renting_vizualisation_slides

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1 Effects of Diamond Characteristics on Their Prices

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1.2 Investigation Overview

In this investigation, I wanted to look at the characteristics of rental house transactions that could be used to predict their prices. The main focus was on maintenance levels, energy labels, and housing type.

1.3 Dataset Overview

The data consisted of prices and features of approximately 534,000 rental transactions. The features included maintenance levels inside, maintenance levels outside, energylabel, housing type, as well as additional measurements such as transaction date, time between online and transaction, location, and neighbourhood. 202.998 data points were removed from the analysis due to inconsistencies or missing information.

```
[2]: # import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

# suppress warnings from final output
import warnings
warnings.simplefilter("ignore")

# load in the dataset into a pandas dataframe
# import all packages and set plots to be embedded inline

from pathlib import Path

%matplotlib inline

# pd.set_option('max_rows',100)
pd.set_option('min_rows',20)
```

```
pd.set_option('max_columns',100)
df_raw = pd.read_csv(
        r'D:\OneDrive -
 →MVGM\WerkbestandenYannick\Werkmap_Python\Projecten\wh\data\batch_huur_20210623\input\factia
, dtype={'SoortGarage':str, 'Land':str, 'HuurprijsConditie':str,
 → 'HuurprijsSpecificatie':str,
               'KadastraalEigendom':str, 'KadastraalOmvang':str, 'MakelaarNaam':str,
 'StatusVerhuurd':str})
df_raw = df_raw[['Bron', 'Bouwjaar', 'EnergieLabel', 'GebruiksOppervlakte', |
 'TypeWoning', 'Looptijd', 'Ingetrokken', 'TransactieHuurPrijs',
               'SoortAppartement',
               'TransactieDatumOndertekeningAkte', 'OnderhoudsNiveauBinnen', |
 'GemeenteNaam','HuurprijsConditie']]
df = df_raw.copy(deep=True)
# Read the data
df = df_raw.copy(deep=True)
# Some data wrangling such that the data can be used for visualisation
# Energielabels / energylabels
df.EnergieLabel = df.EnergieLabel.fillna('C') # Median
df.EnergieLabel = df.EnergieLabel.replace({"A+++++":"A", "A++++":"A", "A++++*":"A", "A++++*":"A", "A++++*":"A", "A++++*":"A", "A++++*":"A", "A++++*":"A", "A++++*":"A", "A+++*":"A", "A+++*":"A", "A+++*":"A", "A+++*":"A", "A+++*":"A", "A+++*":"A", "A+++*":"A", "A++*":"A", "A+*":"A", "A+*":"A", "A+*":"A", "A+*":"A", "A+*":"A", "A**, "A*
 # column formatting
df.OnderhoudsNiveauBinnen = df.OnderhoudsNiveauBinnen.str.capitalize()
df.OnderhoudsNiveauBuiten = df.OnderhoudsNiveauBuiten.str.capitalize()
df.GebruiksOppervlakte = df.GebruiksOppervlakte.round(0)
df.AanmeldDatum = pd.to_datetime(df.AanmeldDatum)
df.TransactieDatumOndertekeningAkte = pd.to_datetime(df.
 →TransactieDatumOndertekeningAkte)
df.TypeWoning = df.TypeWoning.where(df.TypeWoning.notna(), df.SoortAppartement)
df.TypeWoning = df.TypeWoning.str.capitalize()
# Since there are too many municipalities. They are classified in the 4 biggest \Box
 →municipalities, the 5th until the 45th biggest municipalities and the rest.
# This is an usual classification for classifications in the Neterlands
```

```
G4 = ['Amsterdam', 'Utrecht', 'Rotterdam', "'s-Gravenhage"]
G40 = ['Alkmaar', 'Almelo', 'Almere', 'Alphen aan den Rijn', 'Amersfoort',
→'Apeldoorn', 'Arnhem', 'Assen', 'Breda', 'Delft', 'Deventer', 'Dordrecht', □
→ 'Ede', 'Eindhoven', 'Emmen', 'Enschede', 'Gouda', 'Groningen', 'Haarlem', 
→ 'Haarlemmermeer', 'Heerlen', 'Helmond', 'Hengelo', "'s-Hertogenbosch", □
→'Hilversum', 'Hoorn', 'Leeuwarden', 'Leiden', 'Lelystad', 'Maastricht', ⊔
→'Nijmegen', 'Oss', 'Roosendaal', 'Sittard-Geleen', 'Schiedam', 'Tilburg', □
→'Venlo', 'Zaanstad', 'Zoetermeer','Zwolle']
df['GemeenteCat'] = df.GemeenteNaam.where(~df.GemeenteNaam.isin(G4), 'G4').
→where (~df.GemeenteNaam.isin(G4+G40), 'G40').where (df.GemeenteNaam.isin(G4+G40), ∪
→'Overig')
#Categorical values
# Sorted from less good to 'better'
ordinal_var_dict = {'EnergieLabel': ['G','F','E','D','C', 'B', 'A'],
                    'OnderhoudsNiveauBinnen': ['Slecht', 'Slecht tot matig', __
, 'Redelijk', 'Redelijk tot⊔

¬goed', 'Goed', 'Goed tot uitstekend', 'Uitstekend'],
                    'OnderhoudsNiveauBuiten': ['Slecht', 'Slecht tot matig',
→'Matig', 'Matig tot redelijk'
                                               , 'Redelijk', 'Redelijk tot⊔
→goed', 'Goed', 'Goed tot uitstekend', 'Uitstekend'],
                    'GemeenteCat': ['G4', 'G40', 'Overig'],
                   }
for var in ordinal var dict:
   ordered_var = pd.api.types.CategoricalDtype(ordered = True,categories =__
→ordinal_var_dict[var])
   df[var] = df[var].astype(ordered_var)
df.TypeWoning.where(df.TypeWoning.notna(), 'Onbekend', inplace=True)
for i in range(1,9):
   df.TypeWoning.where(~df.TypeWoning.str.contains(f'{i}-k flat'), f'{i}-k_u
→flatwoning', inplace=True)
df.TypeWoning.where(~df.TypeWoning.str.contains('Flat'), 'Flatwoning', u
→inplace=True)
# Only include the 16 most used WoningTypes. All types with more than 10k_{\sqcup}
1 = df.TypeWoning.value_counts(dropna=False).index[:16]
df = df[df.TypeWoning.isin(1)]
# Only look at transactions which are really made.
df = df[df.Ingetrokken==0]
df.drop(columns=['SoortAppartement','Ingetrokken'], inplace=True)
```

Note that the above cells have been set as "Skip"-type slides. That means that when the notebook is rendered as http slides, those cells won't show up.

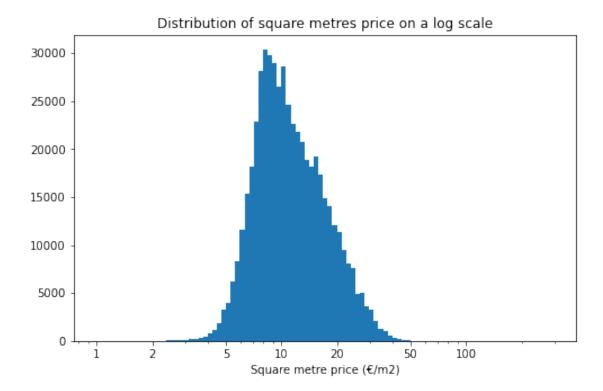
1.4 Distribution of square metre prices

Square metre prices $(\in/m2)$ have a wide range of values from 2 to around 50 but more centered around 10/20. If the square metre prices are plotted on a logarithmic scale the distribution takes on an unimodal shape.

```
[3]: # start with a standard-scaled plot
log_binsize = 0.025
bins = 10 ** np.arange(0, np.log10(df['M2HuurPrijs'].max())+log_binsize,
log_binsize)

plt.figure(figsize=[8, 5])
plt.hist(data = df, x = 'M2HuurPrijs', bins = bins)
plt.xscale('log')
plt.xticks([1, 2, 5, 10, 20, 50, 100], [1, 2, 5, 10, 20, 50, 100]) #[0, 5, 10,
log_binsize,

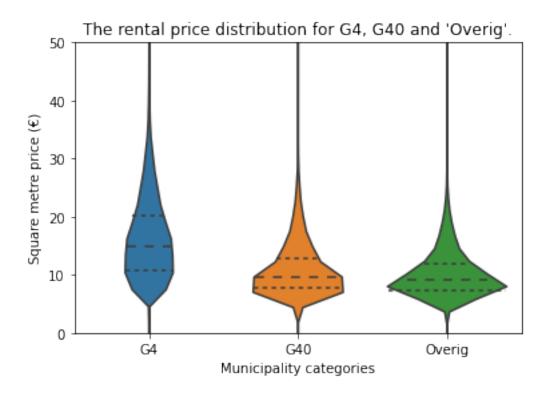
plt.hist(data = df, x = 'M2HuurPrijs', bins = bins)
plt.xscale('log')
plt.xticks([1, 2, 5, 10, 20, 50, 100], [1, 2, 5, 10, 20, 50, 100]) #[0, 5, 10,
log_binsize,
log_binsize = 0.025
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```



1.5 Square metre prices for different municipality categories

The housing types prices vary a lot per municipality category. Every category has a lot of outliers and G40 and 'Overig' are similar. G4 is in a totally different with a median higher than the upper quartiles of the other municipality categories.

```
[4]: sns.violinplot(data=df, y='M2HuurPrijs', x='GemeenteCat', inner='quartile');
plt.ylim(0, 50)
plt.ylabel("Square metre price (€)")
plt.xlabel("Municipality categories")
plt.title("The rental price distribution for G4, G40 and 'Overig'.");
```

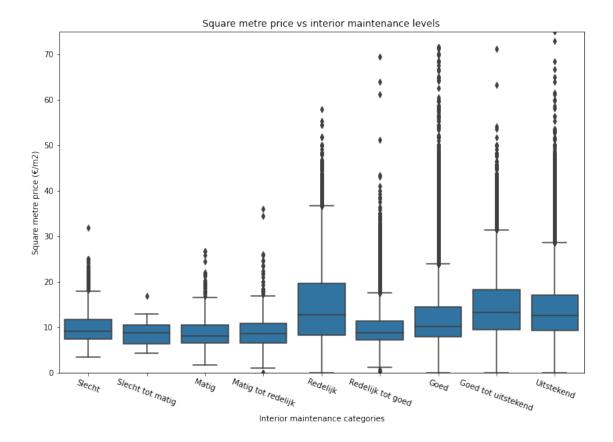


1.6 Square metre prices for different maintenance levels

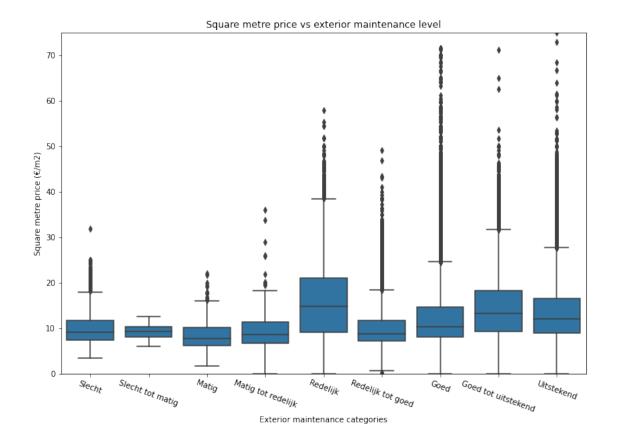
The housing types prices don't vary a lot per housing category. Even though a slight trend can be found in mean square metre price per category. The amount of outliers is higher with higher maintenance levels. 'Redelijk' is an outlier that can be explained by the domain expert, because it is the default value when this data is created.

```
[5]: plt.figure(figsize=[12,8])
base_color = sns.color_palette()[0]
sns.boxplot(data=df, y='M2HuurPrijs', x='OnderhoudsNiveauBinnen',

color=base_color)
plt.title('Square metre price vs interior maintenance levels')
plt.ylim(0, 75)
plt.ylabel('Square metre price (€/m2)')
plt.xlabel('Interior maintenance categories')
plt.xticks(rotation=-20);
plt.show()
```



```
[6]: plt.figure(figsize=[12,8])
sns.boxplot(data=df, y='M2HuurPrijs', x='OnderhoudsNiveauBuiten',
color=base_color)
plt.title('Square metre price vs exterior maintenance level')
plt.ylim(0, 75)
plt.ylabel('Square metre price (€/m2)')
plt.xlabel('Exterior maintenance categories')
plt.xticks(rotation=-20);
plt.show()
```



1.7 Square metre prices for different maintenance levels for different municipality categories

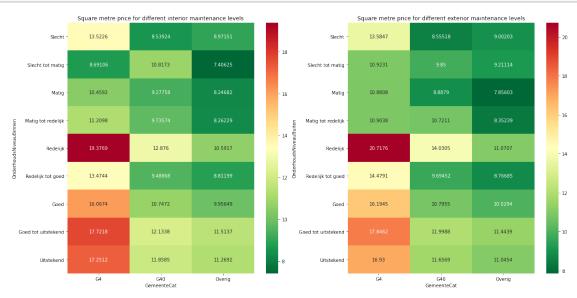
The housing prices seem to increase for higher maintenance levels. Prices for G4 are also higher generally a lot higher than for the other categories. This goes for maintenance levels inside as well as outside. Again, 'Redelijk' can be seen as an outlier. For every category a higher maintenance level implies a higher square metre price.

```
[7]: fig = plt.figure(figsize=(20,10))
    ax1 = fig.add_subplot(121)
    ax2 = fig.add_subplot(122)

plt.title("Square metre prices for different maintenance levels inside and____
    outside.")

ax1.set_title('Square metre price for different interior maintenance levels');
    heat_df = df.groupby(['OnderhoudsNiveauBinnen','GemeenteCat']).
    omean()['M2HuurPrijs'].unstack()
    sns.heatmap(heat_df, cmap='RdYlGn_r', annot=True, fmt='g', ax=ax1);

ax2.set_title('Square metre price for different exterior maintenance levels');
```



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