite un traitement pour extraire et transformer chaque équipement en une variable binaire, puisqu'il s'agit d'une liste d'éléments

Les variables 'id', 'log_price', 'latitude', 'longitude' n'étaient à mon avis pas nécessaires à convertir en variables dummy.

```
[28]: df_bin.head()
```

```
[28]:      id  log_price      amenities \
0   5708593   4.317488 {TV,"Wireless Internet",Kitchen,"Free parking ...
1  14483613   4.007333 {"Wireless Internet","Air conditioning",Kitche...
2  10412649   7.090077 {TV,"Wireless Internet","Air conditioning",Kit...
3  17954362   3.555348 {TV,"Cable TV",Internet,"Wireless Internet","A...
4   9969781   5.480639 {TV,"Cable TV",Internet,"Wireless Internet",Ki...

      latitude  longitude  property_type_Apartment \
0  33.782712 -118.134410                False
1  40.705468  -73.909439                False
2  38.917537  -77.031651                 True
3  40.736001  -73.924248                False
4  37.744896 -122.430665                False

      property_type_Bed & Breakfast  property_type_Boat \
0                        False                False
1                        False                False
2                        False                False
3                        False                False
4                        False                False

      property_type_Boutique hotel  property_type_Bungalow  ...  beds_6.0 \
0                        False                False  ...    False
1                        False                False  ...    False
2                        False                False  ...    False
3                        False                False  ...    False
4                        False                False  ...    False

      beds_7.0  beds_8.0  beds_9.0  beds_10.0  beds_11.0  beds_12.0  beds_13.0 \
0      False      False      False      False      False      False      False
1      False      False      False      False      False      False      False
```

2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False

	beds_16.0	beds_18.0
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

[5 rows x 1348 columns]

Analyse de la répartition des données par catégorie pour les variables catégorielles

- Pour property type :

```
[29]: # Pour voir le log_price en fonction du property_type :
log_price_en_fct_property_type = df_bin.groupby([col for col in df_bin.columns
↪ if 'property_type' in col])['log_price'].mean()

print(log_price_en_fct_property_type)
```

property_type_Apartment	property_type_Bed & Breakfast	property_type_Boat		
property_type_Boutique hotel	property_type_Bungalow	property_type_Cabin		
property_type_Camper/RV	property_type_Castle	property_type_Cave		
property_type_Chalet	property_type Condominium	property_type_Dorm		
property_type_Earth House	property_type_Guest suite	property_type_Guesthouse		
property_type_Hostel	property_type_House	property_type_Hut	property_type_In-	
law	property_type_Island	property_type_Loft	property_type_Other	
property_type_Serviced apartment	property_type_Tent	property_type_Timeshare		
property_type_Tipi	property_type_Townhouse	property_type_Treehouse		
property_type_Vacation home	property_type_Villa	property_type_Yurt		
False	False	False		
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	True
5.289808			True	False
4.977980			False	False
5.531722	True		False	False
True	False		False	False
5.978886				

False			True	
4.822138		False	False	False
		True	False	
False		False	False	False
5.220356				
	True		False	
False		False	False	False
5.585600				
				True
False		False	False	False
False		False	False	4.008937
		True		False
False		False	False	False
False		False	False	5.255823
	True	False		False
False		False	False	False
False		False	False	4.946918
				True
False		False	False	False
False		False	False	False
False			4.994079	
			True	False
False		False	False	False
False		False	False	False
False		False	5.010635	
		True	False	False
False		False	False	False
False		False	False	False
False		False	4.763759	
	True	False	False	False
False		False	False	False
False		False	False	False
False		False	4.291634	
				True
False		False	False	False
False		False	False	False
False		False	False	False
False		False	4.789230	
			True	False
False		False	False	False
False		False	False	False
False		False	False	False
False		False	3.771639	
		True	False	False
False		False	False	False
False		False	False	False
False		False	False	False

False	False	4.678250	True
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	4.655889	False
False	False	True	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	4.174387	False
False	True	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	3.588597	False
True	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	5.041489	False
False	False	True	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	4.618083	False
False	True	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	4.990433	False
False	True	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	5.356599	True
False	False	False	False

False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
4.547690			
		True	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
4.755987			
	True	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
4.823562			
			True
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
5.113796			
		True	
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
5.123347			
	True	False	
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False
False	False	False	False

4.532817

True	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	False	False	False	False

4.762265

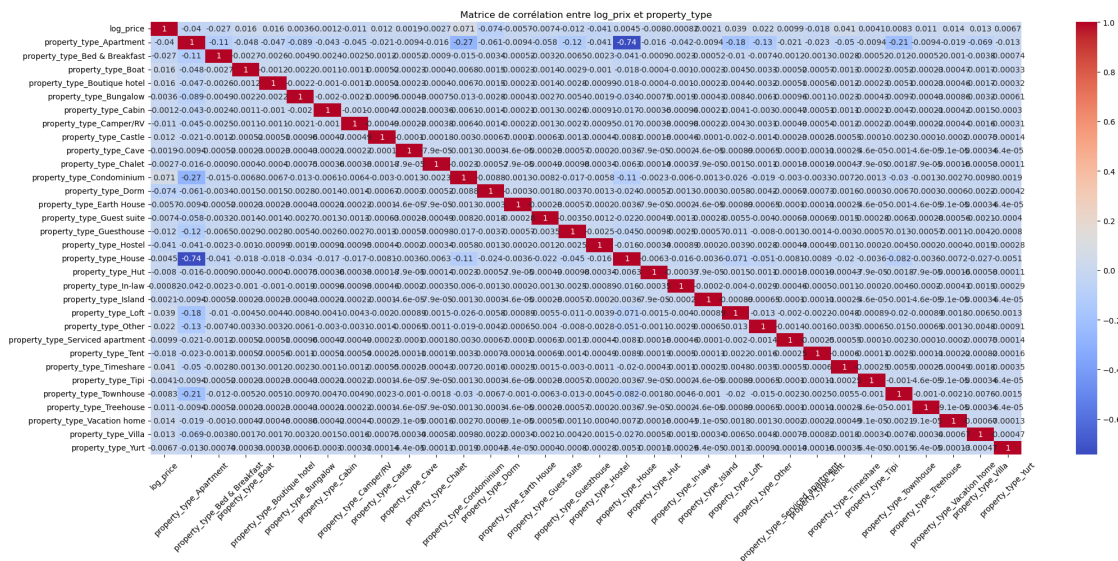
Name: log_price, dtype: float64

```
[30]: # Corr lation forte entre le prix de l'appartement et le property_type ?
# Calcul de la matrice de corr lation
matrice_corr_property_type= df_bin[["log_price"]] + [col for col in df_bin.
↪columns if "property_type" in col]].corr()
```

```
[31]: # heatmap
plt.figure(figsize=(25, 10))
sns.heatmap(matrice_corr_property_type, annot=True, cmap="coolwarm")

plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title("Matrice de corr lation entre log_prix et property_type")

plt.show()
```



Je ne remarque pas de grande influence sur le log_prix

- Pour room_type :

```
[32]: # Pour voir le log_price en fonction du room_type :
log_price_en_fct_room_type = df_bin.groupby([col for col in df_bin.columns if
↳ 'room_type' in col])['log_price'].mean()

print(log_price_en_fct_room_type)
```

```
room_type_Entire home/apt  room_type_Private room  room_type_Shared room
False                      False                      True
3.881240
                        True                      False
4.334213
True                      False                      False
5.167591
Name: log_price, dtype: float64
```

```
[33]: room_type_cols = [col for col in df_bin.columns if 'room_type' in col]
print(room_type_cols)
```

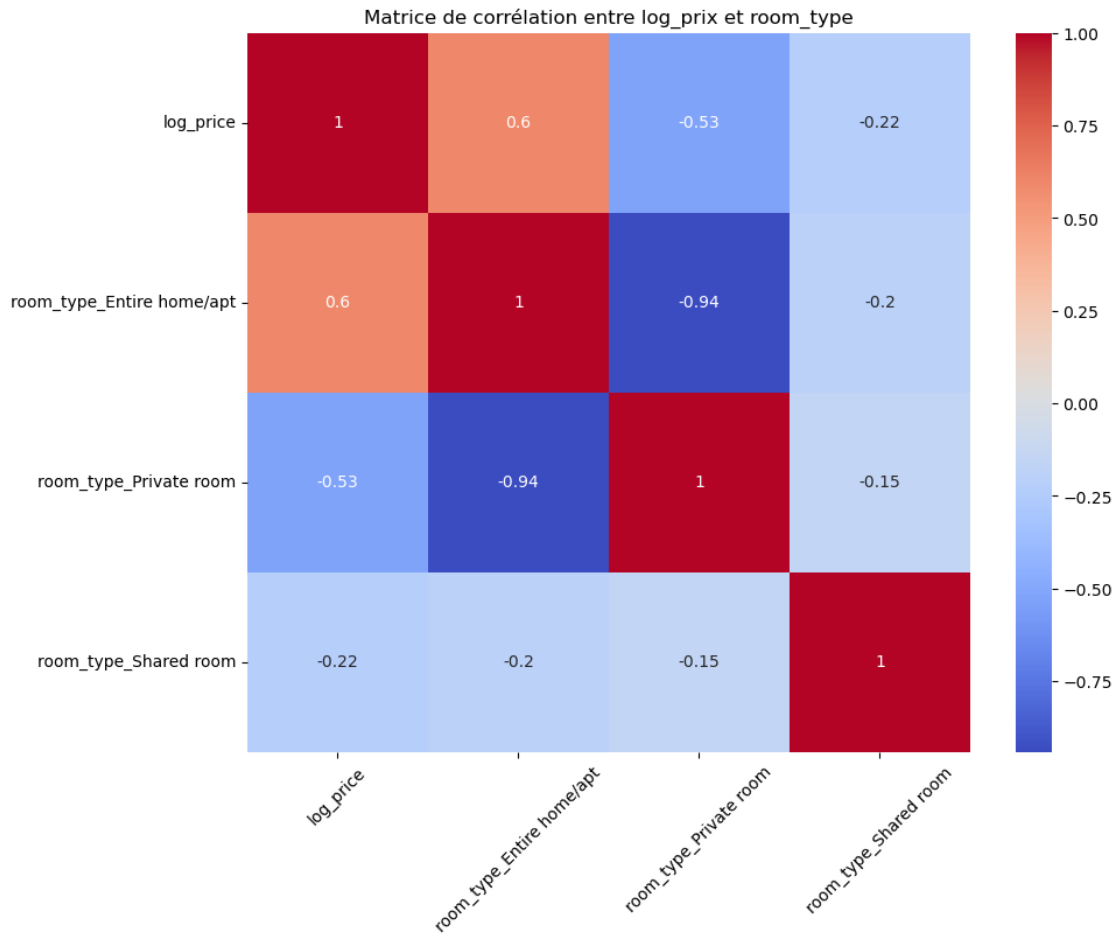
```
['room_type_Entire home/apt', 'room_type_Private room', 'room_type_Shared room']
```

```
[34]: # Corrélation forte entre le prix de l'appartement et le room_type ?
# Calcul de la matrice de corrélation
matrice_corr_room_type= df_bin[["log_price"] + [col for col in df_bin.columns
↳ if "room_type" in col]].corr()
```

```
[35]: # heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(matrice_corr_room_type, annot=True, cmap="coolwarm")

plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title("Matrice de corrélation entre log_prix et room_type")

plt.show()
```



Je remarque une influence sur le prix

- Pour accommodates :

```
[36]: # Pour voir le log_price en fonction du nombre d'accommodates :
log_price_en_fct_accommodates = df_bin.groupby([col for col in df_bin.columns_
↳ if 'accommodates' in col])['log_price'].mean()

print(log_price_en_fct_accommodates)
```

```
accommodates_1  accommodates_2  accommodates_3  accommodates_4  accommodates_5
accommodates_6  accommodates_7  accommodates_8  accommodates_9  accommodates_10
accommodates_11 accommodates_12 accommodates_13 accommodates_14
accommodates_15 accommodates_16
False          False          False          False          False
False          False          False          False          False
False          False          False          False          False
True           6.106292
True
```

False	5.747441			
			True	False
False	5.983674			
		True	False	False
False	5.820231			
	True	False	False	False
False	6.090033			
True	False	False	False	False
False	5.765435			
				True
False	False	False	False	False
False	5.848890			
			True	False
False	False	False	False	False
False	5.773542			
		True	False	False
False	False	False	False	False
False	5.729799			
	True	False	False	False
False	False	False	False	False
False	5.532838			
True	False	False	False	False
False	False	False	False	False
False	5.451785			
				True
False	False	False	False	False
False	False	False	False	False
False	5.223210			
			True	False
False	False	False	False	False
False	False	False	False	False
False	5.079303			
		True	False	False
False	False	False	False	False
False	False	False	False	False
False	4.799170			
	True	False	False	False
False	False	False	False	False
False	False	False	False	False
False	4.554798			
True	False	False	False	False
False	False	False	False	False
False	False	False	False	False
False	4.175041			

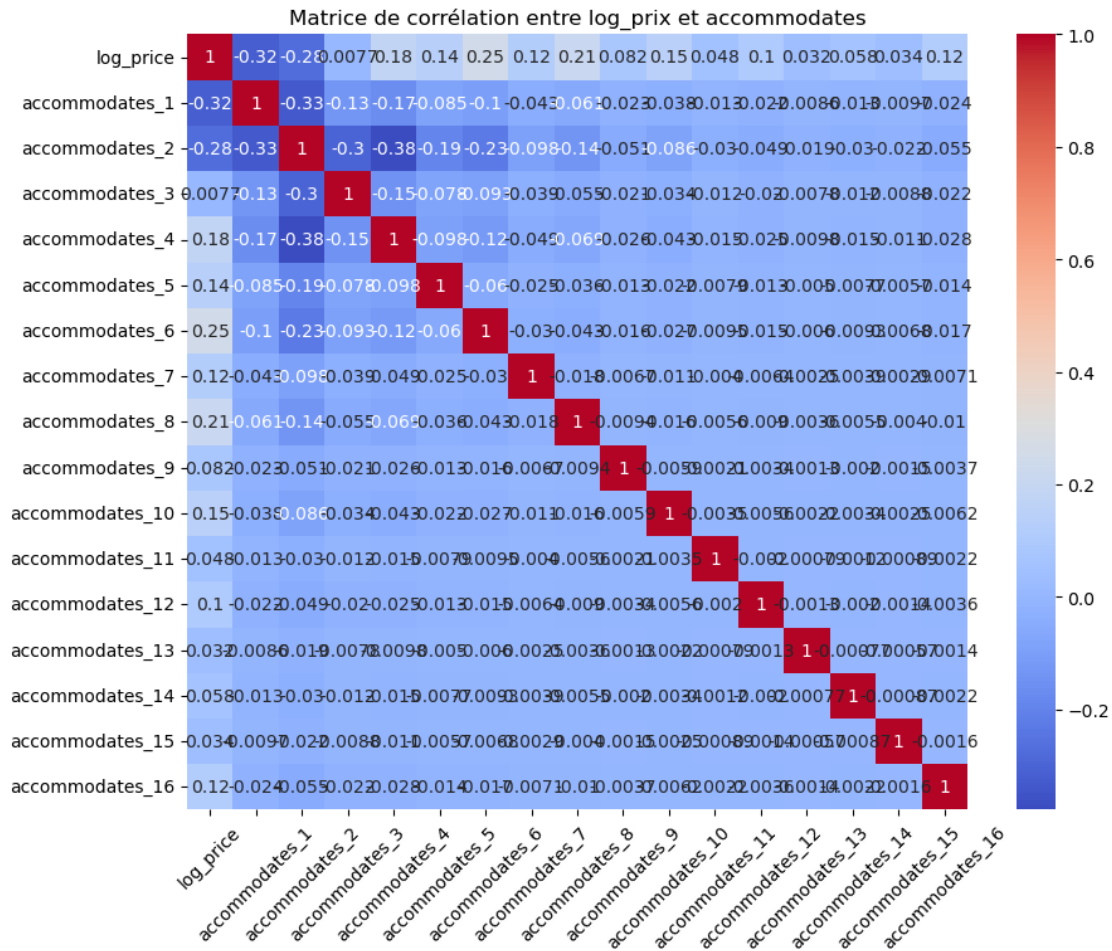
Name: log_price, dtype: float64

```
[37]: # Corrélation forte entre le prix de l'appartement et accomodates ?
# Calcul de la matrice de corrélation
matrice_corr_accommodates= df_bin[["log_price"]] + [col for col in df_bin.
↳columns if "accommodates" in col]].corr()
```

```
[38]: # heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(matrice_corr_accommodates, annot=True, cmap="coolwarm")

plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title("Matrice de corrélation entre log_prix et accomodates")

plt.show()
```



Je ne remarque pas de grande influence

- Pour bathrooms :


```
[39]: # Pour voir le log_price en fonction des bathrooms :
log_price_en_fct_bathrooms = df_bin.groupby([col for col in df_bin.columns if
↳ 'bathrooms' in col])['log_price'].mean()

print(log_price_en_fct_bathrooms)
```

bathrooms_0.0	bathrooms_0.5	bathrooms_1.0	bathrooms_1.5	bathrooms_2.0	
bathrooms_2.5	bathrooms_3.0	bathrooms_3.5	bathrooms_4.0	bathrooms_4.5	
bathrooms_5.0	bathrooms_5.5	bathrooms_6.0	bathrooms_6.5	bathrooms_7.0	
bathrooms_7.5	bathrooms_8.0				
False	False	False	False	False	False
False	False	False	False	False	False
False	False	False	False	False	
4.661688					
True	5.176763				
				True	
False	7.455810				
			True	False	
False	6.795084				
		True	False	False	
False	6.498254				
	True	False	False	False	
False	6.303097				
True	False	False	False	False	
False	6.730003				
					True
False	False	False	False	False	False
6.185231					
				True	False
False	False	False	False	False	False
6.443918					
		True	False	False	False
False	False	False	False	False	False
5.704211					
	True	False	False	False	False
False	False	False	False	False	False
6.075479					
	True	False	False	False	False
False	False	False	False	False	False
5.576488					
					True
False	False	False	False	False	False
False	False	False	False	False	
5.508918					
				True	False
False	False	False	False	False	False
False	False	False	False	False	

```

5.212290
False      False      False      True      False      False
False      False      False      False     False     False
4.780835
False      False      True       False     False     False
False      False      False     False     False     False
False      False      False     False     False     False
4.671342
False      True       False     False     False     False
False      False     False     False     False     False
False      False     False     False     False     False
4.198718
True       False     False     False     False     False
False      False     False     False     False     False
False      False     False     False     False     False
4.266018
Name: log_price, dtype: float64

```

```

[40]: # Corrélation forte entre le prix et bathrooms ?
      # Calcul de la matrice de corrélation
      matrice_corr_bathrooms= df_bin[["log_price"] + [col for col in df_bin.columns_
      ↪if "bathrooms" in col]].corr()

```

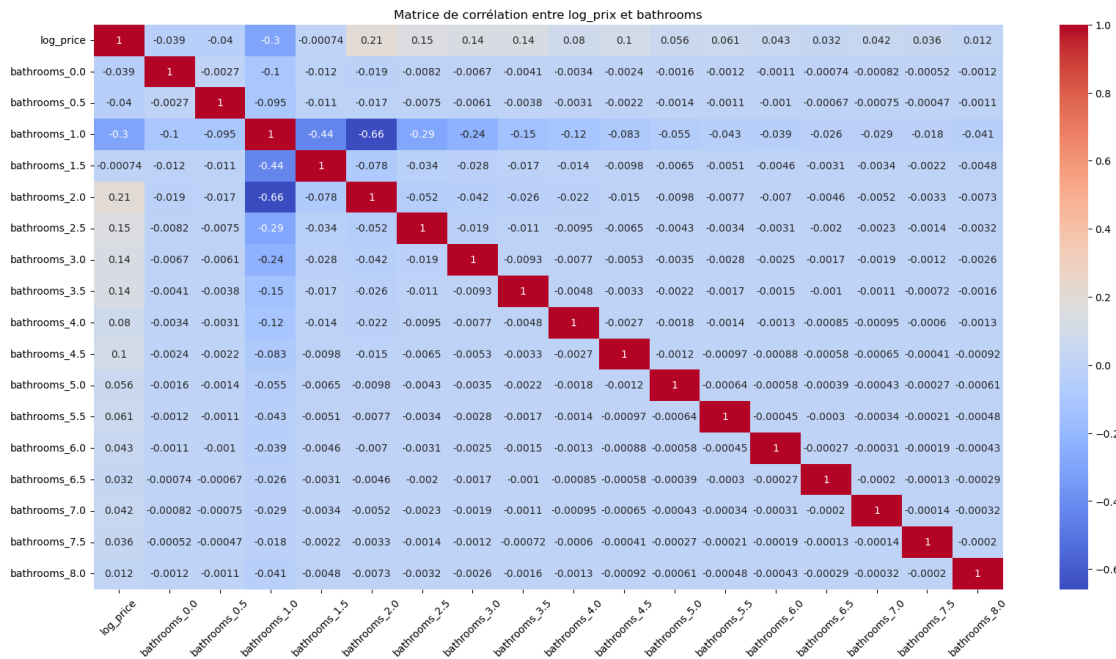
```

[41]: # heatmap
      plt.figure(figsize=(20, 10))
      sns.heatmap(matrice_corr_bathrooms, annot=True, cmap="coolwarm")

      plt.xticks(rotation=45)
      plt.yticks(rotation=0)
      plt.title("Matrice de corrélation entre log_prix et bathrooms")

      plt.show()

```



Je ne remarque pas non plus de grande influence

- Pour le bed_type :

```
[42]: # Pour voir le log_price en fonction du bed_type :
log_price_en_fct_bed_type = df_bin.groupby([col for col in df_bin.columns if
↳ 'bed_type' in col])['log_price'].mean()

print(log_price_en_fct_bed_type)
```

bed_type_Airbed	bed_type_Couch	bed_type_Futon	bed_type_Pull-out	Sofa
bed_type_Real Bed				
False	False	False	False	True
4.795401				
			True	False
4.464975				
		True	False	False
4.287998				
	True	False	False	False
4.334119				
True	False	False	False	False
4.299140				

Name: log_price, dtype: float64

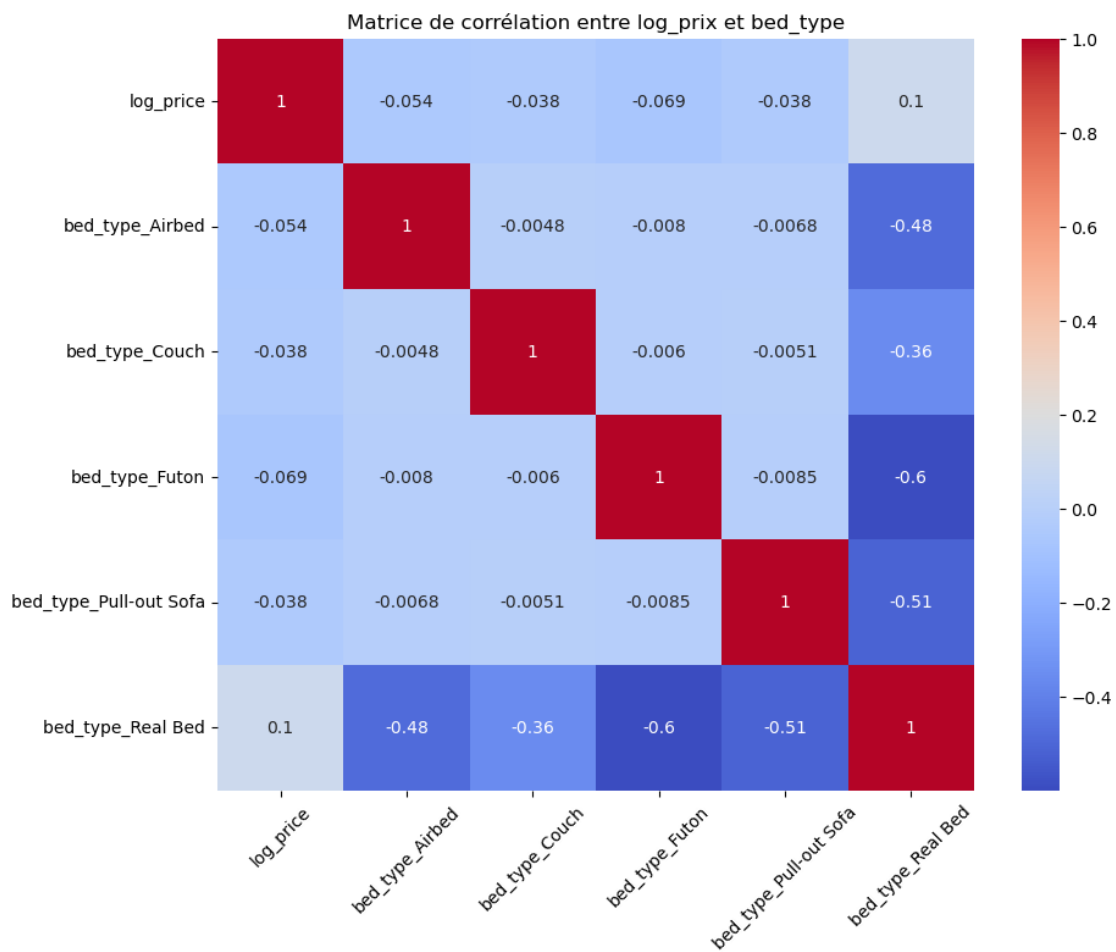
```
[43]: # Corrélation forte entre le prix de l'appartement et le bed_type ?
# Calcul de la matrice de corrélation
```

```
matrice_corr_bed_type= df_bin[["log_price"] + [col for col in df_bin.columns if
↳ "bed_type" in col]].corr()
```

```
[44]: # heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(matrice_corr_bed_type, annot=True, cmap="coolwarm")

plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title("Matrice de corrélation entre log_prix et bed_type")

plt.show()
```



Je ne remarque pas d'influence majeure non plus

- Pour le cancellation_policy :

```
[45]: # Pour voir le log_price en fonction du cancellation_policy :
log_price_en_fct_cancellation_policy = df_bin.groupby([col for col in df_bin.
↳ columns if 'cancellation_policy' in col])['log_price'].mean()

print(log_price_en_fct_cancellation_policy)
```

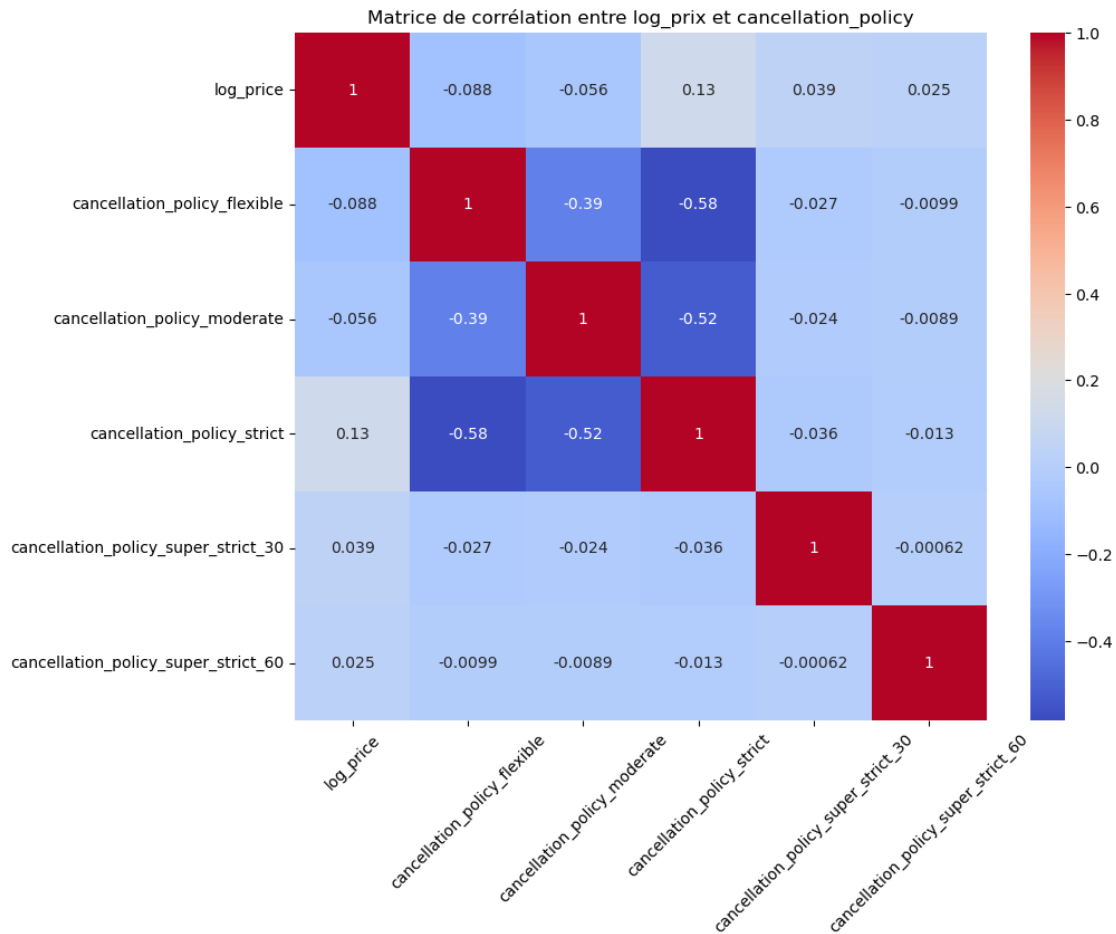
```
cancellation_policy_flexible  cancellation_policy_moderate
cancellation_policy_strict    cancellation_policy_super_strict_30
cancellation_policy_super_strict_60
False                          False                          False
False                          True                           False
5.992353
      True                          False
5.471440
                                True
False                          False
4.886028
                                True                          False
False                          False
4.715328
True                           False                          False
False                          False
4.687225
Name: log_price, dtype: float64
```

```
[46]: # Corrélation forte entre le prix de l'appartement et le cancellation_policy ?
# Calcul de la matrice de corrélation
matrice_corr_cancellation_policy= df_bin[["log_price"] + [col for col in df_bin.
↳ columns if "cancellation_policy" in col]].corr()
```

```
[47]: # heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(matrice_corr_cancellation_policy, annot=True, cmap="coolwarm")

plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title("Matrice de corrélation entre log_prix et cancellation_policy")

plt.show()
```



Ce n'est pas très utile non plus

- Pour le cleaning_fee :

```
[48]: # Pour voir le log_price en fonction du cleaning_fee :
log_price_en_fct_cleaning_fee = df_bin.groupby([col for col in df_bin.columns_
↳if 'cleaning_fee' in col])['log_price'].mean()

print(log_price_en_fct_cleaning_fee)
```

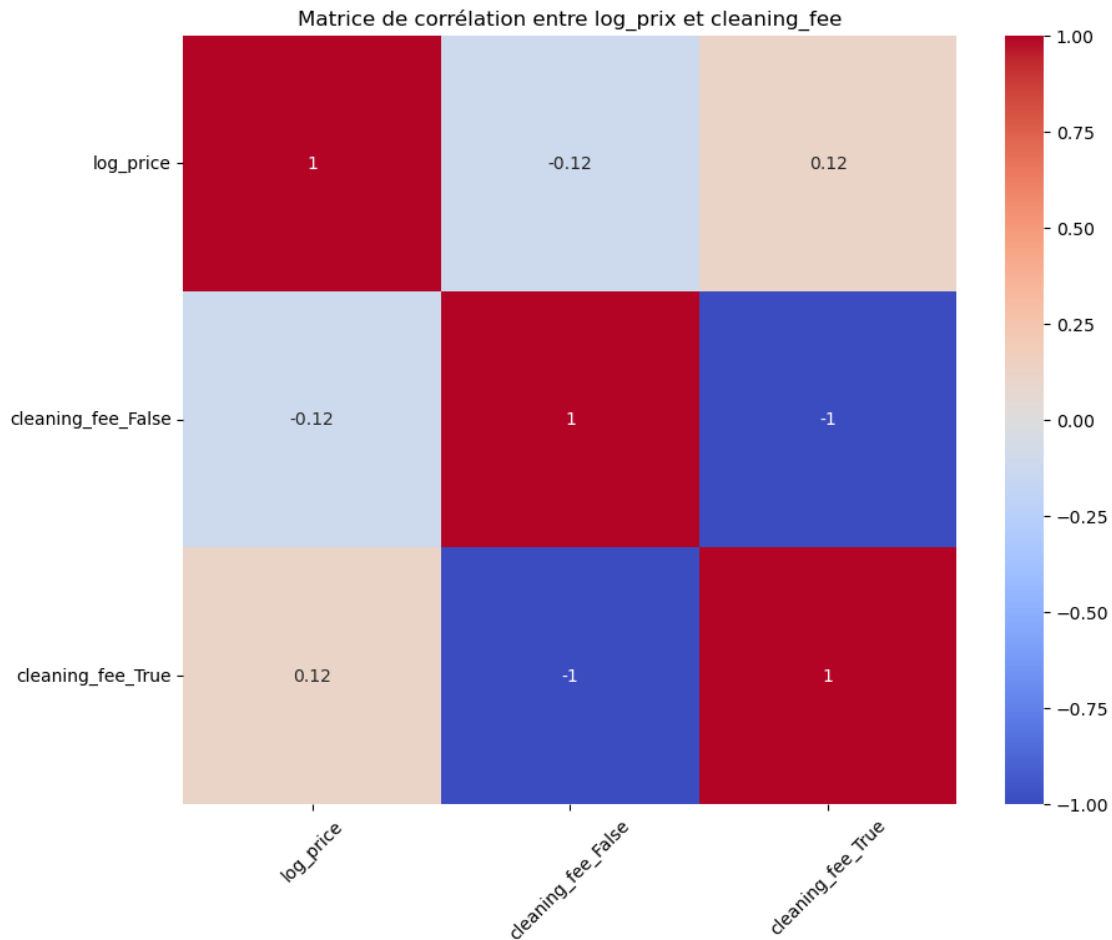
```
cleaning_fee_False  cleaning_fee_True
False              True              4.833382
True              False              4.642555
Name: log_price, dtype: float64
```

```
[49]: # Corrélation forte entre le prix de l'appartement et le cleaning_fee ?
# Calcul de la matrice de corrélation
matrice_corr_cleaning_fee= df_bin[["log_price"] + [col for col in df_bin.
↳columns if "cleaning_fee" in col]].corr()
```

```
[50]: # heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(matrice_corr_cleaning_fee, annot=True, cmap="coolwarm")

plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title("Matrice de corrélation entre log_prix et cleaning_fee")

plt.show()
```



C'est assez intéressant à garder

- Pour la ville :

```
[51]: # Pour voir le log_price en fonction de la ville :
log_price_en_fct_ville = df_bin.groupby([col for col in df_bin.columns if
↳ 'city' in col])['log_price'].mean()
```

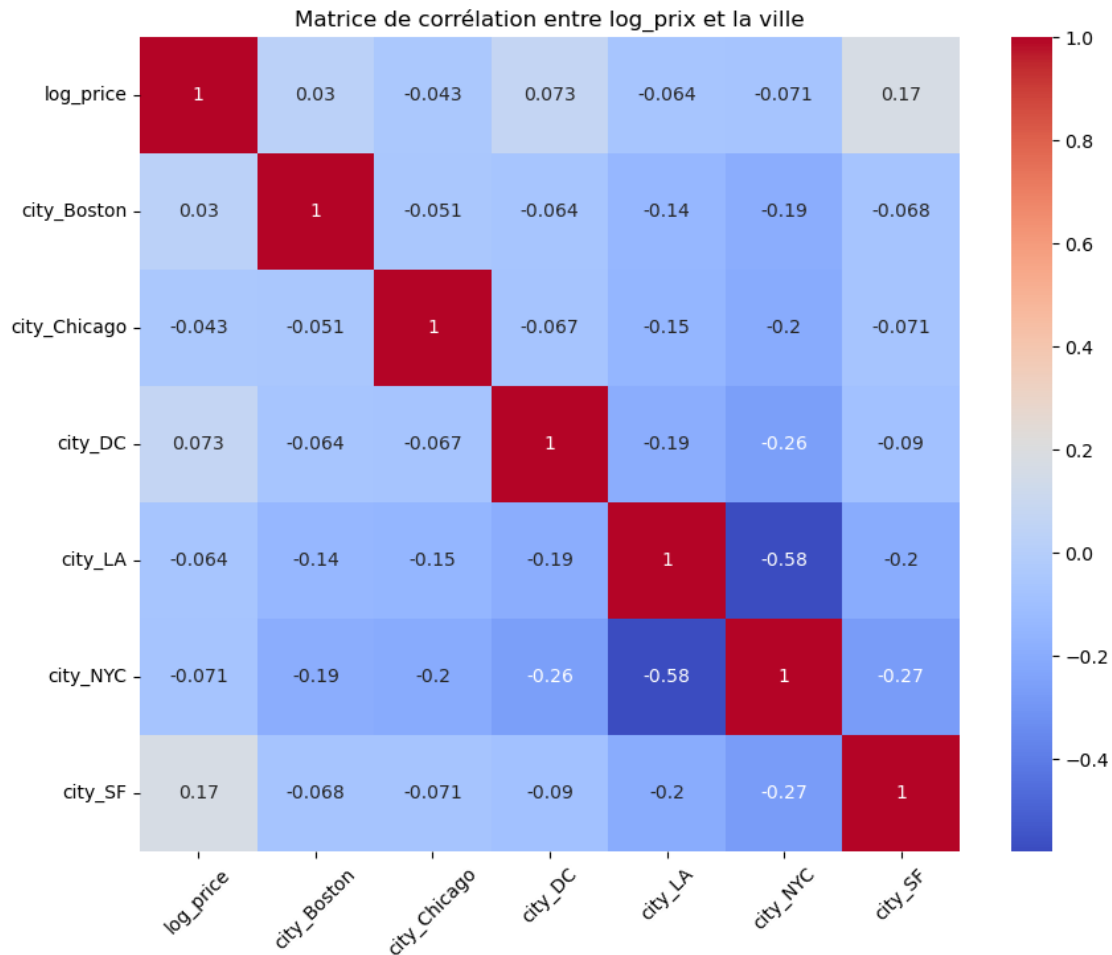
```
print(log_price_en_fct_ville)
```

city_Boston	city_Chicago	city_DC	city_LA	city_NYC	city_SF	
False	False	False	False	False	True	5.183200
				True	False	4.724982
			True	False	False	4.713099
		True	False	False	False	4.964046
	True	False	False	False	False	4.650405
True	False	False	False	False	False	4.879681

Name: log_price, dtype: float64

```
[52]: # Corrélation forte entre le prix de l'appartement et la ville ?  
# Calcul de la matrice de corrélation  
matrice_corr_ville= df_bin[["log_price"]] + [col for col in df_bin.columns if  
↪ "city" in col]].corr()
```

```
[53]: #heatmap  
plt.figure(figsize=(10, 8))  
sns.heatmap(matrice_corr_ville, annot=True, cmap="coolwarm")  
  
plt.xticks(rotation=45)  
plt.yticks(rotation=0)  
plt.title("Matrice de corrélation entre log_prix et la ville")  
  
plt.show()
```

On remarque une légère influence

- Pour le voisinage :

```
[54]: # Pour voir le log_price en fonction du voisinage :
log_price_en_fct_neighbourhood = df_bin.groupby([col for col in df_bin.columns_
    if 'neighbourhood' in col])['log_price'].mean()

print(log_price_en_fct_neighbourhood)
```

```
neighbourhood_16th Street Heights  neighbourhood_Adams Morgan
neighbourhood_Alamo Square  neighbourhood_Albany Park  neighbourhood_Alhambra
neighbourhood_Allerton  neighbourhood_Allston-Brighton  neighbourhood_Alphabet
City  neighbourhood_Altadena  neighbourhood_American University Park
neighbourhood_Anacostia  neighbourhood_Andersonville  neighbourhood_Arboretum
neighbourhood_Arcadia  neighbourhood_Arleta  neighbourhood_Armour Square
neighbourhood_Arts District  neighbourhood_Astoria  neighbourhood_Atwater
Village  neighbourhood_Austin  neighbourhood_Avondale  neighbourhood_Azusa
```

neighbourhood_Back Bay neighbourhood_Back of the Yards neighbourhood_Balboa
Terrace neighbourhood_Baldwin Hills neighbourhood_Baldwin Park
neighbourhood_Barney Circle neighbourhood_Bath Beach neighbourhood_Battery
Park City neighbourhood_Bay Ridge neighbourhood_Baychester
neighbourhood_Bayside neighbourhood_Bayview neighbourhood_Beacon Hill
neighbourhood_Bedford Park neighbourhood_Bedford-Stuyvesant neighbourhood_Bel
Air/Beverly Crest neighbourhood_Bell neighbourhood_Bellevue
neighbourhood_Bellflower neighbourhood_Belmont neighbourhood_Belmont Cragin
neighbourhood_Benning neighbourhood_Benning Ridge neighbourhood_Bensonhurst
neighbourhood_Bergen Beach neighbourhood_Berkley neighbourhood_Bernal Heights
neighbourhood_Beverly neighbourhood_Beverly Hills neighbourhood_Bloomingdale
neighbourhood_Boerum Hill neighbourhood_Borough Park neighbourhood_Boyle
Heights neighbourhood_Boystown neighbourhood_Bradbury neighbourhood_Brentwood
neighbourhood_Bridgeport neighbourhood_Brighton Beach neighbourhood_Brightwood
neighbourhood_Bronxdale neighbourhood_Bronzeville neighbourhood_Brookland
neighbourhood_Brookline neighbourhood_Brooklyn neighbourhood_Brooklyn Heights
neighbourhood_Brooklyn Navy Yard neighbourhood_Brownsville
neighbourhood_Bucktown neighbourhood_Buena Vista neighbourhood_Burbank
neighbourhood_Burleith neighbourhood_Bushwick neighbourhood_Cahuenga Pass
neighbourhood_Canarsie neighbourhood_Canoga Park neighbourhood_Capitol Hill
neighbourhood_Carroll Gardens neighbourhood_Carson neighbourhood_Carver
Langston neighbourhood_Castle Hill neighbourhood_Cathedral Heights
neighbourhood_Central Northeast/Mahoning Heights neighbourhood_Cerritos
neighbourhood_Charlestown neighbourhood_Chatsworth neighbourhood_Chelsea
neighbourhood_Chestnut Hill neighbourhood_Chevy Chase neighbourhood_Chinatown
neighbourhood_City Island neighbourhood_Civic Center neighbourhood_Claremont
neighbourhood_Cleveland Park neighbourhood_Clinton Hill neighbourhood_Co-op
City neighbourhood_Cobble Hill neighbourhood_Cole Valley
neighbourhood_College Point neighbourhood_Colonial Village
neighbourhood_Columbia Heights neighbourhood_Columbia Street Waterfront
neighbourhood_Commerce neighbourhood_Compton neighbourhood_Concourse
neighbourhood_Concourse Village neighbourhood_Coney Island
neighbourhood_Congress Heights neighbourhood_Corona neighbourhood_Covina
neighbourhood_Cow Hollow neighbourhood_Crestwood neighbourhood_Crocker Amazon
neighbourhood_Crotona neighbourhood_Crown Heights neighbourhood_Culver City
neighbourhood_Cypress Park neighbourhood_DUMBO neighbourhood_Daly City
neighbourhood_Deanwood neighbourhood_Del Rey neighbourhood_Diamond Heights
neighbourhood_Ditmars / Steinway neighbourhood_Dogpatch
neighbourhood_Dorchester neighbourhood_Douglass neighbourhood_Downey
neighbourhood_Downtown neighbourhood_Downtown Brooklyn neighbourhood_Downtown
Crossing neighbourhood_Downtown/Penn Quarter neighbourhood_Duarte
neighbourhood_Duboce Triangle neighbourhood_Dunning neighbourhood_Dupont
Circle neighbourhood_Dupont Park neighbourhood_Dyker Heights
neighbourhood_Eagle Rock neighbourhood_East Boston neighbourhood_East Corner
neighbourhood_East Elmhurst neighbourhood_East Flatbush neighbourhood_East
Harlem neighbourhood_East Hollywood neighbourhood_East Los Angeles
neighbourhood_East New York neighbourhood_East San Gabriel neighbourhood_East
Village neighbourhood_Eastchester neighbourhood_Eastland Gardens

neighbourhood_Echo Park neighbourhood_Eckington neighbourhood_Edenwald
neighbourhood_Edgewater neighbourhood_Edgewood neighbourhood_El Monte
neighbourhood_El Segundo neighbourhood_El Sereno neighbourhood_Elm Park
neighbourhood_Elmhurst neighbourhood_Eltingville neighbourhood_Elysian Valley
neighbourhood_Encino neighbourhood_Englewood neighbourhood_Excelsior
neighbourhood_Fairlawn neighbourhood_Fenway/Kenmore neighbourhood_Financial
District neighbourhood_Fisherman's Wharf neighbourhood_Flatbush
neighbourhood_Flatiron District neighbourhood_Flatlands
neighbourhood_Florence-Graham neighbourhood_Flushing neighbourhood_Foggy
Bottom neighbourhood_Fordham neighbourhood_Forest Hill neighbourhood_Forest
Hills neighbourhood_Fort Davis neighbourhood_Fort Greene neighbourhood_Fort
Lincoln neighbourhood_Fort Wadsworth neighbourhood_Foxhall
neighbourhood_Fresh Meadows neighbourhood_Friendship Heights
neighbourhood_Gardena neighbourhood_Garfield Park neighbourhood_Garfield Ridge
neighbourhood_Georgetown neighbourhood_Gerritsen Beach neighbourhood_Glassell
Park neighbourhood_Glen Park neighbourhood_Glendale neighbourhood_Glendora
neighbourhood_Glover Park neighbourhood_Gold Coast neighbourhood_Good Hope
neighbourhood_Gowanus neighbourhood_Gramercy Park neighbourhood_Granada Hills
North neighbourhood_Grant City neighbourhood_Grasmere neighbourhood_Gravesend
neighbourhood_Great Kills neighbourhood_Greenpoint neighbourhood_Greenway
neighbourhood_Greenwich Village neighbourhood_Greenwood Heights
neighbourhood_Grymes Hill neighbourhood_Haight-Ashbury neighbourhood_Hamilton
Heights neighbourhood_Harbor City neighbourhood_Harbor Gateway
neighbourhood_Harlem neighbourhood_Harvard Square neighbourhood_Hawaiian
Gardens neighbourhood_Hawthorne neighbourhood_Hayes Valley
neighbourhood_Hell's Kitchen neighbourhood_Hermon neighbourhood_Hermosa
neighbourhood_Hermosa Beach neighbourhood_Highbridge neighbourhood_Highland
Park neighbourhood_Hillbrook neighbourhood_Hillcrest neighbourhood_Hollywood
neighbourhood_Hollywood Hills neighbourhood_Howard Beach neighbourhood_Hudson
Square neighbourhood_Huguenot neighbourhood_Humboldt Park
neighbourhood_Huntington Park neighbourhood_Hunts Point neighbourhood_Hyde
Park neighbourhood_Ingleside neighbourhood_Inglewood neighbourhood_Inner
Sunset neighbourhood_Inwood neighbourhood_Irving Park neighbourhood_Irwindale
neighbourhood_Ivy City neighbourhood_Jackson Heights neighbourhood_Jamaica
neighbourhood_Jamaica Plain neighbourhood_Japantown neighbourhood_Jefferson
Park neighbourhood_Judiciary Square neighbourhood_Kalorama
neighbourhood_Kensington neighbourhood_Kent neighbourhood_Kenwood
neighbourhood_Kew Garden Hills neighbourhood_Kingman Park
neighbourhood_Kingsbridge neighbourhood_Kingsbridge Heights neighbourhood_Kips
Bay neighbourhood_La Canada Flintridge neighbourhood_La Crescenta-Montrose
neighbourhood_La Habra neighbourhood_La Mirada neighbourhood_La Puente
neighbourhood_Lake Balboa neighbourhood_Lakeshore neighbourhood_Lakeview
neighbourhood_Lakewood neighbourhood_Lamond Riggs neighbourhood_Langdon
neighbourhood_Laurel Canyon neighbourhood_Lawndale neighbourhood_LeDroit Park
neighbourhood_Leather District neighbourhood_Lefferts Garden
neighbourhood_Lincoln Heights neighbourhood_Lincoln Park neighbourhood_Lincoln
Square neighbourhood_Lindenwood neighbourhood_Little Italy
neighbourhood_Little Italy/UIC neighbourhood_Little Village

neighbourhood_Logan Circle neighbourhood_Logan Square neighbourhood_Lomita
neighbourhood_Long Beach neighbourhood_Long Island City neighbourhood_Longwood
neighbourhood_Loop neighbourhood_Los Feliz neighbourhood_Lower East Side
neighbourhood_Lower Haight neighbourhood_Lynwood neighbourhood_Magnificent
Mile neighbourhood_Malibu neighbourhood_Manhattan neighbourhood_Manhattan
Beach neighbourhood_Manor Park neighbourhood_Mar Vista neighbourhood_Marble
Hill neighbourhood_Marina neighbourhood_Marina Del Rey neighbourhood_Marine
Park neighbourhood_Marshall Heights neighbourhood_Maspeth
neighbourhood_Mattapan neighbourhood_McKinley Park neighbourhood_Meatpacking
District neighbourhood_Meiers Corners neighbourhood_Melrose
neighbourhood_Michigan Park neighbourhood_Mid-City neighbourhood_Mid-Wilshire
neighbourhood_Middle Village neighbourhood_Midland Beach neighbourhood_Midtown
neighbourhood_Midtown East neighbourhood_Midwood neighbourhood_Mission Bay
neighbourhood_Mission District neighbourhood_Mission Hill
neighbourhood_Mission Terrace neighbourhood_Monrovia neighbourhood_Montclare
neighbourhood_Montebello neighbourhood_Montecito Heights
neighbourhood_Monterey Hills neighbourhood_Monterey Park neighbourhood_Morgan
Park neighbourhood_Morningside Heights neighbourhood_Morris Heights
neighbourhood_Morrisania neighbourhood_Mott Haven neighbourhood_Mount Eden
neighbourhood_Mount Pleasant neighbourhood_Mount Vernon Square
neighbourhood_Mount Washington neighbourhood_Mt Rainier/Brentwood, MD
neighbourhood_Murray Hill neighbourhood_Navy Yard neighbourhood_Naylor Gardens
neighbourhood_Near North Side neighbourhood_Near Northeast neighbourhood_Near
Northeast/H Street Corridor neighbourhood_Near West Side neighbourhood_New
Brighton neighbourhood_New Dorp Beach neighbourhood_Newton neighbourhood_Nob
Hill neighbourhood_Noel Valley neighbourhood_Noho neighbourhood_Nolita
neighbourhood_North Beach neighbourhood_North Center neighbourhood_North
Cleveland Park neighbourhood_North End neighbourhood_North Hills East
neighbourhood_North Hills West neighbourhood_North Hollywood
neighbourhood_North Lawndale neighbourhood_North Michigan Park
neighbourhood_North Park neighbourhood_Northridge neighbourhood_Norwalk
neighbourhood_Norwood neighbourhood_Norwood Park neighbourhood_O'Hare
neighbourhood_Oakland neighbourhood_Oceanview neighbourhood_Old Town
neighbourhood_Outer Sunset neighbourhood_Ozone Park neighbourhood_Pacific
Heights neighbourhood_Pacific Palisades neighbourhood_Pacoima
neighbourhood_Palisades neighbourhood_Palms neighbourhood_Palos Verdes
neighbourhood_Panorama City neighbourhood_Paramount neighbourhood_Park Slope
neighbourhood_Park Versailles neighbourhood_Park View
neighbourhood_Parkchester neighbourhood_Parkside neighbourhood_Pasadena
neighbourhood_Pelham Bay neighbourhood_Petworth neighbourhood_Pico Rivera
neighbourhood_Pilsen neighbourhood_Pleasant Hill neighbourhood_Pleasant Plains
neighbourhood_Port Morris neighbourhood_Port Richmond neighbourhood_Portage
Park neighbourhood_Porter Ranch neighbourhood_Portola neighbourhood_Potrero
Hill neighbourhood_Presidio neighbourhood_Presidio Heights
neighbourhood_Prospect Heights neighbourhood_Rancho Palos Verdes
neighbourhood_Randall Manor neighbourhood_Randle Highlands neighbourhood_Red
Hook neighbourhood_Redondo Beach neighbourhood_Rego Park neighbourhood_Reseda
neighbourhood_Richmond District neighbourhood_Richmond Hill

neighbourhood_Ridgewood neighbourhood_River North neighbourhood_River Terrace
neighbourhood_River West neighbourhood_Riverdale neighbourhood_Rogers Park
neighbourhood_Rolling Hills neighbourhood_Roosevelt Island
neighbourhood_Roscoe Village neighbourhood_Rosebank neighbourhood_Roseland
neighbourhood_Rosemead neighbourhood_Roslindale neighbourhood_Rossville
neighbourhood_Roxbury neighbourhood_Russian Hill neighbourhood_San Gabriel
neighbourhood_San Marino neighbourhood_San Pedro neighbourhood_Santa Fe
Springs neighbourhood_Santa Monica neighbourhood_Sea Cliff neighbourhood_Sea
Gate neighbourhood_Shaw neighbourhood_Sheepshead Bay neighbourhood_Shepherd
Park neighbourhood_Sherman Oaks neighbourhood_Sierra Madre
neighbourhood_Signal Hill neighbourhood_Silver Lake neighbourhood_Silver
Spring, MD neighbourhood_Skid Row neighbourhood_SoMa neighbourhood_Soho
neighbourhood_Somerville neighbourhood_Soundview neighbourhood_South Beach
neighbourhood_South Boston neighbourhood_South Chicago neighbourhood_South El
Monte neighbourhood_South End neighbourhood_South Gate neighbourhood_South LA
neighbourhood_South Loop/Printers Row neighbourhood_South Ozone Park
neighbourhood_South Pasadena neighbourhood_South Robertson neighbourhood_South
San Gabriel neighbourhood_South Shore neighbourhood_South Street Seaport
neighbourhood_South Whittier neighbourhood_Southwest Waterfront
neighbourhood_Spring Valley neighbourhood_Spuyten Duyvil neighbourhood_St.
Elizabeths neighbourhood_St. George neighbourhood_Stapleton
neighbourhood_Streeterville neighbourhood_Stronghold neighbourhood_Studio City
neighbourhood_Sun Valley neighbourhood_Sunland/Tujunga neighbourhood_Sunnyside
neighbourhood_Sunset Park neighbourhood_Sylmar neighbourhood_Takoma
neighbourhood_Takoma Park, MD neighbourhood_Tarzana neighbourhood_Telegraph
Hill neighbourhood_Temple City neighbourhood_Tenderloin neighbourhood_The
Bronx neighbourhood_The Castro neighbourhood_The Rockaways
neighbourhood_Theater District neighbourhood_Throgs Neck neighbourhood_Times
Square/Theatre District neighbourhood_Toluca Lake neighbourhood_Tompkinsville
neighbourhood_Topanga neighbourhood_Torrance neighbourhood_Tottenville
neighbourhood_Tremont neighbourhood_Tribeca neighbourhood_Trinidad
neighbourhood_Truxton Circle neighbourhood_Twin Peaks neighbourhood_Twining
neighbourhood_U Street Corridor neighbourhood_Ukrainian Village
neighbourhood_Union Square neighbourhood_University Heights
neighbourhood_Upper East Side neighbourhood_Upper West Side
neighbourhood_Uptown neighbourhood_Valley Glen neighbourhood_Valley Village
neighbourhood_Van Nest neighbourhood_Van Nuys neighbourhood_Venice
neighbourhood_Vinegar Hill neighbourhood_Visitacion Valley
neighbourhood_Wakefield neighbourhood_Washington Heights
neighbourhood_Washington Highlands neighbourhood_Watertown neighbourhood_Watts
neighbourhood_Wesley Heights neighbourhood_West Adams neighbourhood_West
Athens neighbourhood_West Brighton neighbourhood_West Covina
neighbourhood_West End neighbourhood_West Farms neighbourhood_West Hills
neighbourhood_West Hollywood neighbourhood_West Lawn neighbourhood_West
Loop/Greektown neighbourhood_West Los Angeles neighbourhood_West Portal
neighbourhood_West Puente Valley neighbourhood_West Ridge neighbourhood_West
Roxbury neighbourhood_West Town/Noble Square neighbourhood_West Village
neighbourhood_Westchester Village neighbourhood_Westchester/Playa Del Rey

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
[55]: # Corrélation forte entre le prix de l'appartement et le neighbourhood ?
      # Calcul de la matrice de corrélation
      matrice_corr_neighbourhood= df_bin[["log_price"]] + [col for col in df_bin.
      columns if "neighbourhood" in col]].corr()
```

```
[56]: # heatmap
plt.figure(figsize=(10, 8))
#sns.heatmap(matrice_corr_neighbourhood, annot=True, cmap="coolwarm")

#plt.xticks(rotation=45)
#plt.yticks(rotation=0)
#plt.title("Matrice de corrélation entre log_prix et le voisinage")

plt.show()
```

```
[56]: <Figure size 1000x800 with 0 Axes>
```

<Figure size 1000x800 with 0 Axes>

Comme il y en a beaucoup, le chargement est très long (et mon pc a presque crashé), mais à mon avis cette donnée joue sur le prix

- Pour les zipcode :

```
[57]: # Pour voir le log_price en fonction du zipcode :
#log_price_en_fct_zipcode = df_bin.groupby([col for col in df_bin.columns if
↳ 'zipcode' in col])['log_price'].mean()
```

```
#print(log_price_en_fct_zipcode)
```

De même, il y en a beaucoup, mais cette donnée joue aussi sur le prix

- Pour le nombre de chambres :

```
[58]: # Pour voir le log_price en fonction du nombre de chambres :
log_price_en_fct_bedrooms = df_bin.groupby([col for col in df_bin.columns if
↳ 'bedrooms' in col])['log_price'].mean()

print(log_price_en_fct_bedrooms)
```

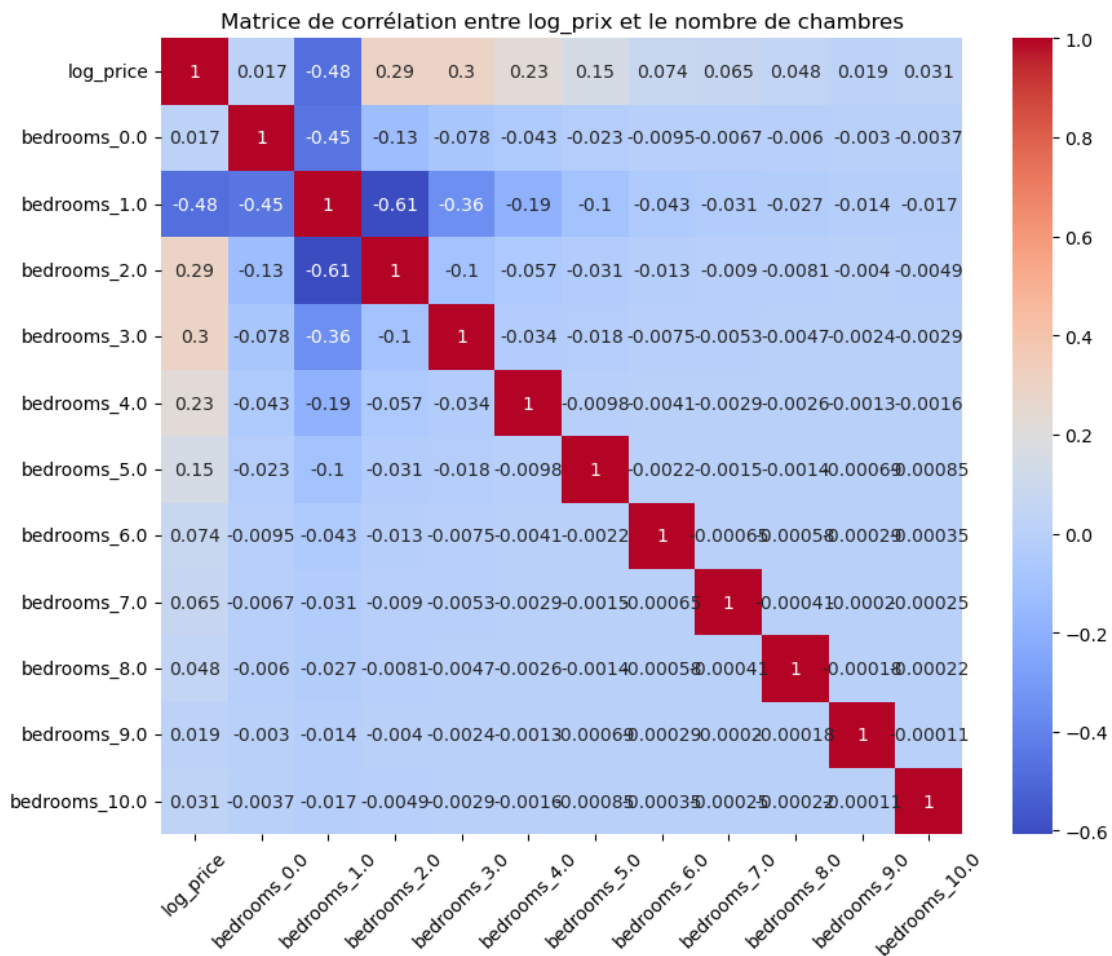
bedrooms_0.0	bedrooms_1.0	bedrooms_2.0	bedrooms_3.0	bedrooms_4.0	
bedrooms_5.0	bedrooms_6.0	bedrooms_7.0	bedrooms_8.0	bedrooms_9.0	
bedrooms_10.0					
False	False	False	False	False	False
False	False	False	False	False	
4.790867					
				True	
6.713924			True	False	
6.224509		True	False	False	
6.605355					
	True	False	False	False	
6.963010					
True	False	False	False	False	
6.541223					
					True
False	False	False	False	False	
6.256977					
				True	False
False	False	False	False	False	
5.978486			True	False	False
False	False	False	False	False	
5.644117					
		True	False	False	False
False	False	False	False	False	
5.279051					
	True	False	False	False	False
False	False	False	False	False	
4.543968					
True	False	False	False	False	False
False	False	False	False	False	
4.820819					
Name: log_price, dtype: float64					

```
[59]: # Corrélation forte entre le prix de l'appartement et le nombre de chambres ?
# Calcul de la matrice de corrélation
matrice_corr_bedrooms= df_bin[["log_price"]] + [col for col in df_bin.columns if
↳ "bedrooms" in col]].corr()
```

```
[60]: # heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(matrice_corr_bedrooms, annot=True, cmap="coolwarm")

plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title("Matrice de corrélation entre log_prix et le nombre de chambres")

plt.show()
```



Cette donnée a une influence sur le prix

- Pour le nombre de lits :

```
[61]: # Pour voir le log_price en fonction du nombre de lits :
log_price_en_fct_beds = df_bin.groupby([col for col in df_bin.columns if 'beds' in col])['log_price'].mean()

print(log_price_en_fct_beds)
```

beds_0.0	beds_1.0	beds_2.0	beds_3.0	beds_4.0	beds_5.0	beds_6.0	beds_7.0
beds_8.0	beds_9.0	beds_10.0	beds_11.0	beds_12.0	beds_13.0	beds_16.0	
beds_18.0							
False	False	False	False	False	False	False	False
False	False	False	False	False	False	False	False
4.476913							
							True
6.684612							
						True	False
5.982366							
					True	False	False
5.922091				True	False	False	False
5.770915			True	False	False	False	False
			True	False	False	False	False
5.960961		True	False	False	False	False	False
4.657515	True	False	False	False	False	False	False
5.961424	True	False	False	False	False	False	False
True	False	False	False	False	False	False	False
5.330195							True
False	False	False	False	False	False	False	False
5.984289							
						True	False
False	False	False	False	False	False	False	False
5.682948					True	False	False
					False	False	False
False	False	False	False	False	False	False	False
5.741630				True	False	False	False
				False	False	False	False
False	False	False	False	False	False	False	False
5.466450			True	False	False	False	False
			False	False	False	False	False
False	False	False	False	False	False	False	False
5.289058		True	False	False	False	False	False
		False	False	False	False	False	False
False	False	False	False	False	False	False	False
5.003002	True	False	False	False	False	False	False

```

False      False      False      False      False      False      False      False
4.530720
True       False      False      False      False      False      False      False
False      False      False      False      False      False      False      False
5.991465
Name: log_price, dtype: float64

```

```

[62]: # Corrélation forte entre le prix de l'appartement et le nombre de lits ?
      # Calcul de la matrice de corrélation
      matrice_corr_beds= df_bin[["log_price"]] + [col for col in df_bin.columns if
      ↪ "beds" in col]].corr()

```

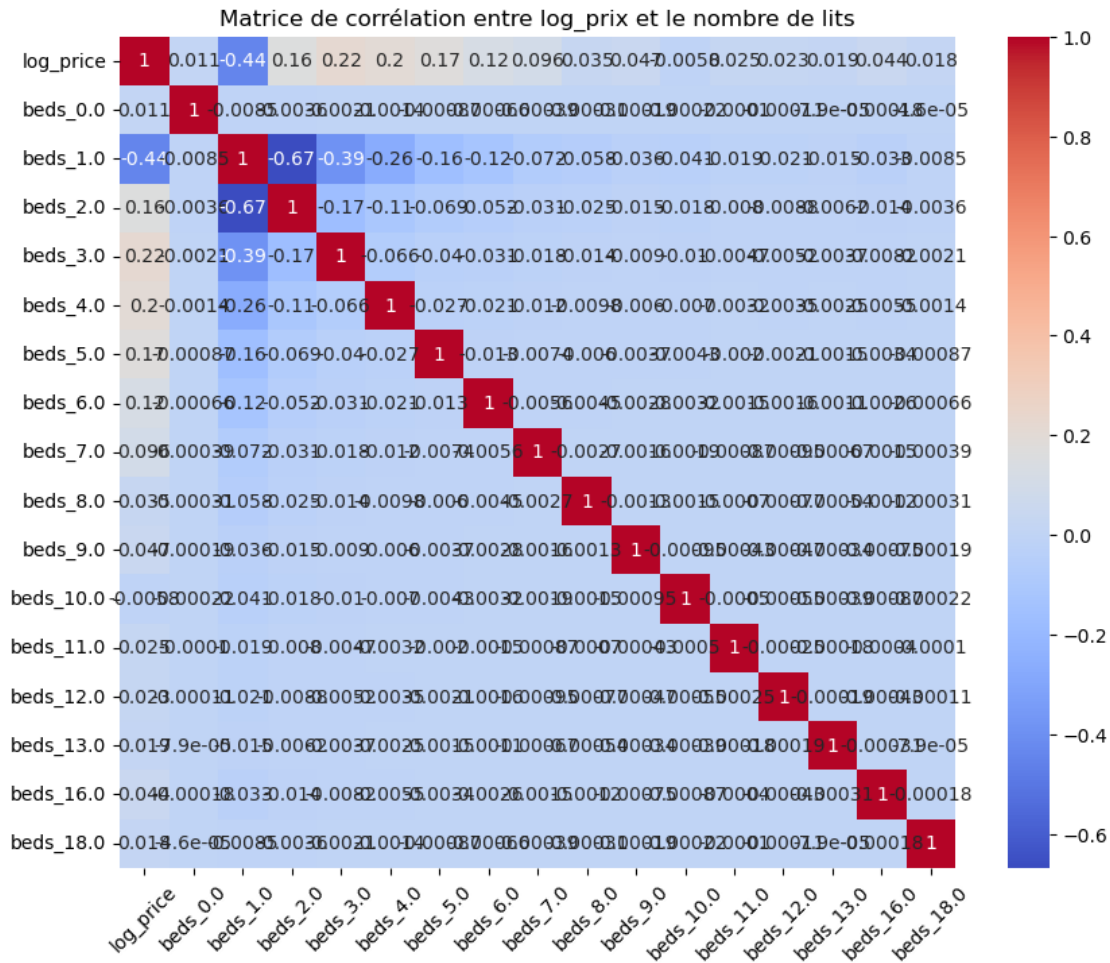
```

[63]: # heatmap
      plt.figure(figsize=(10, 8))
      sns.heatmap(matrice_corr_beds, annot=True, cmap="coolwarm")

      plt.xticks(rotation=45)
      plt.yticks(rotation=0)
      plt.title("Matrice de corrélation entre log_prix et le nombre de lits")

      plt.show()

```

Je remarque une influence sur le prix

Donc les corrélations que je garde :

```
[64]: colonnes = ['property_type', 'room_type', 'cleaning_fee', 'city',
    ↪ 'neighbourhood', 'zipcode', 'bedrooms', 'beds']
```

Diagrammes (pour voir la distribution des prix en fonction des variables fortement corrélées) :

```
[65]: fig = px.histogram(df, x = 'log_price', title = 'Distribution du log_price')
fig.show()
```

```
[66]: # Box plot pour visualiser la distribution du log_price pour chaque type de
    ↪ propriété
fig = px.box(df, x = 'property_type', y = 'log_price', title = 'log_price par
    ↪ property_type')
fig.show()
```

```
[67]: # log_price par type de chambre
fig = px.bar(df, x='room_type', y='log_price', title='log_price par room_type',
             labels={'log_price': 'log_price'})
fig.show()
```

```
[68]: # Box plot des types de chambres et du log_price
fig = px.box(df, x='room_type', y='log_price', title='log_price par room_type')
fig.show()
```

```
[69]: # Histogramme des accomodates et du log_price
fig = px.histogram(df, x='accommodates', y='log_price', title='log_price par_
↳ Accommodates', histfunc='avg')
fig.show()
```

```
[70]: # Diagramme en barres des politiques d'annulation et du log_price
fig = px.bar(df, x='cancellation_policy', y='log_price', title='log_price par_
↳ cancellation_policy',
             labels={'log_price': 'log_price'})
fig.show()
```

```
[71]: # Box plot des quartiers et du log_price
fig = px.box(df, x='neighbourhood', y='log_price', title='log_price par_
↳ neighbourhood')
fig.show()
```

```
[72]: # Box plot des codes postaux et du log_price
fig = px.box(df, x='zipcode', y='log_price', title='log_price par zipcode')
fig.show()
```

```
[73]: # Nuage de points pour visualiser la relation entre le nombre de salles de_
↳ bains et le log_price

fig = px.scatter(df, x='bathrooms', y='log_price', title='log_price et_
↳ bathrooms',
                labels={'bathrooms': 'nombre de salles de bain', 'log_price':_
↳ 'Log Price'})
fig.show()
```

```
[74]: # Nuage de points pour visualiser la relation entre le nombre de chambres et le_
↳ log_price
fig = px.scatter(df, x='bedrooms', y='log_price', title='log_price et bedrooms',
                labels={'bedrooms': 'nombre de chambres', 'log_price':_
↳ 'log_price'})
fig.show()
```

- Pour les amenities :

J'essaie de créer des variables binaires à partir de la colonne 'amenities' pour indiquer la présence ou l'absence de certains équipements (en considérant qu'ils ont la même valeur)

```
[75]: # Fonction pour extraire les équipements
def extraire_amenities(amenities_str):
    if isinstance(amenities_str, list):
        return amenities_str
    amenities_liste = amenities_str.strip('{}').split(',')
    amenities_extr = [amenity.strip('" ') for amenity in amenities_liste]
    return amenities_extr

df['amenities'] = df['amenities'].apply(extraire_amenities)
```

```
[76]: df['amenities']
```

```
[76]: 0      [TV, Wireless Internet, Kitchen, Free parking ...
1      [Wireless Internet, Air conditioning, Kitchen,...
2      [TV, Wireless Internet, Air conditioning, Kitc...
3      [TV, Cable TV, Internet, Wireless Internet, Ai...
4      [TV, Cable TV, Internet, Wireless Internet, Ki...
...
22229                                     []
22230      [TV, Cable TV, Internet, Wireless Internet, Ki...
22231      [TV, Internet, Wireless Internet, Air conditio...
22232      [TV, Wireless Internet, Air conditioning, Kitc...
22233      [TV, Internet, Wireless Internet, Kitchen, Fre...
Name: amenities, Length: 21931, dtype: object
```

Si j'essaie de compter le nombre d'équipements par logement/offre :

```
[77]: df['nb_amenities'] = df['amenities'].apply(lambda x: len(x))
```

```
[78]: df['nb_amenities']
```

```
[78]: 0      15
1      25
2      20
3      30
4      24
...
22229      1
22230     16
22231     31
22232     15
22233     18
Name: nb_amenities, Length: 21931, dtype: int64
```

```
[79]: # Visualisation de la relation entre le nombre d'équipements et le log_price
      ↪ avec un nuage de points :
fig = px.scatter(df, x='nb_amenities', y='log_price', hover_data=['id'])
fig.show()
```

Je veux ajouter la colonne “nb_amenities” à df_bin tout en supprimant la colonne “amenities” du dataframe d’origine df :

```
[80]: # Suppression de la colonne "amenities" du DataFrame d'origine
df_temp = df.drop('amenities', axis=1)

categories = ['property_type', 'room_type', 'accommodates', 'bathrooms',
      ↪ 'bed_type', 'cancellation_policy', 'cleaning_fee', 'city', 'neighbourhood',
      ↪ 'zipcode', 'bedrooms', 'beds']

# Création des variables dummy à partir des colonnes de categories
df_bin = pd.get_dummies(df_temp, columns=categories)

df_bin['nb_amenities'] = df['nb_amenities']
```

```
[81]: df_bin.head()
```

```
[81]:
```

	id	log_price	latitude	longitude	nb_amenities	\
0	5708593	4.317488	33.782712	-118.134410	15	
1	14483613	4.007333	40.705468	-73.909439	25	
2	10412649	7.090077	38.917537	-77.031651	20	
3	17954362	3.555348	40.736001	-73.924248	30	
4	9969781	5.480639	37.744896	-122.430665	24	

	property_type_Apartment	property_type_Bed & Breakfast	property_type_Boat	\
0	False	False	False	
1	False	False	False	
2	True	False	False	
3	False	False	False	
4	False	False	False	

	property_type_Boutique hotel	property_type_Bungalow	...	beds_6.0	\
0	False	False	...	False	
1	False	False	...	False	
2	False	False	...	False	
3	False	False	...	False	
4	False	False	...	False	

	beds_7.0	beds_8.0	beds_9.0	beds_10.0	beds_11.0	beds_12.0	beds_13.0	\
0	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	

3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False

	beds_16.0	beds_18.0
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

[5 rows x 1348 columns]

- Pour les cartes :

J'ai aussi utilisé le fichier GeoJSON contenant le jeu de données entier disponible sur le site suivant : <https://public.opendatasoft.com/explore/dataset/georef-united-states-of-america-zc-point/export/?location=2,40.5661,39.98938&basemap=jawg.light>

```
[82]: # Scatter plot des latitude, longitude et du log_price
fig = px.scatter(df, x='longitude', y='latitude', color='log_price',
    ↪title='Distribution géographique du log_price', color_continuous_scale=px.
    ↪colors.sequential.Viridis)
fig.show()
```

```
[83]: # Carte centrée sur les données
map = folium.Map(location=[df['latitude'].mean(), df['longitude'].mean()],
    ↪zoom_start=10)

# Marqueur pour chaque point avec une couleur basée sur le prix
for idx, row in df.iterrows():
    folium.CircleMarker(
        location=[row['latitude'], row['longitude']],
        radius=5,
        color='crimson',
        fill=True,
        fill_color='crimson',
        fill_opacity=0.5,
        popup=f"Prix: {row['log_price']}")
    .add_to(map)

map
```

```
[83]: <folium.folium.Map at 0x1292ae39490>
```

(dézoomer pour voir les Etats-Unis dans son ensemble)

```
[84]: import geopandas as gpd
```

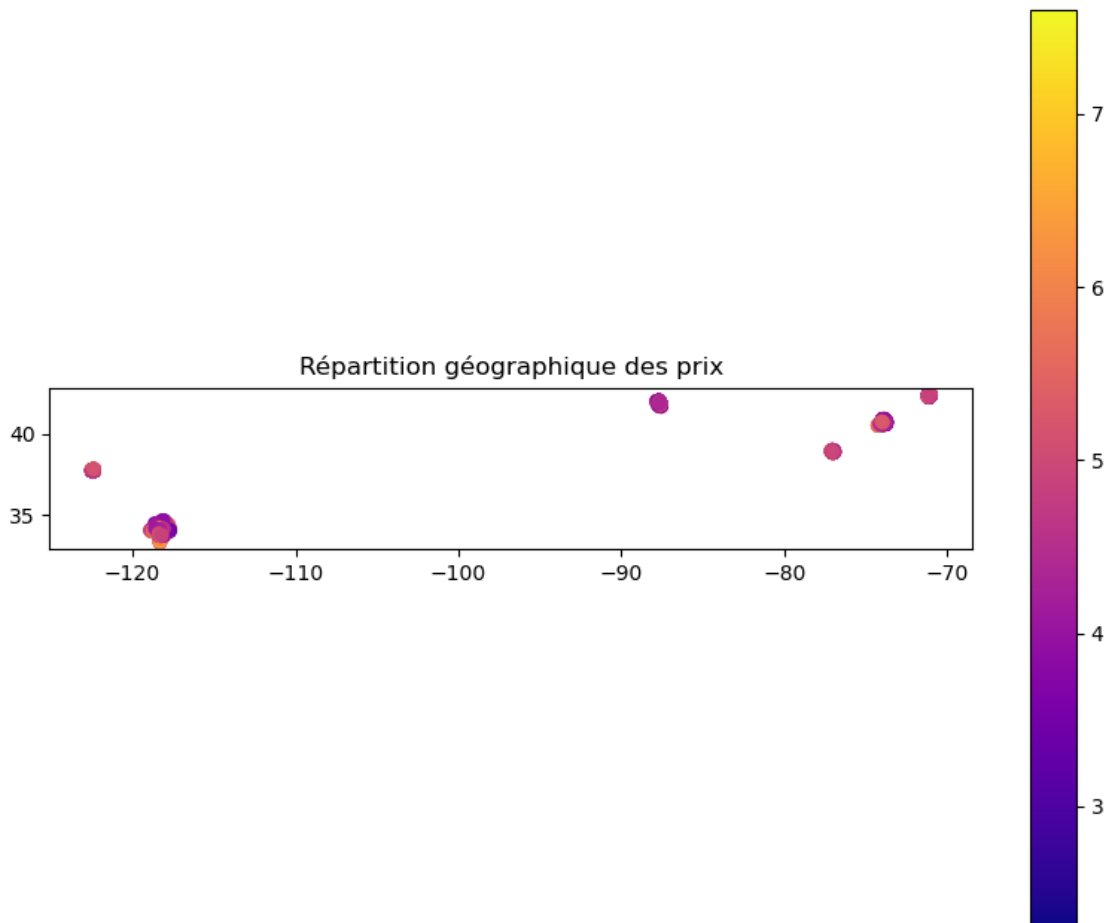
```

# Conversion du DataFrame en GeoDataFrame
gdf = gpd.GeoDataFrame(
    df, geometry=gpd.points_from_xy(df.longitude, df.latitude)
)

# Création d'une carte de chaleur basée sur les prix
fig, ax = plt.subplots(figsize=(10, 8))
gdf.plot(column='log_price', cmap='plasma', ax=ax, legend=True)
ax.set_title("Répartition géographique des prix")

plt.show()

```



```

[85]: geo_data = gpd.read_file('usa_zipcodes.geojson')

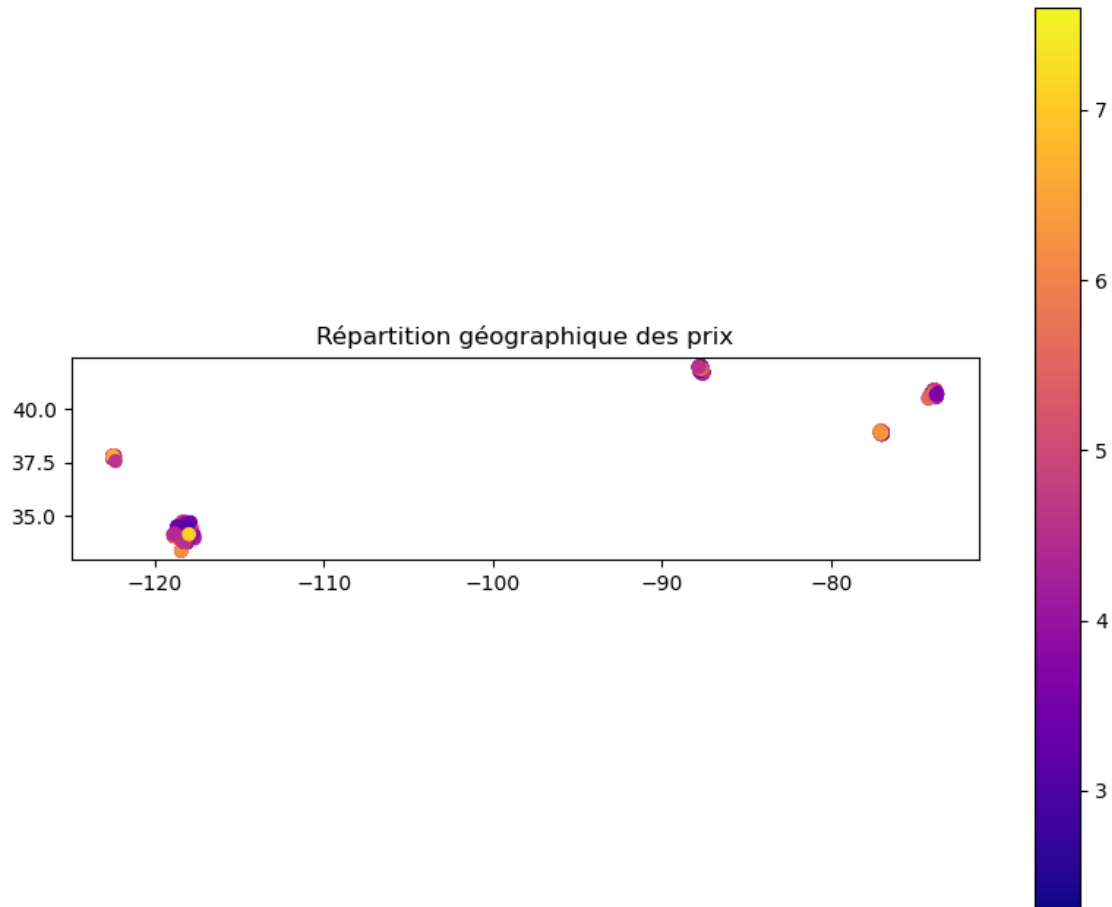
# Jointure au DataFrame
df = df.merge(geo_data[['zip_code', 'geometry']], left_on='zipcode',
    right_on='zip_code')

```

```
# Conversion en GeoDataFrame
gdf = gpd.GeoDataFrame(df, geometry='geometry')

# Carte
fig, ax = plt.subplots(figsize=(10, 8))
gdf.plot(column='log_price', cmap='plasma', ax=ax, legend=True)
ax.set_title("Répartition géographique des prix")

plt.show()
```



3 II. Partie prédiction

A l'aide du cours et des éléments de <https://scikit-learn.org/stable/>

3.1 1. Préparation des données

3.1.1 Sélection des données

```
[86]: X = df_bin.loc[:, df_bin.columns != "log_price"]
      y = df_bin["log_price"] # Prédiction du log du prix
```

```
[87]: X.head()
```

```
[87]:
```

	id	latitude	longitude	nb_amenities	property_type_Apartment	\
0	5708593	33.782712	-118.134410	15	False	
1	14483613	40.705468	-73.909439	25	False	
2	10412649	38.917537	-77.031651	20	True	
3	17954362	40.736001	-73.924248	30	False	
4	9969781	37.744896	-122.430665	24	False	

	property_type_Bed & Breakfast	property_type_Boat	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	property_type_Boutique hotel	property_type_Bungalow	property_type_Cabin	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	

	...	beds_6.0	beds_7.0	beds_8.0	beds_9.0	beds_10.0	beds_11.0	\
0	...	False	False	False	False	False	False	
1	...	False	False	False	False	False	False	
2	...	False	False	False	False	False	False	
3	...	False	False	False	False	False	False	
4	...	False	False	False	False	False	False	

	beds_12.0	beds_13.0	beds_16.0	beds_18.0
0	False	False	False	False
1	False	False	False	False
2	False	False	False	False
3	False	False	False	False
4	False	False	False	False

[5 rows x 1347 columns]

```
[88]: y.head()
```



```
[88]: 0    4.317488
      1    4.007333
      2    7.090077
      3    3.555348
      4    5.480639
      Name: log_price, dtype: float64
```

3.1.2 Analyse en Composantes Principales (PCA)

```
[89]: from sklearn.decomposition import PCA

pca = PCA(n_components=0.95) # On conserve 95% de la variance
X_pca = pca.fit_transform(X)
```

3.1.3 Séparation train/test

```
[90]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳ random_state=42)
```

```
[91]: print ("Dimension pour X_train:", X_train.shape)
      print ("Dimension pour X_test:", X_test.shape)
      print ("Dimension pour y_train:", y_train.shape)
      print ("Dimension pour y_test:", y_test.shape)
```

```
Dimension pour X_train: (17544, 1347)
Dimension pour X_test: (4387, 1347)
Dimension pour y_train: (17544,)
Dimension pour y_test: (4387,)
```

3.1.4 Standardisation

```
[92]: from sklearn.preprocessing import StandardScaler

scaler_X = StandardScaler()
X_train_scaled = scaler_X.fit_transform(X_train)
X_test_scaled = scaler_X.transform(X_test)
```

```
[93]: X_train
```

```
[93]:
```

	id	latitude	longitude	nb_amenities	property_type_Apartment \
7240	14609935	40.689492	-73.917084	7	True
11169	16002569	42.351714	-71.061075	11	True
3226	18449729	34.126614	-118.174707	20	False
9379	53579	40.688980	-73.947558	22	True
11654	6324190	40.795911	-73.933164	22	True

...
12144	14100670	40.843931	-73.939488	14		True
21874	13461289	37.787820	-122.456031	1		True
5480	10167436	34.104489	-118.373349	10		False
872	16722017	40.800658	-73.969408	7		True
16025	13916918	40.809920	-73.958592	5		True

	property_type_Bed & Breakfast	property_type_Boat \
7240	False	False
11169	False	False
3226	False	False
9379	False	False
11654	False	False

...
12144	False	False
21874	False	False
5480	False	False
872	False	False
16025	False	False

	property_type_Boutique hotel	property_type_Bungalow \
7240	False	False
11169	False	False
3226	False	False
9379	False	False
11654	False	False

...
12144	False	False
21874	False	False
5480	False	False
872	False	False
16025	False	False

	property_type_Cabin	...	beds_6.0	beds_7.0	beds_8.0	beds_9.0 \
7240	False	...	False	False	False	False
11169	False	...	False	False	False	False
3226	False	...	False	False	False	False
9379	False	...	False	False	False	False
11654	False	...	False	False	False	False

...
12144	False	...	False	False	False
21874	False	...	False	False	False
5480	False	...	False	False	False
872	False	...	False	False	False
16025	False	...	False	False	False

beds_10.0	beds_11.0	beds_12.0	beds_13.0	beds_16.0	beds_18.0
-----------	-----------	-----------	-----------	-----------	-----------

7240	False	False	False	False	False	False
11169	False	False	False	False	False	False
3226	False	False	False	False	False	False
9379	False	False	False	False	False	False
11654	False	False	False	False	False	False
...
12144	False	False	False	False	False	False
21874	False	False	False	False	False	False
5480	False	False	False	False	False	False
872	False	False	False	False	False	False
16025	False	False	False	False	False	False

[17544 rows x 1347 columns]

[94]: X_train_scaled

```
[94]: array([[ 0.55775262,  0.72116905,  0.84459889, ..., -0.01307776,
             -0.02826006, -0.00755002],
             [ 0.78653847,  1.26199317,  0.9764602 , ..., -0.01307776,
             -0.02826006, -0.00755002],
             [ 1.18856483, -1.414143  , -1.19876596, ..., -0.01307776,
             -0.02826006, -0.00755002],
             ...,
             [-0.17207368, -1.42134138, -1.20793723, ..., -0.01307776,
             -0.02826006, -0.00755002],
             [ 0.90473142,  0.75733826,  0.84218312, ..., -0.01307776,
             -0.02826006, -0.00755002],
             [ 0.44390183,  0.76035203,  0.84268249, ..., -0.01307776,
             -0.02826006, -0.00755002]])
```

[95]: X_test

```
[95]:
```

	id	latitude	longitude	nb_amenities	property_type_Apartment \
11319	7919542	38.843454	-76.976974	29	False
3894	5683405	34.179263	-118.387062	17	False
12213	19711234	34.093560	-118.273078	7	True
8802	17112616	34.104154	-118.302914	11	True
17439	11626795	34.099800	-118.314924	26	True
...
12624	20879290	40.584594	-73.935001	12	False
10791	17295824	40.689487	-73.927841	5	True
19388	8909891	40.708304	-74.004147	17	True
10121	18991641	40.645826	-74.013066	12	True
12505	7072404	34.023719	-118.487040	12	True

	property_type_Bed & Breakfast	property_type_Boat \
11319	False	False

3894	True	False
12213	False	False
8802	False	False
17439	False	False
...
12624	False	False
10791	False	False
19388	False	False
10121	False	False
12505	False	False

	property_type_Boutique hotel	property_type_Bungalow \
11319	False	False
3894	False	False
12213	False	False
8802	False	False
17439	False	False
...
12624	False	False
10791	False	False
19388	False	False
10121	False	False
12505	False	False

	property_type_Cabin ...	beds_6.0	beds_7.0	beds_8.0	beds_9.0 \
11319	False ...	False	False	False	False
3894	False ...	False	False	False	False
12213	False ...	False	False	False	False
8802	False ...	False	False	False	False
17439	False ...	False	False	False	False
...
12624	False ...	False	False	False	False
10791	False ...	False	False	False	False
19388	False ...	False	False	False	False
10121	False ...	False	False	False	False
12505	False ...	False	False	False	False

	beds_10.0	beds_11.0	beds_12.0	beds_13.0	beds_16.0	beds_18.0
11319	False	False	False	False	False	False
3894	False	False	False	False	False	False
12213	False	False	False	False	False	False
8802	False	False	False	False	False	False
17439	False	False	False	False	False	False
...
12624	False	False	False	False	False	False
10791	False	False	False	False	False	False
19388	False	False	False	False	False	False

10121	False	False	False	False	False	False
12505	False	False	False	False	False	False

[4387 rows x 1347 columns]

```
[96]: X_test_scaled
```

```
[96]: array([[ -0.54136406,  0.12053842,  0.70332441, ..., -0.01307776,
          -0.02826006, -0.00755002],
          [-0.90872297, -1.39701276, -1.20857033, ..., -0.01307776,
          -0.02826006, -0.00755002],
          [ 1.39580844, -1.4248973 , -1.20330773, ..., -0.01307776,
          -0.02826006, -0.00755002],
          ...,
          [-0.37866673,  0.72729001,  0.8405792 , ..., -0.01307776,
          -0.02826006, -0.00755002],
          [ 1.27759167,  0.7069618 ,  0.84016743, ..., -0.01307776,
          -0.02826006, -0.00755002],
          [-0.68053429, -1.44762106, -1.21318631, ..., -0.01307776,
          -0.02826006, -0.00755002]])
```

```
[97]: scaler_y = StandardScaler()
y_train_scaled = scaler_y.fit_transform(y_train.values.reshape(-1, 1))
y_test_scaled = scaler_y.transform(y_test.values.reshape(-1, 1))
```

```
[98]: y_train_scaled
```

```
[98]: array([[ -0.8527163 ],
          [-0.26742265],
          [-0.98744698],
          ...,
          [-0.25344133],
          [ 0.05698033],
          [-0.56386298]])
```

```
[99]: y_test_scaled
```

```
[99]: array([[ -1.39553187],
          [-0.32479696],
          [-0.47952626],
          ...,
          [ 0.40039475],
          [-0.47952626],
          [ 0.45160777]])
```

3.2 2. Régression linéaire (LinearRegression)

Premier modèle de test : une modélisation de la relation entre la variable à prédire (`log_prix`) et les variables indépendantes (caractéristiques), en supposant une relation linéaire entre elles

```
[100]: from sklearn.linear_model import LinearRegression
      from sklearn.metrics import mean_squared_error, r2_score
```

```
[101]: # Modèle
      regressor_lin = LinearRegression()
```

```
[102]: # Entraînement du modèle sur les données d'entraînement
      regressor_lin.fit(X_train_scaled, y_train_scaled.ravel())
```

```
[102]: LinearRegression()
```

```
[103]: # Prédiction sur l'ensemble d'entraînement
      y_train_pred_lin = regressor_lin.predict(X_train_scaled)

      # Prédiction sur l'ensemble de test
      y_test_pred_lin = regressor_lin.predict(X_test_scaled)
```

```
[104]: # Évaluation des performances sur les ensembles d'entraînement et de test
      train_mse_lin = mean_squared_error(y_train_scaled, y_train_pred_lin)
      test_mse_lin = mean_squared_error(y_test_scaled, y_test_pred_lin)

      train_rmse_lin = np.sqrt(train_mse_lin)
      test_rmse_lin = np.sqrt(test_mse_lin)

      train_r2_lin = r2_score(y_train_scaled, y_train_pred_lin)
      test_r2_lin = r2_score(y_test_scaled, y_test_pred_lin)

      print(f"Entraînement : MSE={train_mse_lin:.3f}, RMSE={train_rmse_lin:.3f},  

      ↪R²={train_r2_lin:.3f}")
      print(f"Test : MSE={test_mse_lin:.3f}, RMSE={test_rmse_lin:.3f},  

      ↪R²={test_r2_lin:.3f}")
```

Entraînement : MSE=0.314, RMSE=0.561, $R^2=0.686$

Test : MSE=67891222065180629262139392.000, RMSE=8239612980303.179,
 $R^2=-68497857738577027335716864.000$

Plus le score R^2 est proche de 1, plus la prédiction est bonne.

```
[105]: # Graphique de résidus : différence entre les valeurs réelles et prédites
      residus_lin = y_train - y_train_pred_lin
      fig = px.scatter(x=y_train_pred_lin, y=residus_lin, labels={"x": "Valeurs  

      ↪prédites par la régression linéaire", "y": "Résidus"})
      fig.show()
```

```
[106]: # Distribution des erreurs
fig = px.histogram(residus_lin, nbins=30, labels={"value": "Résidus"},
    ↪title="Distribution des erreurs pour la régression linéaire")
fig.show()
```

Conclusion : j'obtiens

- en entraînement : MSE=0.314, RMSE=0.561, $R^2=0.686$
- en test : MSE=67891222065180629262139392.000, RMSE=8239612980303.179, $R^2=-68497857738577027335716864.000$

Ici, le modèle s'ajuste très bien aux données d'entraînement, mais en voyant les résultats du test, le modèle semble souffrir d'un sur-apprentissage donc il échoue complètement à généraliser sur les données de test.

3.3 3. Régression par support vector machine (SVR)

L'objectif est de trouver une limite de décision (hyperplan) qui sépare au mieux les jeux de données, en maximisant la marge et en minimisant l'erreur de classification. Cela permet de capturer des relations non linéaires entre les variables et la variable cible (log_prix).

```
[107]: # Modèle
from sklearn.svm import SVR
regressor = SVR(kernel = 'rbf')
regressor.fit(X_train_scaled, y_train_scaled.ravel())
```

[107]: SVR()

(4 min pour charger[^])

```
[108]: # Évaluation des performances sur les ensembles d'entraînement et de test
y_train_pred = regressor.predict(X_train_scaled)
y_test_pred = regressor.predict(X_test_scaled)

train_mse = mean_squared_error(y_train_scaled, y_train_pred)
test_mse = mean_squared_error(y_test_scaled, y_test_pred)
train_rmse = np.sqrt(train_mse)
test_rmse = np.sqrt(test_mse)

train_r2 = r2_score(y_train_scaled, y_train_pred)
test_r2 = r2_score(y_test_scaled, y_test_pred)

print(f"Entraînement : MSE={train_mse:.3f}, RMSE={train_rmse:.3f}, R²={train_r2:
    ↪.3f}")
print(f"Test : MSE={test_mse:.3f}, RMSE={test_rmse:.3f}, R²={test_r2:.3f}")
```

Entraînement : MSE=0.314, RMSE=0.561, $R^2=0.686$

Test : MSE=0.432, RMSE=0.658, $R^2=0.564$

(+6 min pour charger[^])

```
[109]: # Prédiction d'une nouvelle valeur
new_x = np.zeros(shape=(1, X_train.shape[1])) # Créer un vecteur de zéros de
↳ la même longueur que X_train
new_x[0, 0] = 6.5 # Remplacer la première caractéristique par 6.5

# Normalisation de la nouvelle donnée
new_x_scaled = scaler_X.transform(new_x)

# La prédiction
y_pred_scaled = regressor.predict(new_x_scaled)
y_pred = scaler_y.inverse_transform(y_pred_scaled.reshape(-1, 1))
print("Log_prix prédit : ", y_pred[0, 0])
```

Log_prix prédit : 4.599430606613116

C:\Users\wwuky\Anaconda\Lib\site-packages\sklearn\base.py:464: UserWarning:

X does not have valid feature names, but StandardScaler was fitted with feature names

On rq si la prédiction du modèle est 0 = 6.5, on obtient : Log_prix prédit : 4.599430606613116

```
[110]: # Graphique de résidus : différence entre les valeurs réelles et prédites
residus_svr = y_train - y_train_pred
fig = px.scatter(x=y_train_pred, y=residus_svr, labels={"x": "Valeurs prédites",
↳ par la SVR", "y": "Résidus"})
fig.show()
```

```
[111]: # Distribution des erreurs
fig = px.histogram(residus_svr, nbins=30, labels={"value": "Résidus"},
↳ title="Distribution des erreurs pour la SVR")
fig.show()
```

Conclusion : j'obtiens

- en entraînement : MSE=0.314, RMSE=0.561, $R^2=0.686$
- en test : MSE=0.432, RMSE=0.658, $R^2=0.564$

Ce modèle semble s'ajuster raisonnablement bien aux données d'entraînement et généralise de manière satisfaisante sur les données de test. Mais il y a une certaine différence de performances entre l'entraînement et le test, ce qui pourrait indiquer un léger sur-apprentissage.

3.3.1 4. Régression par forêt aléatoire (RandomForestRegressor)

C'est un autre algorithme d'apprentissage supervisé utilisé pour résoudre des problèmes de régression, grâce à un ensemble d'arbres ("forêt") de décision entraînés sur des sous-ensembles différents

des données d'entraînement, et en utilisant la méthode du bagging (bootstrap aggregating). Il prend en compte les relations non linéaires entre les variables prédictives et la variable cible (log_prix).

```
[112]: from sklearn.ensemble import RandomForestRegressor
```

```
[113]: # Modèle
regression_rfr = RandomForestRegressor(n_estimators=100, max_depth=10,
    ↪random_state=42)
```

```
[114]: # Entraînement du modèle sur les données d'entraînement
regression_rfr.fit(X_train_scaled, y_train_scaled.ravel())
```

```
[114]: RandomForestRegressor(max_depth=10, random_state=42)
```

```
[115]: # Prédiction sur l'ensemble d'entraînement
y_train_pred_rfr = regression_rfr.predict(X_train_scaled)

# Prédiction sur l'ensemble de test
y_test_pred_rfr = regression_rfr.predict(X_test_scaled)
```

```
[116]: # Évaluation des performances sur les ensembles d'entraînement et de test
train_mse_rfr = mean_squared_error(y_train_scaled, y_train_pred_rfr)
test_mse_rfr = mean_squared_error(y_test_scaled, y_test_pred_rfr)
train_rmse_rfr = np.sqrt(train_mse_rfr)
test_rmse_rfr = np.sqrt(test_mse_rfr)

train_r2_rfr = r2_score(y_train_scaled, y_train_pred_rfr)
test_r2_rfr = r2_score(y_test_scaled, y_test_pred_rfr)

print(f"Entraînement : MSE={train_mse_rfr:.3f}, RMSE={train_rmse_rfr:.3f},
    ↪R²={train_r2_rfr:.3f}")
print(f"Test : MSE={test_mse_rfr:.3f}, RMSE={test_rmse_rfr:.3f},
    ↪R²={test_r2_rfr:.3f}")
```

Entraînement : MSE=0.270, RMSE=0.520, R²=0.730

Test : MSE=0.375, RMSE=0.613, R²=0.621

```
[117]: # Graphique de résidus : différence entre les valeurs réelles et prédites
residus_rfr = y_train - y_train_pred_rfr
fig = px.scatter(x=y_train_pred_rfr, y=residus_rfr, labels={"x": "Valeurs
    ↪prédites par la régression par forêt aléatoire", "y": "Résidus"})
fig.show()
```

```
[118]: # Distribution des erreurs
fig = px.histogram(residus_rfr, nbins=30, labels={"value": "Résidus"},
    ↪title="Distribution des erreurs pour la régression par forêt aléatoire")
fig.show()
```

Conclusion : j'obtiens

- en entraînement : MSE=0.270, RMSE=0.520, $R^2=0.730$
- en test : MSE=0.375, RMSE=0.613, $R^2=0.621$

Globalement, il semble que ce modèle s'ajuste bien aux données d'entraînement tout en généralisant de manière satisfaisante sur les nouvelles données du test. La différence entre les performances sur l'entraînement et le test n'est pas trop grande, ce qui me paraît être un bon compromis entre biais et variance.

3.3.2 5. Régression ridge (Ridge) (1)

La régression ridge est une méthode de régularisation qui pénalise les coefficients élevés, ce qui réduit la variance du modèle et améliore sa capacité de généralisation, mais avec un petit biais supplémentaire par rapport à la régression linéaire classique.

```
[119]: from sklearn.linear_model import Ridge
```

```
[120]: # Modèle
regression_ridge1 = Ridge(alpha=1.0)
```

Test avec alpha = 1

```
[121]: # Entraînement du modèle sur les données d'entraînement
regression_ridge1.fit(X_train_scaled, y_train_scaled.ravel())
```

```
[121]: Ridge()
```

```
[122]: # Prédiction sur l'ensemble d'entraînement
y_train_pred_ridge1 = regression_ridge1.predict(X_train_scaled)

# Prédiction sur l'ensemble de test
y_test_pred_ridge1 = regression_ridge1.predict(X_test_scaled)

# Évaluation des performances sur les ensembles d'entraînement et de test
train_mse_ridge1 = mean_squared_error(y_train_scaled, y_train_pred_ridge1)
test_mse_ridge1 = mean_squared_error(y_test_scaled, y_test_pred_ridge1)
train_rmse_ridge1 = np.sqrt(train_mse_ridge1)
test_rmse_ridge1 = np.sqrt(test_mse_ridge1)

train_r2_ridge1 = r2_score(y_train_scaled, y_train_pred_ridge1)
test_r2_ridge1 = r2_score(y_test_scaled, y_test_pred_ridge1)

print(f"Entraînement : MSE={train_mse_ridge1:.3f}, RMSE={train_rmse_ridge1:.3f}, R²={train_r2_ridge1:.3f}")
print(f"Test : MSE={test_mse_ridge1:.3f}, RMSE={test_rmse_ridge1:.3f}, R²={test_r2_ridge1:.3f}")
```

Entraînement : MSE=0.304, RMSE=0.551, $R^2=0.696$
Test : MSE=0.365, RMSE=0.604, $R^2=0.632$

```
[123]: # Graphique de résidus : différence entre les valeurs réelles et prédites
residus_ridge1 = y_train - y_train_pred_ridge1
fig = px.scatter(x=y_train_pred_ridge1, y=residus_ridge1, labels={"x": "Valeurs_
↳prédites par la régression ridge (alpha = 1)", "y": "Résidus"})
fig.show()
```

```
[124]: # Distribution des erreurs
fig = px.histogram(residus_ridge1, nbins=30, labels={"value": "Résidus"},
↳title="Distribution des erreurs pour la régression ridge (alpha = 1)")
fig.show()
```

Conclusion : j'obtiens (avec $\alpha = 1$)

- en entraînement : MSE=0.304, RMSE=0.551, $R^2=0.696$
- en test : MSE=0.365, RMSE=0.604, $R^2=0.632$

Globalement, il semble que le modèle Ridge s'ajuste de manière satisfaisante aux données d'entraînement et généralise raisonnablement bien sur les nouvelles données du test. La différence entre les performances sur l'entraînement et le test n'est pas trop grande non plus, ce qui semble être un bon compromis entre biais et variance.

3.3.3 Régression ridge (Ridge) (2)

```
[125]: # Modèle
regression_ridge2 = Ridge(alpha=5) #test avec une autre valeur de alpha
```

```
[126]: # Entraînement du modèle sur les données d'entraînement
regression_ridge2.fit(X_train_scaled, y_train_scaled.ravel())
```

```
[126]: Ridge(alpha=5)
```

```
[127]: # Prédictions sur l'ensemble d'entraînement
y_train_pred_ridge2 = regression_ridge2.predict(X_train_scaled)

# Prédictions sur l'ensemble de test
y_test_pred_ridge2 = regression_ridge2.predict(X_test_scaled)

# Évaluation des performances sur les ensembles d'entraînement et de test
train_mse_ridge2 = mean_squared_error(y_train_scaled, y_train_pred_ridge2)
test_mse_ridge2 = mean_squared_error(y_test_scaled, y_test_pred_ridge2)
train_rmse_ridge2 = np.sqrt(train_mse_ridge2)
test_rmse_ridge2 = np.sqrt(test_mse_ridge2)

train_r2_ridge2 = r2_score(y_train_scaled, y_train_pred_ridge2)
test_r2_ridge2 = r2_score(y_test_scaled, y_test_pred_ridge2)
```

```
print(f"Entraînement : MSE={train_mse_ridge2:.3f}, RMSE={train_rmse_ridge2:.3f}, R²={train_r2_ridge2:.3f}")
print(f"Test : MSE={test_mse_ridge2:.3f}, RMSE={test_rmse_ridge2:.3f}, R²={test_r2_ridge2:.3f}")
```

Entraînement : MSE=0.304, RMSE=0.551, R²=0.696

Test : MSE=0.364, RMSE=0.604, R²=0.632

On obtient sensiblement les mêmes résultats

3.3.4 6. Régression par arbre de décision (DecisionTreeRegressor) (1)

La régression par arbre de décision peut capturer des relations complexes entre les caractéristiques et la variable cible (log_prix), en partitionnant récursivement l'espace des prédicteurs en régions distinctes. Elle prédit la valeur moyenne de la cible dans chaque région. Cependant, le modèle est plus susceptible de sur-apprendre les données d'entraînement si la profondeur de l'arbre n'est pas contrôlée.

```
[128]: from sklearn.tree import DecisionTreeRegressor
```

```
[129]: # Modèle
regression_tree = DecisionTreeRegressor(max_depth=5, random_state=42)
```

Test avec une profondeur de 5

```
[130]: regression_tree.fit(X_train_scaled, y_train_scaled.ravel())
```

```
[130]: DecisionTreeRegressor(max_depth=5, random_state=42)
```

```
[131]: # Prédiction sur l'ensemble d'entraînement
y_train_pred_tree = regression_tree.predict(X_train_scaled)

# Prédiction sur l'ensemble de test
y_test_pred_tree = regression_tree.predict(X_test_scaled)

# Évaluation des performances sur les ensembles d'entraînement et de test
train_mse_tree = mean_squared_error(y_train_scaled, y_train_pred_tree)
test_mse_tree = mean_squared_error(y_test_scaled, y_test_pred_tree)
train_rmse_tree = np.sqrt(train_mse_tree)
test_rmse_tree = np.sqrt(test_mse_tree)

train_r2_tree = r2_score(y_train_scaled, y_train_pred_tree)
test_r2_tree = r2_score(y_test_scaled, y_test_pred_tree)

print(f"Entraînement : MSE={train_mse_tree:.3f}, RMSE={train_rmse_tree:.3f}, R²={train_r2_tree:.3f}")
```

```
print(f"Test : MSE={test_mse_tree:.3f}, RMSE={test_rmse_tree:.3f},  
↪R²={test_r2_tree:.3f}")
```

Entraînement : MSE=0.452, RMSE=0.672, $R^2=0.548$

Test : MSE=0.481, RMSE=0.694, $R^2=0.514$

Conclusion : j'obtiens

- en entraînement : MSE=0.452, RMSE=0.672, $R^2=0.548$
- en test : MSE=0.481, RMSE=0.694, $R^2=0.514$

Globalement, il semble que ce modèle d'arbre de décision ne s'ajuste pas très bien aux données d'entraînement et ne généralise pas de manière satisfaisante sur les nouvelles données du test.

3.3.5 Régression par arbre de décision (DecisionTreeRegressor) (2)

Avec une profondeur de 10

```
[132]: regression_tree_2 = DecisionTreeRegressor(max_depth=10, random_state=42)
regression_tree_2.fit(X_train_scaled, y_train_scaled.ravel())

# Prédiction sur l'ensemble d'entraînement
y_train_pred_tree_2 = regression_tree_2.predict(X_train_scaled)

# Prédiction sur l'ensemble de test
y_test_pred_tree_2 = regression_tree_2.predict(X_test_scaled)

# Évaluation des performances sur les ensembles d'entraînement et de test
train_mse_tree_2 = mean_squared_error(y_train_scaled, y_train_pred_tree_2)
test_mse_tree_2 = mean_squared_error(y_test_scaled, y_test_pred_tree_2)
train_rmse_tree_2 = np.sqrt(train_mse_tree_2)
test_rmse_tree_2 = np.sqrt(test_mse_tree_2)

train_r2_tree_2 = r2_score(y_train_scaled, y_train_pred_tree_2)
test_r2_tree_2 = r2_score(y_test_scaled, y_test_pred_tree_2)

print(f"Entraînement : MSE={train_mse_tree_2:.3f}, RMSE={train_rmse_tree_2:.  
↪3f}, R²={train_r2_tree_2:.3f}")
print(f"Test : MSE={test_mse_tree_2:.3f}, RMSE={test_rmse_tree_2:.3f},  
↪R²={test_r2_tree_2:.3f}")
```

Entraînement : MSE=0.298, RMSE=0.546, $R^2=0.702$

Test : MSE=0.457, RMSE=0.676, $R^2=0.539$

3.3.6 Régression par arbre de décision (DecisionTreeRegressor) (3)

Avec une profondeur de 3

```
[133]: regression_tree_3 = DecisionTreeRegressor(max_depth=3, random_state=42)
regression_tree_3.fit(X_train_scaled, y_train_scaled.ravel())
```

```

# Prédiction sur l'ensemble d'entraînement
y_train_pred_tree_3 = regression_tree_3.predict(X_train_scaled)

# Prédiction sur l'ensemble de test
y_test_pred_tree_3 = regression_tree_3.predict(X_test_scaled)

# Évaluation des performances sur les ensembles d'entraînement et de test
train_mse_tree_3 = mean_squared_error(y_train_scaled, y_train_pred_tree_3)
test_mse_tree_3 = mean_squared_error(y_test_scaled, y_test_pred_tree_3)
train_rmse_tree_3 = np.sqrt(train_mse_tree_3)
test_rmse_tree_3 = np.sqrt(test_mse_tree_3)

train_r2_tree_3 = r2_score(y_train_scaled, y_train_pred_tree_3)
test_r2_tree_3 = r2_score(y_test_scaled, y_test_pred_tree_3)

print(f"Entraînement : MSE={train_mse_tree_3:.3f}, RMSE={train_rmse_tree_3:.3f}, R²={train_r2_tree_3:.3f}")
print(f"Test : MSE={test_mse_tree_3:.3f}, RMSE={test_rmse_tree_3:.3f}, R²={test_r2_tree_3:.3f}")

```

Entraînement : MSE=0.508, RMSE=0.713, R²=0.492

Test : MSE=0.518, RMSE=0.719, R²=0.478

Avec des depths = 10 ou 3, on n'obtient pas de résultat assez satisfaisant non plus : + En augmentant la profondeur maximale de l'arbre à 10, le modèle peut capturer des relations plus complexes entre les caractéristiques et le log du prix. Mais une profondeur trop élevée peut également entraîner un sur-apprentissage. + En définissant la profondeur maximale de l'arbre à 3, l'arbre de décision est assez très simple, avec seulement trois nœuds de décision. Mais une profondeur aussi faible peut entraîner un sous-apprentissage et une mauvaise performance du modèle sur nos données.

```

[134]: # Graphique de résidus : différence entre les valeurs réelles et prédites
residus_tree = y_train - y_train_pred_tree
fig = px.scatter(x=y_train_pred_tree, y=residus_tree, labels={"x": "Valeurs_
    ↪prédites par la régression par arbre de décision", "y": "Résidus"})
fig.show()

```

```

[135]: # Distribution des erreurs
fig = px.histogram(residus_tree, nbins=30, labels={"value": "Résidus"},
    ↪title="Distribution des erreurs pour la régression par arbre de décision")
fig.show()

```

3.3.7 Conclusion de la partie

[(E) pour entraînement et (T) pour test]

Régression linéaire : R²=0.686 (E), R² négatif (T), le modèle échoue à généraliser sur les données de test.

SVR : $R^2=0.686$ (E), $R^2=0.564$ (T), ce modèle semble moyennement satisfaisant.

Régression par forêt aléatoire : $R^2=0.730$ (E), $R^2=0.621$ (T), ce modèle semble assez satisfaisant.

Ridge : $R^2=0.696$ (E), $R^2=0.632$ (T), ce modèle semble assez satisfaisant également, mais moins qu'avec la précédente.

Arbre de décision : $R^2=0.548$ (E) , $R^2=0.514$ (T), ce modèle semble moyennement satisfaisant.

Par manque de temps, je n'ai pas pu tester d'autres modèles cités sur le site de la documentation de scikitlearn (Régression ElasticNet, régression par gradient boosting...) meme si j'aurais bien voulu...

=> Le modèle de régression par forêt aléatoire me paraît ici être le plus efficace.

3.3.8 6. Prédiction sur le fichier de test

```
[136]: airbnb_test = pd.read_csv("airbnb_test.csv")
```

```
[137]: airbnb_test.head()
```

```
[137]: Unnamed: 0 property_type room_type \
0 14282777 Apartment Entire home/apt
1 17029381 Apartment Entire home/apt
2 7824740 Apartment Entire home/apt
3 19811650 House Entire home/apt
4 12410741 Apartment Entire home/apt

amenities accommodates bathrooms \
0 {"Wireless Internet","Air conditioning",Kitche... 3 1.0
1 {"Wireless Internet","Air conditioning",Kitche... 7 1.0
2 {TV,"Cable TV","Wireless Internet","Air condit... 5 1.0
3 {TV,"Cable TV",Internet,"Wireless Internet",Ki... 4 1.0
4 {TV,Internet,"Wireless Internet","Air conditio... 2 1.0

bed_type cancellation_policy cleaning_fee city ... last_review \
0 Real Bed strict True NYC ... 2016-07-18
1 Real Bed strict True NYC ... 2017-09-23
2 Real Bed moderate True NYC ... 2017-09-14
3 Real Bed flexible True SF ... NaN
4 Real Bed moderate True DC ... 2017-01-22

latitude longitude name \
0 40.696524 -73.991617 Beautiful brownstone 1-bedroom
1 40.766115 -73.989040 Superb 3BR Apt Located Near Times Square
2 40.808110 -73.943756 The Garden Oasis
3 37.772004 -122.431619 Beautiful Flat in the Heart of SF!
4 38.925627 -77.034596 Great studio in midtown DC

neighbourhood number_of_reviews review_scores_rating zipcode bedrooms \
0 Brooklyn Heights 2 100.0 11201 1.0
```

1	Hell's Kitchen	6	93.0	10019	3.0
2	Harlem	10	92.0	10027	1.0
3	Lower Haight	0	NaN	94117.0	2.0
4	Columbia Heights	4	40.0	20009	0.0

```

beds
0    1.0
1    3.0
2    3.0
3    2.0
4    1.0

```

[5 rows x 27 columns]

```
[138]: airbnb_test.shape
```

```
[138]: (51877, 27)
```

Comme j'avais un problème de longueur de données, je vérifie au fur et à mesure :

```
[139]: print(f"Nombre initial de lignes dans airbnb_test: {len(airbnb_test)}")
```

Nombre initial de lignes dans airbnb_test: 51877

Même traitement que le fichier entraînement :

```
[140]: airbnb_test = airbnb_test.drop(['description', 'first_review',
    ↪ 'host_has_profile_pic',
    ↪ 'host_identity_verified', 'host_response_rate',
    ↪ 'host_since',
    ↪ 'instant_bookable', 'last_review', 'name',
    ↪ 'number_of_reviews',
    ↪ 'review_scores_rating'], axis=1)

#airbnb_test = airbnb_test.dropna(subset=['zipcode']) c'est ici que j'avais le
    ↪ changement de len...!!
```

```
[141]: print(f"Nombre de lignes après suppression des NA dans 'zipcode':
    ↪ {len(airbnb_test)}")
```

Nombre de lignes après suppression des NA dans 'zipcode': 51877

```
[142]: categories = ['property_type', 'room_type', 'accommodates', 'bathrooms',
    ↪ 'bed_type', 'cancellation_policy', 'cleaning_fee', 'city', 'neighbourhood',
    ↪ 'zipcode', 'bedrooms', 'beds']
airbnb_test_bin = pd.get_dummies(airbnb_test, columns=categories)
```



```
[143]: colonnes = ['property_type', 'room_type', 'cleaning_fee', 'city',
↳ 'neighbourhood', 'zipcode', 'bedrooms', 'beds']

[144]: # Appliquer la fonction extraire_amenities à la colonne 'amenities'
airbnb_test['amenities'] = airbnb_test['amenities'].apply(extraire_amenities)

# pour avoir le nombre d'équipements par offre
airbnb_test['nb_amenities'] = airbnb_test['amenities'].apply(lambda x: len(x))
```

De même qu’avec df_bin, je veux ajouter la colonne “nb_amenities” à airbnb_test_bin, tout en supprimant la colonne “amenities” du dataframe d’origine airbnb_test :

```
[145]: # Supprimer la colonne "amenities" du fichier d'origine
airbnb_temp = airbnb_test.drop('amenities', axis=1)

[146]: # Créer les variables dummy à partir des colonnes catégorielles
airbnb_test_bin = pd.get_dummies(airbnb_temp, columns=categories)

# Ajouter la colonne "nb_amenities" à df_bin
airbnb_test_bin['nb_amenities'] = airbnb_test['nb_amenities']

[147]: X.head()
```

```
[147]:
```

	id	latitude	longitude	nb_amenities	property_type_Apartment	\
0	5708593	33.782712	-118.134410	15	False	
1	14483613	40.705468	-73.909439	25	False	
2	10412649	38.917537	-77.031651	20	True	
3	17954362	40.736001	-73.924248	30	False	
4	9969781	37.744896	-122.430665	24	False	

	property_type_Bed & Breakfast	property_type_Boat	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	property_type_Boutique hotel	property_type_Bungalow	property_type_Cabin	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	

	...	beds_6.0	beds_7.0	beds_8.0	beds_9.0	beds_10.0	beds_11.0	\
0	...	False	False	False	False	False	False	
1	...	False	False	False	False	False	False	

2	...	False	False	False	False	False	False
3	...	False	False	False	False	False	False
4	...	False	False	False	False	False	False

	beds_12.0	beds_13.0	beds_16.0	beds_18.0
0	False	False	False	False
1	False	False	False	False
2	False	False	False	False
3	False	False	False	False
4	False	False	False	False

[5 rows x 1347 columns]

```
[148]: airbnb_test_bin.head()
```

```
[148]: Unnamed: 0  latitude  longitude  nb_amenities  property_type_Apartment  \
0      14282777  40.696524  -73.991617           9                True
1      17029381  40.766115  -73.989040          15                True
2       7824740  40.808110  -73.943756          19                True
3      19811650  37.772004 -122.431619          15                False
4      12410741  38.925627  -77.034596          12                True
```

	property_type_Bed & Breakfast	property_type_Boat	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	property_type_Boutique hotel	property_type_Bungalow	property_type_Cabin	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	

	...	beds_7.0	beds_8.0	beds_9.0	beds_10.0	beds_11.0	beds_12.0	\
0	...	False	False	False	False	False	False	
1	...	False	False	False	False	False	False	
2	...	False	False	False	False	False	False	
3	...	False	False	False	False	False	False	
4	...	False	False	False	False	False	False	

	beds_13.0	beds_14.0	beds_15.0	beds_16.0
0	False	False	False	False
1	False	False	False	False
2	False	False	False	False

3	False	False	False	False
4	False	False	False	False

[5 rows x 1450 columns]

On remarque que X a 1347 columns, et `airbnb_test_bin` a 1449 columns : mais `RandomForestRegressor` attend 1347 caractéristiques en input.

J'ai besoin de supprimer les colonnes de `airbnb_test_bin` qui n'ont pas le même nom que dans X, et d'ajouter celles qui manquent en utilisant une méthode d'imputation pour remplacer les valeurs manquantes par des valeurs estimées (la moyenne des colonnes correspondantes par exemple).

```
[149]: from sklearn.impute import SimpleImputer

# Obtenir les noms de colonnes communes
colonnes_communes = list(set(X.columns) & set(airbnb_test_bin.columns))

# Supprimer les colonnes de airbnb_test_bin qui ne sont pas dans la liste des
↳ colonnes communes
airbnb_test_bin = airbnb_test_bin[colonnes_communes]

# Ajout des colonnes manquantes à airbnb_test_bin et remplacer les valeurs
↳ manquantes par la moyenne
imputer = SimpleImputer(strategy='mean')

[150]: missing_cols = X.drop(columns=colonnes_communes)
print(f"Ajout des colonnes manquantes: {missing_cols.columns}")

airbnb_test_bin = pd.concat([airbnb_test_bin, X.
↳ drop(columns=colonnes_communes)], axis=1)
airbnb_test_bin_imputed = imputer.fit_transform(airbnb_test_bin)

# Remplacer airbnb_test_bin par les données imputées
airbnb_test_bin = pd.DataFrame(airbnb_test_bin_imputed, columns=airbnb_test_bin.
↳ columns)
```

```
Ajout des colonnes manquantes: Index(['id', 'property_type_Island',
'neighbourhood_Arboretum',
'neighbourhood_Commerce', 'neighbourhood_Gerritsen Beach',
'neighbourhood_Grant City', 'neighbourhood_Harvard Square',
'neighbourhood_Irwindale', 'neighbourhood_La Habra',
'neighbourhood_Magnificent Mile', 'neighbourhood_Montclare',
'neighbourhood_Near Northeast', 'neighbourhood_New Dorp Beach',
'neighbourhood_Newton', 'neighbourhood_Rolling Hills',
'neighbourhood_Rossville', 'neighbourhood_South El Monte',
'neighbourhood_Takoma Park, MD', 'neighbourhood_Watertown',
'neighbourhood_Woodland', 'zipcode_02138', 'zipcode_02186',
'zipcode_02458', 'zipcode_02472', 'zipcode_10004.0', 'zipcode_10007.0',
```

```

'zipcode_10012.0', 'zipcode_10162', 'zipcode_10279', 'zipcode_10282.0',
'zipcode_10307.0', 'zipcode_10308.0', 'zipcode_10309', 'zipcode_10704',
'zipcode_11001', 'zipcode_11209.0', 'zipcode_11215.0',
'zipcode_11239.0', 'zipcode_11411', 'zipcode_11412.0',
'zipcode_11429.0', 'zipcode_11509.0', 'zipcode_1m', 'zipcode_20912',
'zipcode_60603', 'zipcode_60633', 'zipcode_60660-1448', 'zipcode_60805',
'zipcode_7302.0', 'zipcode_90034-2203', 'zipcode_90035-4475',
'zipcode_90036-2514', 'zipcode_9004', 'zipcode_90222',
'zipcode_90403-2638', 'zipcode_91377', 'zipcode_91708', 'zipcode_91786',
'zipcode_91802', 'zipcode_94401', 'beds_18.0'],
dtype='object')

```

```
[151]: airbnb_test_bin.head()
```

```

[151]:  property_type_Cave  zipcode_11228  property_type_Serviced apartment  \
0                0.0          0.0                                0.0
1                0.0          0.0                                0.0
2                0.0          0.0                                0.0
3                0.0          0.0                                0.0
4                0.0          0.0                                0.0

      zipcode_90022  zipcode_10312  neighbourhood_Rego Park  zipcode_10459.0  \
0                0.0          0.0                        0.0            0.0
1                0.0          0.0                        0.0            0.0
2                0.0          0.0                        0.0            0.0
3                0.0          0.0                        0.0            0.0
4                0.0          0.0                        0.0            0.0

      zipcode_90245  zipcode_90755  bathrooms_2.0  ...  zipcode_90036-2514  \
0                0.0          0.0          0.0  ...            0.0
1                0.0          0.0          0.0  ...            0.0
2                0.0          0.0          0.0  ...            0.0
3                0.0          0.0          0.0  ...            0.0
4                0.0          0.0          0.0  ...            0.0

      zipcode_9004  zipcode_90222  zipcode_90403-2638  zipcode_91377  \
0                0.0          0.0          0.0          0.0
1                0.0          0.0          0.0          0.0
2                0.0          0.0          0.0          0.0
3                0.0          0.0          0.0          0.0
4                0.0          0.0          0.0          0.0

      zipcode_91708  zipcode_91786  zipcode_91802  zipcode_94401  beds_18.0
0                0.0          0.0          0.0          0.0          0.0
1                0.0          0.0          0.0          0.0          0.0
2                0.0          0.0          0.0          0.0          0.0
3                0.0          0.0          0.0          0.0          0.0

```

4	0.0	0.0	0.0	0.0	0.0
---	-----	-----	-----	-----	-----

[5 rows x 1347 columns]

```
[152]: airbnb_test_bin.shape
```

```
[152]: (51877, 1347)
```

Mais il faut que les noms des colonnes correspondent à ceux du dataframe de comparaison, et dans le même ordre

```
[153]: # Ordre des colonnes de X (en excluant les colonnes 'id')
x_column_order = [col for col in X.columns if col != 'id']

# Réorganisation des colonnes de airbnb_test_bin
airbnb_test_bin = airbnb_test_bin[x_column_order]
```

```
[154]: # Première colonne
first_column = airbnb_test_bin.iloc[:, 0]

# Ajout de la première colonne à gauche du DataFrame
airbnb_test_bin.insert(0, 'id', first_column)

airbnb_test_bin.rename(columns={'id': 'id'}, inplace=True)
```

Au lieu de None, il faut des False

```
[155]: # Remplacer les valeurs None par False dans airbnb_test_bin
airbnb_test_bin = airbnb_test_bin.fillna(False)
```

```
[156]: airbnb_test_bin.head()
```

```
[156]:
```

	id	latitude	longitude	nb_amenities	property_type_Apartment	\
0	40.696524	40.696524	-73.991617	9.0	1.0	
1	40.766115	40.766115	-73.989040	15.0	1.0	
2	40.808110	40.808110	-73.943756	19.0	1.0	
3	37.772004	37.772004	-122.431619	15.0	0.0	
4	38.925627	38.925627	-77.034596	12.0	1.0	

	property_type_Bed & Breakfast	property_type_Boat	\
0	0.0	0.0	
1	0.0	0.0	
2	0.0	0.0	
3	0.0	0.0	
4	0.0	0.0	

	property_type_Boutique hotel	property_type_Bungalow	property_type_Cabin	\
0	0.0	0.0	0.0	

1		0.0		0.0		0.0
2		0.0		0.0		0.0
3		0.0		0.0		0.0
4		0.0		0.0		0.0

	...	beds_6.0	beds_7.0	beds_8.0	beds_9.0	beds_10.0	beds_11.0	\
0	...	0.0	0.0	0.0	0.0	0.0	0.0	
1	...	0.0	0.0	0.0	0.0	0.0	0.0	
2	...	0.0	0.0	0.0	0.0	0.0	0.0	
3	...	0.0	0.0	0.0	0.0	0.0	0.0	
4	...	0.0	0.0	0.0	0.0	0.0	0.0	

		beds_12.0	beds_13.0	beds_16.0	beds_18.0
0		0.0	0.0	0.0	0.0
1		0.0	0.0	0.0	0.0
2		0.0	0.0	0.0	0.0
3		0.0	0.0	0.0	0.0
4		0.0	0.0	0.0	0.0

[5 rows x 1347 columns]

[157]: X.head()

[157]:

	id	latitude	longitude	nb_amenities	property_type_Apartment	\
0	5708593	33.782712	-118.134410	15	False	
1	14483613	40.705468	-73.909439	25	False	
2	10412649	38.917537	-77.031651	20	True	
3	17954362	40.736001	-73.924248	30	False	
4	9969781	37.744896	-122.430665	24	False	

	property_type_Bed & Breakfast	property_type_Boat	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	property_type_Boutique hotel	property_type_Bungalow	property_type_Cabin	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	

	...	beds_6.0	beds_7.0	beds_8.0	beds_9.0	beds_10.0	beds_11.0	\
0	...	False	False	False	False	False	False	
1	...	False	False	False	False	False	False	

2	...	False	False	False	False	False	False
3	...	False	False	False	False	False	False
4	...	False	False	False	False	False	False

	beds_12.0	beds_13.0	beds_16.0	beds_18.0
0	False	False	False	False
1	False	False	False	False
2	False	False	False	False
3	False	False	False	False
4	False	False	False	False

[5 rows x 1347 columns]

```
[158]: airbnb_test_bin.shape
```

```
[158]: (51877, 1347)
```

```
[159]: # Réentraîner rfr
regression_rfr.fit(X_train, y_train)
```

```
[159]: RandomForestRegressor(max_depth=10, random_state=42)
```

```
[160]: y_prediction_finale = regression_rfr.predict(airbnb_test_bin)
```

```
[161]: print(y_prediction_finale)
```

```
[4.97902898 5.69309137 4.96575722 ... 5.21462967 4.25130552 5.23377134]
```

```
[162]: y_prediction_finale.shape
```

```
[162]: (51877,)
```

Sauvegarde dans le fichier de prédiction :

```
[163]: # Récupérer la première colonne de airbnb_test_bin
premiere_col_airbnb_test = airbnb_test.iloc[:, 0]

# Convertir les valeurs en entiers et ensuite en chaînes de caractères
premiere_col_airbnb_test = premiere_col_airbnb_test.astype(str)

# Créer un DataFrame à partir de la première colonne
df_premiere_col = pd.DataFrame(premiere_col_airbnb_test)

# Créer un DataFrame à partir des prédictions
df_predictions = pd.DataFrame(y_prediction_finale)
```

```
[164]: # Vérifier les longueurs avant sauvegarde
assert len(df_premiere_col) == len(df_predictions), f"Les longueurs des
↳DataFrames ne correspondent pas: {len(df_premiere_col)} //
↳{len(df_predictions)}"

[165]: # Concaténer les deux DataFrames côte à côte
prediction_fichier = pd.concat([df_premiere_col, df_predictions], axis=1)

[166]: # Renommer les colonnes
prediction_fichier.columns = ['', 'logpred']

# Sauvegarder les prédictions dans un fichier CSV
prediction_fichier.to_csv("mes_predictions.csv", index=False) # index=False
↳pour éviter d'ajouter l'index interne à pandas

[167]: prediction_fichier.head()
```

```
[167]:          logpred
0  14282777  4.979029
1  17029381  5.693091
2   7824740  4.965757
3  19811650  5.410258
4  12410741  4.823811
```

Test du fichier :

```
[168]: def estConforme(monFichier_csv):
    votre_prediction = pd.read_csv("mes_predictions.csv")

    fichier_exemple = pd.read_csv("prediction_exemple.csv")

    assert votre_prediction.columns[1] == fichier_exemple.columns[1],
↳f"Attention, votre colonne de prédiction doit s'appeler {fichier_exemple.
↳columns[1]}, elle s'appelle '{votre_prediction.columns[1]}'"
    assert len(votre_prediction) == len(fichier_exemple), f"Attention, vous
↳devriez avoir {len(fichier_exemple)} prédictions dans votre fichier, il en
↳contient {len(votre_prediction)}"

    assert np.all(votre_prediction.iloc[:,0] == fichier_exemple.iloc[:, 0])

    print("Fichier conforme!")

    estConforme("mes_predictions.csv")
```

Fichier conforme!

```
[ ]:
```