Melbourne Housing Market

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FITS

En esta seccion podemos encontrar los métodos para ejecutar el entrenamiento:

```
-train
- regresion_lineal
- arbol_de_regresion_test
- arbol_decision
- random_forest
- regresion_svr
- xgboost
```

In [2]:

```
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
import xgboost as xgb
from sklearn.model_selection import train_test_split

def train(pd):
    wine = pd.copy()
    y = wine["Price"].copy()
    x = wine[["Rooms","Distance", "Bathroom","Bedroom2",'YearBuilt','Lattitude','Longtit
ude','CouncilArea_Int','Regionname_Int','Car','BuildingArea']]

    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_stat
e=4)

    print(f'({len(x_train)+len(y_train)},{(len(x_test)+len(y_test))})')

    return x_train, y_train,x_test,y_test
```

```
def regresion_lineal(pd):
    print('------------Regresion Lineal-------------')
    x_train,y_train,x_test,y_test=train(pd)

    scaler = StandardScaler()

    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)

    lin_reg= LinearRegression()

    lin_reg.fit(x_train,y_train)

    predicciones = lin_reg.predict(x_train)

    mse = mean_squared_error(y_train, predicciones)
    mse = np.sqrt(mse)
    mae = mean_absolute_error(y_train, predicciones)

    score = r2_score(y_train, predicciones)

    print(f"mae: {mae}   rmse: {mse} r2_score: {score}")

def arbol_de_regresion_test(pd):
    print('----------Arbol de regresión-----------')
    x_train,y_train,x_test,y_test=train(pd)

    scaler = StandardScaler()
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)

    tree_reg = DecisionTreeRegressor()
    tree_reg.fit(x_train, y_train)

    predicciones = tree_reg.predict(x_train)

    mse = mean_squared_error(y_train, predicciones)
    mse = np.sqrt(mse)
    mae = mean_absolute_error(y_train, predicciones)
    score = r2_score(y_train, predicciones)
    print(f"mae: {mae}   rmse: {mse} r2_score: {score}")

def arbol_decision(pd):
    # cross-validation arbol decision
    print('---------------Arbol de decision---------------')
    x_train,y_train,x_test,y_test=train(pd)
    scaler = StandardScaler()
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)
    tree_reg = DecisionTreeRegressor()
    tree_reg.fit(x_train, y_train)
    lin_score = cross_val_score(tree_reg, x_train, y_train,
                                scoring = "neg_mean_squared_error", cv=10)
    root_lin_score = np.sqrt(-lin_score)
    print("Scores: ", root_lin_score)
    print("Media: ", root_lin_score.mean())
    print("Desviación Std", root_lin_score.std())
    predicciones = tree_reg.predict(x_test)

    mse = mean_squared_error(y_test, predicciones)
    mse = np.sqrt(mse)
    mae = mean_absolute_error(y_test, predicciones)
    score = r2_score(y_test, predicciones)

    print(f"mae: {mae}   rmse: {mse} r2_score: {score}")

def random_forest(pd):
    print('---------------Random forest---------------')
    x_train,y_train,x_test,y_test=train(pd)

    scaler = StandardScaler()
```

```python
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)

    rf_reg = RandomForestRegressor(n_estimators=100)
    rf_reg.fit(x_train, y_train)

    rf_score = cross_val_score(rf_reg, x_test, y_test,
                               scoring = "neg_mean_squared_error", cv=10)
    root_lin_score = np.sqrt(-rf_score)
    print("Scores: ", root_lin_score)
    print("Media: ", root_lin_score.mean())
    print("Desviación Std", root_lin_score.std())
    predicciones = rf_reg.predict(x_test)

    mse = mean_squared_error(y_test, predicciones)
    mse = np.sqrt(mse)
    mae = mean_absolute_error(y_test, predicciones)
    score = r2_score(y_test, predicciones)

    print(f"mae: {mae}   rmse: {mse} r2_score: {score}")

def regresion_svr(pd):
    print('---------------Regresion svr---------------')
    x_train,y_train,x_test,y_test=train(pd)
    scaler = StandardScaler()
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)

    sv_reg = SVR()

    sv_reg.fit(x_train, y_train)
    predicciones = sv_reg.predict(x_test)

    mse = mean_squared_error(y_test, predicciones)
    mse = np.sqrt(mse)
    mae = mean_absolute_error(y_test, predicciones)
    score = r2_score(y_test, predicciones)
    rf_score = cross_val_score(sv_reg, x_train, y_train,
                               scoring = "neg_mean_squared_error", cv=10)
    root_lin_score = np.sqrt(-rf_score)
    print("SV cross")
    print("Scores: ", root_lin_score)
    print("Media: ", root_lin_score.mean())
    print("Desviación Std", root_lin_score.std())
    print(f"mae: {mae}   rmse: {mse} r2_score: {score}")

def xgboost(pd):
    print('---------------Xboost---------------')
    x_train,y_train,x_test,y_test=train(pd)
    # scaler = StandardScaler()
    # x_train = scaler.fit_transform(x_train)
    # x_test = scaler.transform(x_test)
    xgb_reg = xgb.XGBRegressor()
    xgb_reg.fit(x_train, y_train)
    predicciones = xgb_reg.predict(x_test)
    mse = mean_squared_error(y_test, predicciones)
    mse = np.sqrt(mse)
    mae = mean_absolute_error(y_test, predicciones)
    score = r2_score(y_test, predicciones)
    rf_score = cross_val_score(xgb_reg, x_train, y_train,
                               scoring = "neg_mean_squared_error", cv=10)
    root_lin_score = np.sqrt(-rf_score)
    print("XGB cross")
    print("Scores: ", root_lin_score)
    print("Media: ", root_lin_score.mean())
    print("Desviación Std", root_lin_score.std())
    print(f"mae: {mae}   rmse: {mse} r2_score: {score}")
```

DEFINICION_METODOS_BOXPLOT_Y_MAPA_DE_CALOR

Recoge las definiciones para hacer mapas de calor, boxplots y mapas de calor:

In [3]:

```
import matplotlib.pyplot as plt
def boxplot_general(pd,cadena):
    for tipo in pd.columns:
        if tipo !=cadena:
            data_to_plot = [pd[pd[cadena] == i][tipo].values for i in sorted(pd[cadena].unique())]
            plt.figure(figsize=(10, 6))
            plt.boxplot(data_to_plot, labels=sorted(pd[cadena].unique()),notch=True,patch_artist=True,
                        showmeans=True,whiskerprops=dict(color='deeppink',linewidth=1),
                        medianprops=dict(color='deeppink'),
                        flierprops=dict(color='deeppink', markerfacecolor='pink', linestyle= "none", markeredgecolor="none", markersize=9),
                        boxprops=dict(edgecolor='deeppink',  facecolor='pink', linewidth=2),
                        capprops=dict(color='deeppink', linewidth=2)
                        )
            plt.xlabel(cadena)
            plt.ylabel(f'{tipo}')
            plt.title(f'Boxplot Quality/ {tipo}')
            plt.show()
def boxplot(pd,y,x):
        data_to_plot = [pd[pd[x] == i][y].values for i in sorted(pd[x].unique())]
        plt.figure(figsize=(10, 6))
        plt.boxplot(data_to_plot, labels=sorted(pd[x].unique()),notch=True,patch_artist=True,
                    showmeans=True,whiskerprops=dict(color='deeppink',linewidth=1),
                    medianprops=dict(color='deeppink'),
                    flierprops=dict(color='deeppink', markerfacecolor='pink', linestyle="none", markeredgecolor="none", markersize=9),
                    boxprops=dict(edgecolor='deeppink',  facecolor='pink', linewidth=2),
                    capprops=dict(color='deeppink', linewidth=2)
                    )
        plt.xlabel(x)
        plt.ylabel(f'{y}')
        plt.title(f'Boxplot Quality/ {y}')
        plt.show()
def mapa_calor(corr_matrix):
  fig, ax = plt.subplots(figsize=(15, 8))
  text_colors = ("black" , "white" )
  im = ax.imshow(corr_matrix, cmap= "Greens" ) # mapa de calor
  cbar = fig.colorbar(im, ax=ax, label= "Correlacion" ) # leyenda
  cbar.outline.set_visible(False)

  x = corr_matrix.columns
  y = corr_matrix.index
  # Mostrar las etiquetas. El color del texto cambia en función de su normalización
  for i in range(len(y)):
    for j in range(len(x)):
      value = corr_matrix.iloc[i, j]
      text_color = text_colors[int(im.norm(value) > 0.5)] # color etiqueta
      ax.text(j, i, f"{value:.2f}" , color=text_color, va= "center" , ha= "center" )



  # Formateo de los ejes
  ax.set_xticks(range(len(x)))
  ax.set_xticklabels(x, rotation=90)
  ax.set_yticks(range(len(y)))
  ax.set_yticklabels(y)
  ax.invert_yaxis()
  ax.spines["right"].set_visible(False) # ocultar borde derecho
  ax.spines["top"].set_visible(False) # ocultar borde superior
  fig.tight_layout()
```

IMPORTACION DE CSV

IMPORTACION_DE_CSV

Aquí comienza la importación del `Melbourne_housing_FULL.csv` a partir de aquí vamos a observar la informacion relativa al Dataframe

In [4]:

```
import pandas as pd
import numpy as np
mel_full = pd.read_csv('Melbourne_housing_FULL.csv')
```

In [5]:

```
mel_full
```

Out[5]:

	Suburb	Address	Rooms	Type	Price	Method	SellerG	Date	Distance	Postcode	...	Bathro
0	Abbotsford	68 Studley St	2	h	NaN	SS	Jellis	3/09/2016	2.5	3067.0	...	
1	Abbotsford	85 Turner St	2	h	1480000.0	S	Biggin	3/12/2016	2.5	3067.0	...	
2	Abbotsford	25 Bloomburg St	2	h	1035000.0	S	Biggin	4/02/2016	2.5	3067.0	...	
3	Abbotsford	18/659 Victoria St	3	u	NaN	VB	Rounds	4/02/2016	2.5	3067.0	...	
4	Abbotsford	5 Charles St	3	h	1465000.0	SP	Biggin	4/03/2017	2.5	3067.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
34852	Yarraville	13 Burns St	4	h	1480000.0	PI	Jas	24/02/2018	6.3	3013.0	...	
34853	Yarraville	29A Murray St	2	h	888000.0	SP	Sweeney	24/02/2018	6.3	3013.0	...	
34854	Yarraville	147A Severn St	2	t	705000.0	S	Jas	24/02/2018	6.3	3013.0	...	
34855	Yarraville	12/37 Stephen St	3	h	1140000.0	SP	hockingstuart	24/02/2018	6.3	3013.0	...	
34856	Yarraville	3 Tarrengower St	2	h	1020000.0	PI	RW	24/02/2018	6.3	3013.0	...	

34857 rows × 21 columns

Proporciona información detallada sobre el DataFrame `mel_full`, incluyendo el número de filas, el nombre y tipo de cada columna, y el número de valores no nulos en cada columna. Esto puede ayudarte a comprender mejor la estructura y la calidad de los datos cargados desde el archivo CSV

In [6]:

```
mel_full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34857 entries, 0 to 34856
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Suburb          34857 non-null  object
 1   Address         34857 non-null  object
 2   Rooms           34857 non-null  int64
 3   Type            34857 non-null  object
 4   Price           27247 non-null  float64
 5   Method          34857 non-null  object
```

```
 5   Method         34857 non-null  object
 6   SellerG        34857 non-null  object
 7   Date           34857 non-null  object
 8   Distance       34856 non-null  float64
 9   Postcode       34856 non-null  float64
 10  Bedroom2       26640 non-null  float64
 11  Bathroom       26631 non-null  float64
 12  Car            26129 non-null  float64
 13  Landsize       23047 non-null  float64
 14  BuildingArea   13742 non-null  float64
 15  YearBuilt      15551 non-null  float64
 16  CouncilArea    34854 non-null  object
 17  Lattitude      26881 non-null  float64
 18  Longtitude     26881 non-null  float64
 19  Regionname     34854 non-null  object
 20  Propertycount  34854 non-null  float64
dtypes: float64(12), int64(1), object(8)
memory usage: 5.6+ MB
```

Observamos que hai tipos object, primeramente vamos a pasarlos a string y el Date pasarlo a formato datetime

In [7]:

```python
columnas = ['Suburb', 'Address', 'Type', 'Method', 'SellerG', 'CouncilArea','Regionname']

for col in columnas:
    mel_full[col] = mel_full[col].astype('string')

mel_full['Date']=pd.to_datetime(mel_full['Date'], format="%d/%m/%Y")
mel_full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34857 entries, 0 to 34856
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Suburb         34857 non-null  string
 1   Address        34857 non-null  string
 2   Rooms          34857 non-null  int64
 3   Type           34857 non-null  string
 4   Price          27247 non-null  float64
 5   Method         34857 non-null  string
 6   SellerG        34857 non-null  string
 7   Date           34857 non-null  datetime64[ns]
 8   Distance       34856 non-null  float64
 9   Postcode       34856 non-null  float64
 10  Bedroom2       26640 non-null  float64
 11  Bathroom       26631 non-null  float64
 12  Car            26129 non-null  float64
 13  Landsize       23047 non-null  float64
 14  BuildingArea   13742 non-null  float64
 15  YearBuilt      15551 non-null  float64
 16  CouncilArea    34854 non-null  string
 17  Lattitude      26881 non-null  float64
 18  Longtitude     26881 non-null  float64
 19  Regionname     34854 non-null  string
 20  Propertycount  34854 non-null  float64
dtypes: datetime64[ns](1), float64(12), int64(1), string(7)
memory usage: 5.6 MB
```

Si realizamos un len podemos ver todo el conjunto de datos que posee el Dataframe

In [8]:

```python
len(mel_full)
```

Out[8]:

```
34857
```

Utiliza el método `describe()` del DataFrame `mel_full` para obtener estadísticas descriptivas sobre las

columnas numéricas del DataFrame.

In [9]:

```
mel_full.describe()
```

Out[9]:

	Rooms	Price	Date	Distance	Postcode	Bedroom2	Bathroom	Ca
count	34857.000000	2.724700e+04	34857	34856.000000	34856.000000	26640.000000	26631.000000	26129.00000
mean	3.031012	1.050173e+06	2017-05-23 11:01:38.838109696	11.184929	3116.062859	3.084647	1.624798	1.72884
min	1.000000	8.500000e+04	2016-01-28 00:00:00	0.000000	3000.000000	0.000000	0.000000	0.00000
25%	2.000000	6.350000e+05	2016-11-19 00:00:00	6.400000	3051.000000	2.000000	1.000000	1.00000
50%	3.000000	8.700000e+05	2017-07-08 00:00:00	10.300000	3103.000000	3.000000	2.000000	2.00000
75%	4.000000	1.295000e+06	2017-10-28 00:00:00	14.000000	3156.000000	4.000000	2.000000	2.00000
max	16.000000	1.120000e+07	2018-03-17 00:00:00	48.100000	3978.000000	30.000000	12.000000	26.00000
std	0.969933	6.414671e+05	NaN	6.788892	109.023903	0.980690	0.724212	1.01077

Histogramas_de_las_columnas_del_DataFrame

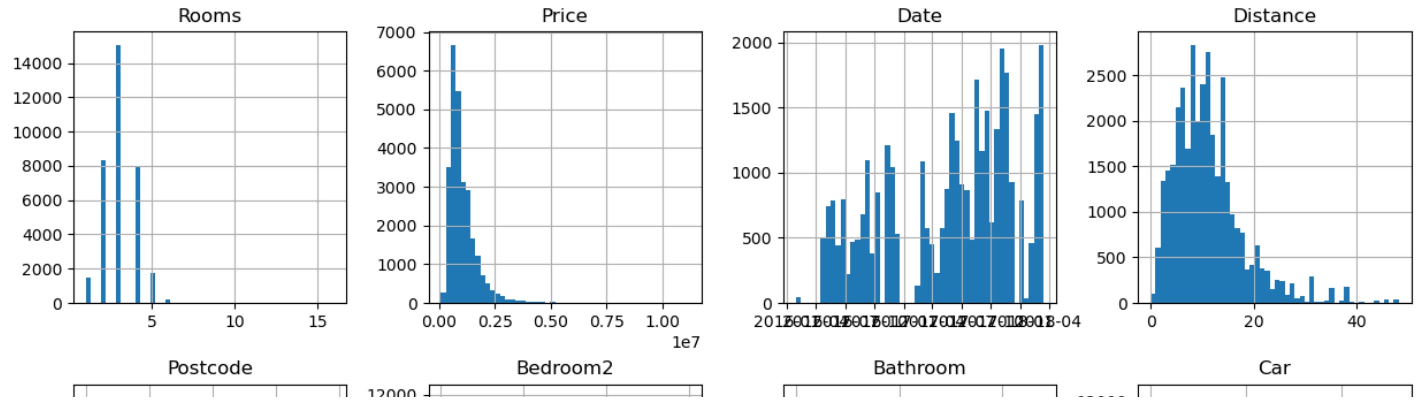
Se utiliza el método `hist()` **del DataFrame** `mel_full` **para generar histogramas de las columnas del DataFrame.**

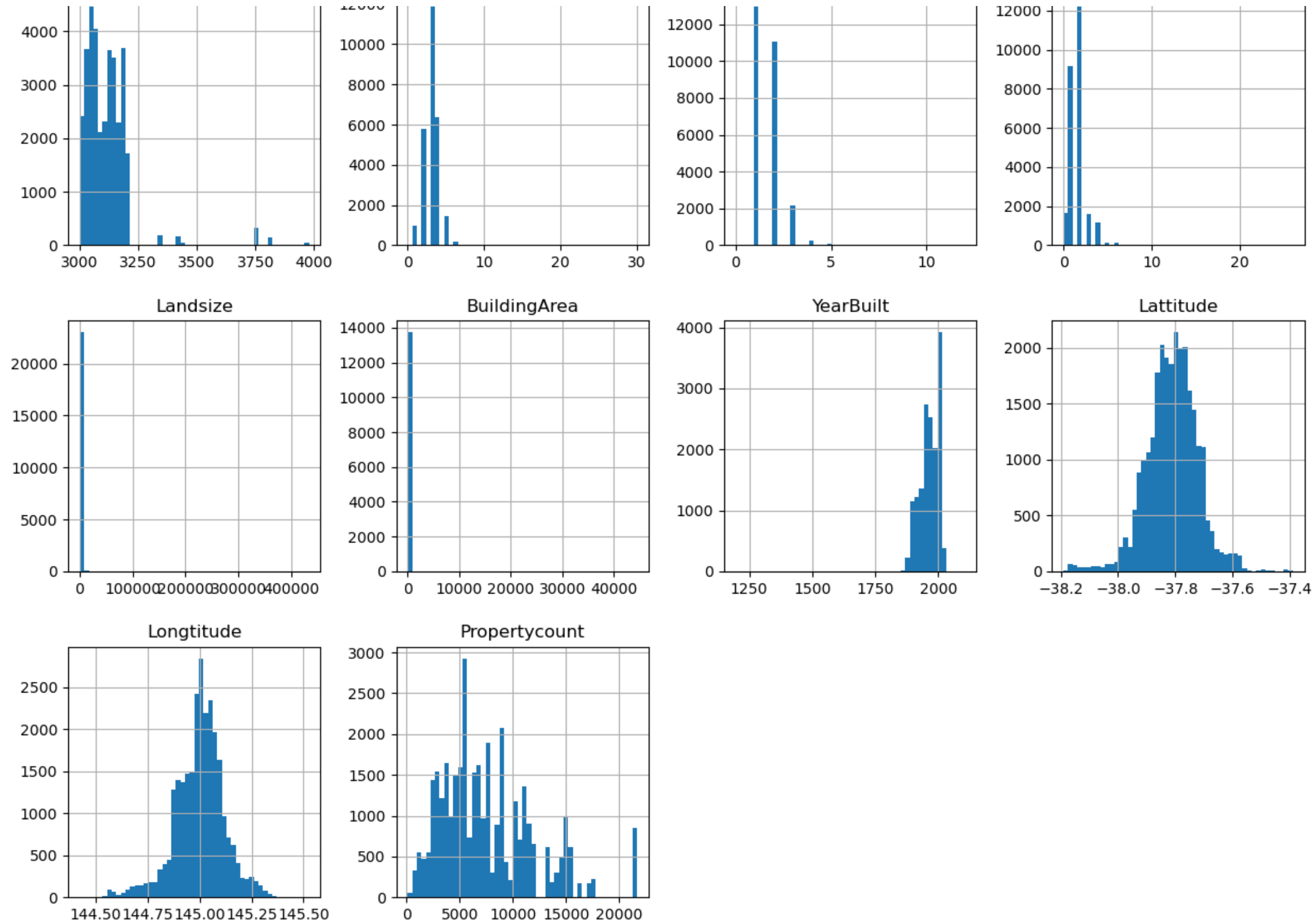
In [10]:

```
mel_full.hist(bins=50, figsize=(15,15))
```

Out[10]:

```
array([[<Axes: title={'center': 'Rooms'}>,
        <Axes: title={'center': 'Price'}>,
        <Axes: title={'center': 'Date'}>,
        <Axes: title={'center': 'Distance'}>],
       [<Axes: title={'center': 'Postcode'}>,
        <Axes: title={'center': 'Bedroom2'}>,
        <Axes: title={'center': 'Bathroom'}>,
        <Axes: title={'center': 'Car'}>],
       [<Axes: title={'center': 'Landsize'}>,
        <Axes: title={'center': 'BuildingArea'}>,
        <Axes: title={'center': 'YearBuilt'}>,
        <Axes: title={'center': 'Lattitude'}>],
       [<Axes: title={'center': 'Longtitude'}>,
        <Axes: title={'center': 'Propertycount'}>, <Axes: >, <Axes: >]],
      dtype=object)
```





In [11]:

```
mel_full.isna().sum()
```

Out[11]:

```
Suburb              0
Address             0
Rooms               0
Type                0
Price            7610
Method              0
SellerG             0
Date                0
Distance            1
Postcode            1
Bedroom2         8217
Bathroom         8226
Car              8728
Landsize        11810
BuildingArea    21115
YearBuilt       19306
CouncilArea         3
Lattitude        7976
Longtitude       7976
Regionname          3
Propertycount       3
dtype: int64
```

In [12]:

```
mel_full.drop_duplicates(inplace=True)
mel_sin_string=mel_full.copy()
mel_sin_string=mel_sin_string.drop(['Suburb','Address','SellerG'],axis=1)
```

In [13]:

```
mel_sin_string[['Method']].value_counts()
```

Out[13]:

```
Method
S         19744
SP         5094
PI         4850
VB         3108
SN         1317
PN          308
SA          226
W           173
SS           36
Name: count, dtype: int64
```

Ahora vamos pasar a numerico los distintos strings

In [14]:

```
mel_sin_string[['Type']].value_counts()
```

Out[14]:

```
Type
h       23980
u        7297
t        3579
Name: count, dtype: int64
```

In [15]:

```
mel_sin_string['CouncilArea'].value_counts()
```

Out[15]:

```
CouncilArea
Boroondara City Council           3675
Darebin City Council              2851
Moreland City Council             2122
Glen Eira City Council            2006
Melbourne City Council            1952
Banyule City Council              1861
Moonee Valley City Council        1791
Bayside City Council              1764
Brimbank City Council             1593
Monash City Council               1466
Stonnington City Council          1460
Maribyrnong City Council          1451
Port Phillip City Council         1280
Hume City Council                 1214
Yarra City Council                1186
Manningham City Council           1045
Hobsons Bay City Council           942
Kingston City Council              871
Whittlesea City Council            828
Wyndham City Council               624
Whitehorse City Council            618
Maroondah City Council             506
Knox City Council                  371
Greater Dandenong City Council     314
Melton City Council                292
Frankston City Council             290
Casey City Council                 176
Yarra Ranges Shire Council         102
Nillumbik Shire Council             88
Macedon Ranges Shire Council        46
Cardinia Shire Council              41
Mitchell Shire Council              20
Moorabool Shire Council              7
Name: count, dtype: Int64
```

In [16]:

```
from sklearn.preprocessing import OrdinalEncoder
oe= OrdinalEncoder()
housing_cat_encoded = oe.fit_transform(mel_sin_string[['Method']])
mel_sin_string['Method_Int'] = housing_cat_encoded
mel_sin_string[['Method_Int']].value_counts()
```

Out[16]:

```
Method_Int
2.0           19744
5.0            5094
0.0            4850
7.0            3108
4.0            1317
1.0             308
3.0             226
8.0             173
6.0              36
Name: count, dtype: int64
```

In [17]:

```
oe= OrdinalEncoder()
mel_sin_string['CouncilArea'].replace(['NAType', 'str'], None)
mel_sin_string['CouncilArea'] = mel_sin_string['CouncilArea'].astype(str)
housing_cat_encoded = oe.fit_transform(mel_sin_string[['CouncilArea']])
mel_sin_string['CouncilArea_Int'] = housing_cat_encoded
mel_sin_string[['CouncilArea_Int']].value_counts()
```

Out[17]:

```
CouncilArea_Int
3.0                3675
7.0                2851
25.0               2122
9.0                2006
19.0               1952
1.0                1861
23.0               1791
2.0                1764
4.0                1593
22.0               1466
28.0               1460
17.0               1451
27.0               1280
12.0               1214
32.0               1186
16.0               1045
11.0                942
13.0                871
30.0                828
31.0                624
29.0                618
18.0                506
14.0                371
10.0                314
20.0                292
8.0                 290
6.0                 176
33.0                102
26.0                 88
15.0                 46
5.0                  41
21.0                 20
24.0                  7
0.0                   3
Name: count, dtype: int64
```

In [18]:

```
oe= OrdinalEncoder()
mel_sin_string['Regionname'].replace(['NAType', 'str'], None)
```

```
mel_sin_string['Regionname'] = mel_sin_string['Regionname'].astype(str)
housing_cat_encoded = oe.fit_transform(mel_sin_string[['Regionname']])
mel_sin_string['Regionname_Int'] = housing_cat_encoded
mel_sin_string[['Regionname_Int']].value_counts()
```

Out[18]:

```
Regionname_Int
6.0               11836
3.0                9557
7.0                6799
1.0                4376
5.0                1739
2.0                 228
4.0                 203
8.0                 115
0.0                   3
Name: count, dtype: int64
```

Borraremos las columnas que sean String y que han sido pasadas a Int mediante OrdinalEncoder()

In [19]:

```
mel_sin_string=mel_sin_string[mel_sin_string['Type']=='h']
dfmelboune=mel_sin_string.drop(['Type','Method','CouncilArea','Regionname'],axis=1)
dfmelboune
```

Out[19]:

	Rooms	Price	Date	Distance	Postcode	Bedroom2	Bathroom	Car	Landsize	BuildingArea	YearBuilt	Lattitud
0	2	NaN	2016-09-03	2.5	3067.0	2.0	1.0	1.0	126.0	NaN	NaN	37.8014
1	2	1480000.0	2016-12-03	2.5	3067.0	2.0	1.0	1.0	202.0	NaN	NaN	37.7996
2	2	1035000.0	2016-02-04	2.5	3067.0	2.0	1.0	0.0	156.0	79.0	1900.0	37.8079
4	3	1465000.0	2017-03-04	2.5	3067.0	3.0	2.0	0.0	134.0	150.0	1900.0	37.8093
5	3	850000.0	2017-03-04	2.5	3067.0	3.0	2.0	1.0	94.0	NaN	NaN	37.7969
...	...	...	...	...	...	...	...	...	...	...	...	.
34851	3	1101000.0	2018-02-24	6.3	3013.0	3.0	1.0	NaN	288.0	NaN	NaN	37.8109
34852	4	1480000.0	2018-02-24	6.3	3013.0	4.0	1.0	3.0	593.0	NaN	NaN	37.8105
34853	2	888000.0	2018-02-24	6.3	3013.0	2.0	2.0	1.0	98.0	104.0	2018.0	37.8155
34855	3	1140000.0	2018-02-24	6.3	3013.0	NaN	NaN	NaN	NaN	NaN	NaN	Nal
34856	2	1020000.0	2018-02-24	6.3	3013.0	2.0	1.0	0.0	250.0	103.0	1930.0	37.8181

23980 rows × 17 columns

MATRIZ_DE_CORRELACION

In [20]:

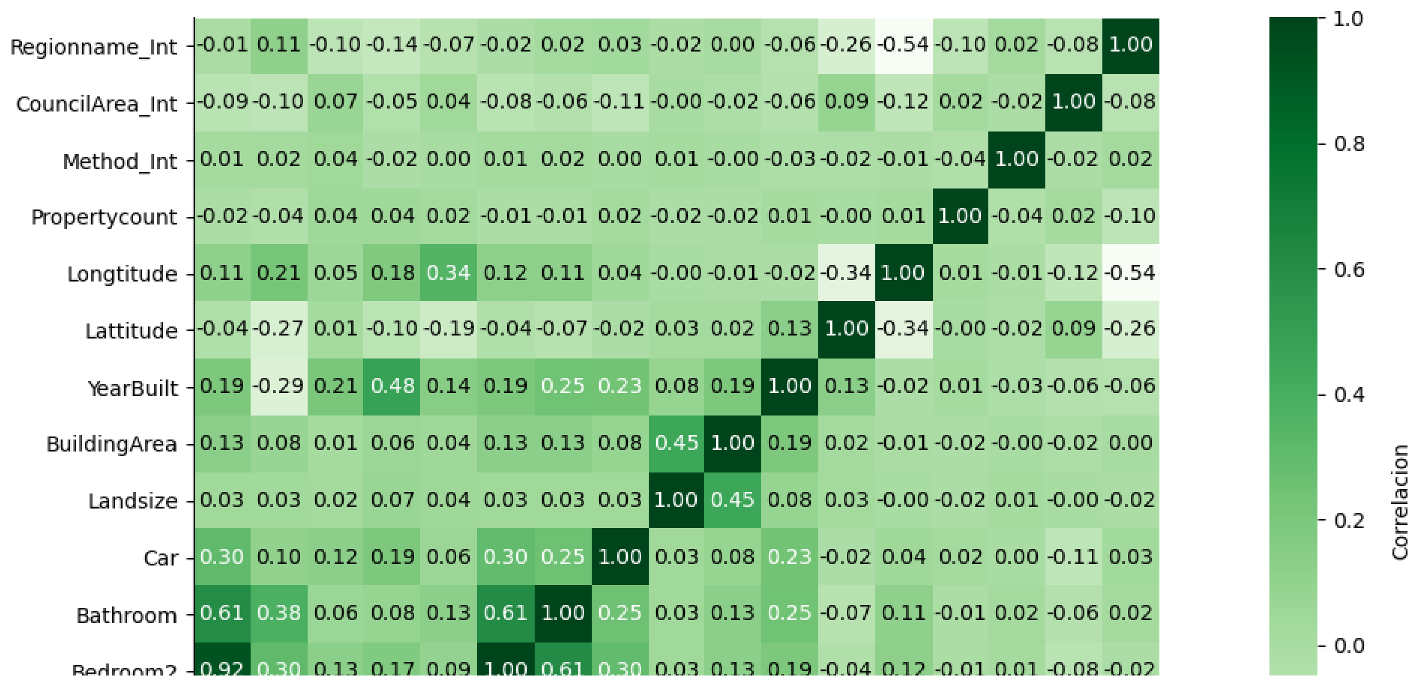
```
corr_matrix= dfmelboune.corr()
corr_matrix
```

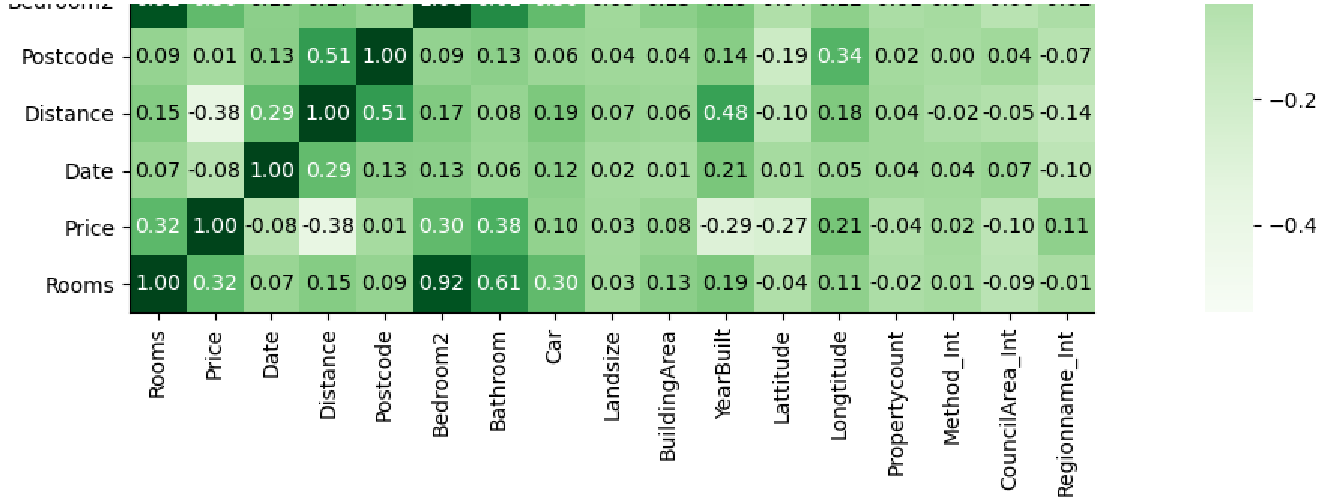
Out[20]:

	Rooms	Price	Date	Distance	Postcode	Bedroom2	Bathroom	Car	Landsize	BuildingArea
Rooms	1.000000	0.318045	0.072691	0.153622	0.087980	0.922920	0.608162	0.302227	0.034242	0.128913
Price	0.318045	1.000000	-0.079137	-0.381498	0.012566	0.298083	0.383945	0.099694	0.025981	0.075080
Date	0.072691	-0.079137	1.000000	0.294207	0.133470	0.125187	0.063975	0.122260	0.023495	0.008947
Distance	0.153622	-0.381498	0.294207	1.000000	0.514903	0.170186	0.082597	0.193485	0.068879	0.058115
Postcode	0.087980	0.012566	0.133470	0.514903	1.000000	0.094036	0.127039	0.059431	0.043416	0.038030
Bedroom2	0.922920	0.298083	0.125187	0.170186	0.094036	1.000000	0.609537	0.296184	0.033627	0.126028
Bathroom	0.608162	0.383945	0.063975	0.082597	0.127039	0.609537	1.000000	0.253745	0.032408	0.126933
Car	0.302227	0.099694	0.122260	0.193485	0.059431	0.296184	0.253745	1.000000	0.032769	0.083840
Landsize	0.034242	0.025981	0.023495	0.068879	0.043416	0.033627	0.032408	0.032769	1.000000	0.447785
BuildingArea	0.128913	0.075080	0.008947	0.058115	0.038030	0.126028	0.126933	0.083840	0.447785	1.000000
YearBuilt	0.187893	-0.293182	0.206005	0.480643	0.141168	0.192316	0.246768	0.232787	0.082807	0.192845
Lattitude	-0.038916	-0.265892	0.012316	-0.099426	-0.187658	-0.038036	-0.071983	-0.020660	0.025445	0.016726
Longtitude	0.114497	0.214247	0.051383	0.178340	0.344997	0.116559	0.113262	0.038273	-0.000713	-0.005809
Propertycount	-0.016720	-0.039029	0.039238	0.040408	0.022386	-0.011998	-0.012341	0.016498	-0.021777	-0.016698
Method_Int	0.010991	0.024109	0.036485	-0.018816	0.000729	0.009498	0.016608	0.000772	0.010204	-0.000949
CouncilArea_Int	-0.091053	-0.100556	0.073476	-0.047082	0.035784	-0.084978	-0.058349	-0.111453	-0.001196	-0.024003
Regionname_Int	-0.008853	0.112618	-0.104387	-0.142311	-0.073262	-0.017551	0.023204	0.031774	-0.015724	0.002805

In [21]:

```
mapa_calor(corr_matrix)
```





In [22]:

```
# train(corr_matrix)
# regresion_lineal(dfmelboune)
dfmelburne_sinpricesnulos = dfmelboune.dropna(subset=['Price'])
```

In [23]:

```
dfmelboune.isna().sum()
```

Out[23]:

```
Rooms                0
Price             5508
Date                 0
Distance             1
Postcode             1
Bedroom2          3558
Bathroom          3564
Car               4048
Landsize          6286
BuildingArea     13567
YearBuilt        12527
Lattitude         3440
Longtitude        3440
Propertycount        2
Method_Int           0
CouncilArea_Int      0
Regionname_Int       0
dtype: int64
```

In [24]:

```
from sklearn.impute import SimpleImputer
def simpleimputer(cadena,df):
    imp_mean = SimpleImputer()
    df2 = df.copy()

    imp_mean.fit(df2[[cadena]])

    df2[cadena] = imp_mean.transform(df2[[cadena]])

    return df2[cadena]
df2=dfmelboune.copy()
df2['Bathroom']=simpleimputer('Bathroom',dfmelboune).copy()
df2['Bathroom']=simpleimputer('Bathroom',dfmelboune).copy()
df2['Bedroom2']=simpleimputer('Bedroom2',dfmelboune).copy()
df2['Bathroom']=simpleimputer('Bathroom',dfmelboune).copy()
df2['Car']=simpleimputer('Car',dfmelboune).copy()
df2['Landsize']=simpleimputer('Landsize',dfmelboune).copy()
df2['BuildingArea']=simpleimputer('BuildingArea',dfmelboune).copy()
df2['YearBuilt']=simpleimputer('YearBuilt',dfmelboune).copy()
df2['Lattitude']=simpleimputer('Lattitude',dfmelboune).copy()
df2['Longtitude']=simpleimputer('Longtitude',dfmelboune).copy()
```

```
df2['Propertycount']=simpleimputer('Propertycount',dfmelboune).copy()
df2['Distance']=simpleimputer('Distance',dfmelboune).copy()
df2['Postcode']=simpleimputer('Postcode',dfmelboune).copy()

df2.isna().sum()
```

Out[24]:

```
Rooms                 0
Price              5508
Date                  0
Distance              0
Postcode              0
Bedroom2              0
Bathroom              0
Car                   0
Landsize              0
BuildingArea          0
YearBuilt             0
Lattitude             0
Longtitude            0
Propertycount         0
Method_Int            0
CouncilArea_Int       0
Regionname_Int        0
dtype: int64
```

ENTRENAMIENTO

Se realiza un análisis de

```
- regresion_lineal(df3)
- arbol_de_regresion_test(df3)
- arbol_decision(df3)
- random_forest(df3)
- regresion_svr(df3)
```

Utilizando la biblioteca `scikit-learn` para ajustar un modelo de regresión lineal, un arbol de regresion,random forest,XGboost y SGV a los datos del DataFrame `df3`.

In [25]:

```
df3=df2.dropna()
df3.isna().sum()
train(df3)
```

```
(29554,7390)
```

Out[25]:

```
(       Rooms  Distance  Bathroom  Bedroom2    YearBuilt  Lattitude  \
 16522      3      19.9       2.0       3.0  1980.000000  -37.78649
 21721      4      10.5       1.0       4.0  1925.000000  -37.93091
 24949      4      14.8       3.0       4.0  1957.841439  -37.76264
 7783       3       3.8       1.0       3.0  1890.000000  -37.83850
 8627       1      11.2       1.0       1.0  2014.000000  -37.71860
 ...      ...       ...       ...       ...          ...        ...
 31918      4      20.0       1.0       4.0  1970.000000  -37.97644
 23155      4       7.3       2.0       4.0  1925.000000  -37.85645
 32400      3      12.0       1.0       3.0  1957.841439  -37.70891
 16849      3      23.0       1.0       3.0  1957.841439  -37.81263
 33193      5      17.9       2.0       5.0  1957.841439  -37.96234

        Longtitude  CouncilArea_Int  Regionname_Int  Car  BuildingArea
 16522   145.24836             18.0             1.0  2.0    178.201163
 21721   144.99266              2.0             6.0  2.0    177.000000
 24949   144.78245              4.0             7.0  4.0    178.201163
 7783    144.94090             19.0             6.0  0.0    167.000000
 8627    145.01100              7.0             3.0  1.0     50.000000
```

```
...          ...                ...                ...  ...          ...
31918   145.05597              13.0                5.0  4.0    114.000000
23155   145.06472               3.0                6.0  2.0    324.000000
32400   145.02801               7.0                3.0  1.0    178.201163
16849   145.27588              18.0                1.0  2.0    178.201163
33193   145.06218               2.0                6.0  3.0    178.201163

[14777 rows x 11 columns],
16522    1085000.0
21721    1740000.0
24949    1206000.0
7783      985000.0
8627      395000.0
           ...
31918    1270000.0
23155    2850000.0
32400     822000.0
16849     800000.0
33193    1350000.0
Name: Price, Length: 14777, dtype: float64,
       Rooms  Distance  Bathroom  Bedroom2    YearBuilt  Lattitude  \
17094      3      16.3       2.0       3.0  1980.000000  -37.67323
24110      3      14.5       2.0       3.0  1952.000000  -37.70595
24730      3      31.7       2.0       3.0  2000.000000  -37.57076
17268      3      19.9       1.0       3.0  1957.841439  -37.80237
6956       3      14.6       2.0       3.0  1970.000000  -37.94280
...      ...       ...       ...       ...          ...        ...
16481      2       8.5       1.0       2.0  1940.000000  -37.71949
21860      4       7.5       2.0       4.0  2011.000000  -37.74807
33772      3      14.0       1.0       3.0  1957.841439  -37.75709
16353      3      15.5       1.0       3.0  1990.000000  -37.72545
23766      3      38.0       1.0       3.0  1970.000000  -38.17433

       Longtitude  CouncilArea_Int  Regionname_Int       Car  BuildingArea
17094   145.03976             30.0             3.0  2.000000    121.000000
24110   145.08493              1.0             3.0  2.000000    134.000000
24730   144.70343             12.0             7.0  1.866697    178.201163
17268   145.23404             18.0             1.0  1.000000    178.201163
6956    145.04400             13.0             6.0  2.000000    150.000000
...           ...              ...             ...       ...           ...
16481   144.94283             25.0             3.0  1.000000     88.000000
21860   144.89492             23.0             7.0  2.000000    178.201163
33772   144.80162              4.0             7.0  1.000000    178.201163
16353   144.80397              4.0             7.0  1.000000    178.201163
23766   145.13866              8.0             5.0  1.000000    120.000000

[3695 rows x 11 columns],
17094     600000.0
24110    1035000.0
24730     555000.0
17268     930000.0
6956     1000000.0
           ...
16481     740000.0
21860    2053000.0
33772     670000.0
16353     575000.0
23766     563000.0
Name: Price, Length: 3695, dtype: float64)
```

In [26]:

```
regresion_lineal(df3)
arbol_de_regresion_test(df3)
arbol_decision(df3)
random_forest(df3)
regresion_svr(df3)
```

```
------------Regresion Lineal-------------
(29554,7390)
mae: 332927.49382430664   rmse: 509844.6977975496 r2_score: 0.45568197173357494
----------Arbol de regresión-----------
```

```
(29554,7390)
mae: 23546.60896120442   rmse: 112507.42968026568 r2_score: 0.9734942980304307
---------------Arbol de decision---------------
(29554,7390)
Scores:  [511245.50720451 430304.19740522 508750.42204203 528591.73851253
 472257.33244872 441348.73550307 456549.78123603 519024.56331913
 438321.54514975 454885.74909064]
Media:  476127.95719116257
Desviación Std 35324.62148123848
mae: 269937.00336822146   rmse: 462802.81436852296 r2_score: 0.5301402272518456
---------------Random forest---------------
(29554,7390)
Scores:  [295008.35817555 498565.03912245 370617.02439013 367288.97792382
 349184.01773039 336041.20611125 338182.88178902 410158.2644821
 354340.16947021 375085.89132594]
Media:  369447.1830520864
Desviación Std 51613.95792089028
mae: 207428.45266274808   rmse: 349947.2024800637 r2_score: 0.731353409067065
---------------Regresion svr---------------
(29554,7390)
SV cross
Scores:  [762697.30329465 683634.67184933 772351.0870935  700560.27509395
 695500.10961719 701477.90371948 712644.38769467 734187.20653268
 693848.26176702 695151.90210968]
Media:  715205.3108772158
Desviación Std 29213.32146290287
mae: 460743.87778517645   rmse: 697104.3981899002 r2_score: -0.06603613815076925
```

In [27]:

```
xgboost(df3)
```

```
---------------Xboost---------------
(29554,7390)
XGB cross
Scores:  [394889.01987696 300538.4722076  392609.98149774 349687.29046565
 370199.18289074 352790.45440768 364383.93584304 355084.13128598
 359360.78987677 323565.48881635]
Media:  356310.8747168504
Desviación Std 27044.132720065874
mae: 205972.5154939107   rmse: 343030.487356563 r2_score: 0.7418680736553485
```

Eliminamos outliers en el Dataframe `df3`

In [28]:

```
for datos in df3.columns:
    if datos!='Price':
        q_low = df3[datos].quantile(0.0001)
        q_hi  = df3[datos].quantile(0.9999)
        df_filtrado = df3[(df3[datos] < q_hi) & (df3[datos] > q_low)]
xgboost(df_filtrado)
```

```
---------------Xboost---------------
(29400,7352)
XGB cross
Scores:  [366974.05807904 335896.05771849 342368.71869129 349551.2949085
 328129.29553169 414213.67090621 313881.95987189 323613.79307296
 355043.94116551 422528.02943362]
Media:  355220.0819379205
Desviación Std 34872.92567555151
mae: 207060.04670497825   rmse: 340918.44801306736 r2_score: 0.7469630370517376
```