Parcial 2 Santiago Uribe

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```
import pandas as pd
import statsmodels.formula.api as smf
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

Punto 1

```
df = pd.read_excel('Datos_Vivienda.xlsx', sheet_name='Datos Vivienda')
dim_df = df.shape
print(f"The dataset consists of {dim_df[0]} rows and {dim_df[1]} columns")
```

```
The dataset consists of 8322 rows and 12 columns
```

Let's check how much missing data there is by columns

```
# Missing values by column
df.isnull().sum()
```

	0
Zona	3
piso	2638
Estrato	3
precio_millon	2
Area_contruida	3
parqueaderos	1605
Banos	3
Habitaciones	3
Tipo	3
Barrio	3
cordenada_longitud	3
Cordenada_latitud	3

```
# delete records that have more than 6 missing data in their columns
df = df.dropna(thresh=len(df.columns)-6)
```

```
dim_df = df.shape
print(f"The dataset consists of {dim_df[0]} rows and {dim_df[1]} columns")
```

```
The dataset consists of 8319 rows and 12 columns
```

```
# Missing values by column
df.isnull().sum()
```

	0
Zona	0
piso	2635
Estrato	0
precio_millon	0
Area_contruida	0
parqueaderos	1602
Banos	0
Habitaciones	0
Tipo	0
Barrio	0
cordenada_longitud	0
Cordenada_latitud	0

Since the ‘piso’ and ‘parqueaderos’ attributes will not be used in this study, we eliminated the columns by having so much missing data, % and 20% respectively.

```
df.drop('piso', axis=1, inplace=True)
df.drop('parqueaderos', axis=1, inplace=True)
```

Descriptive Statistics

Let’s look at some graphs and measures of central tendency of our variables of interest.

```
df.describe()
```

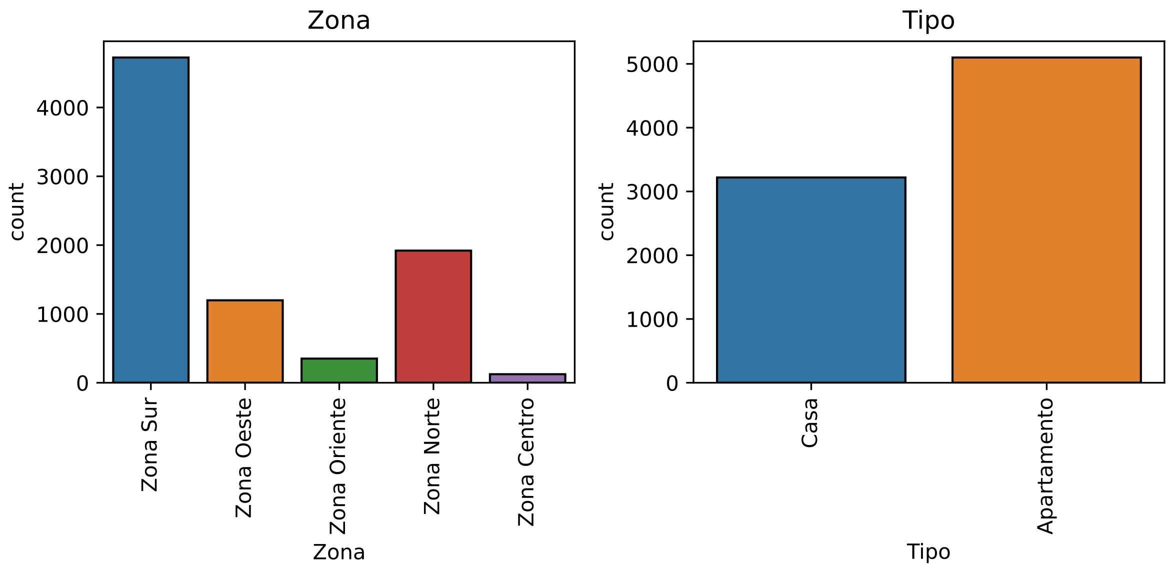
	Estrato	precio_millon	Area_contruida	Banos	Habitaciones	cordenada_longitud
count	8319.000000	8319.000000	8319.000000	8319.000000	8319.000000	8319.000000
mean	4.633610	433.904436	174.934938	3.111311	3.605361	-76.528606
std	1.029222	328.665025	142.964126	1.428210	1.459537	0.017398
min	3.000000	58.000000	30.000000	0.000000	0.000000	-76.589150
25%	4.000000	220.000000	80.000000	2.000000	3.000000	-76.541580
50%	5.000000	330.000000	123.000000	3.000000	3.000000	-76.530000
75%	5.000000	540.000000	229.000000	4.000000	4.000000	-76.518890
max	6.000000	1999.000000	1745.000000	10.000000	10.000000	-76.463000

```
#Separate attributes by type
obj_attributes = df.select_dtypes(include=['object']).columns.to_list()
float_attributes = df.select_dtypes(include=['float']).columns.to_list()
```

Bar Diagrams and Pie Diagram

```
fig, axs = plt.subplots(1, 2, figsize=(8,4))
axs = axs.ravel()

for i, col in enumerate(obj_attributes):
  if col != 'Barrio':
    sns.countplot(x=col, data=df, ax=axs[i], edgecolor='black')
    axs[i].set_title(col)
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)
```

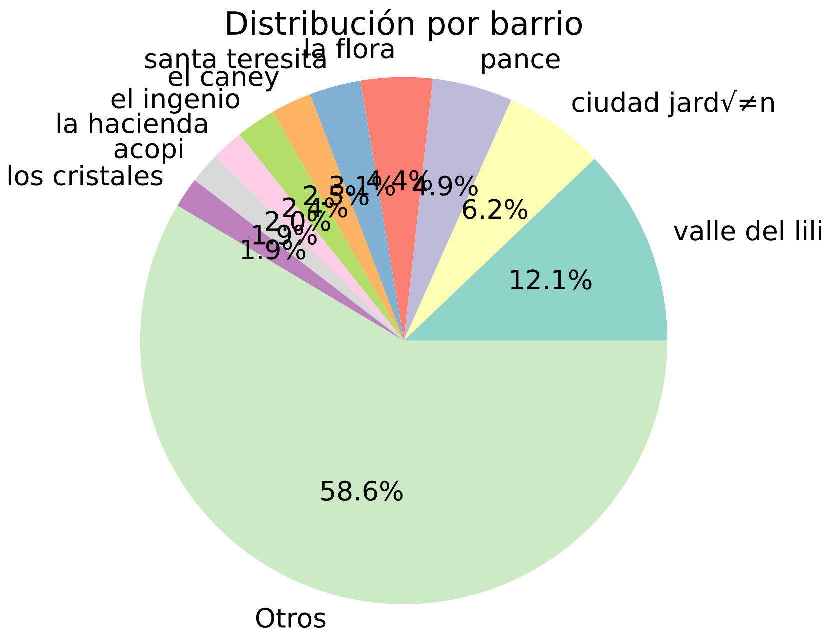
```
plt.tight_layout()
plt.show()
```



Let's see the proportion of neighborhoods in the dataset.

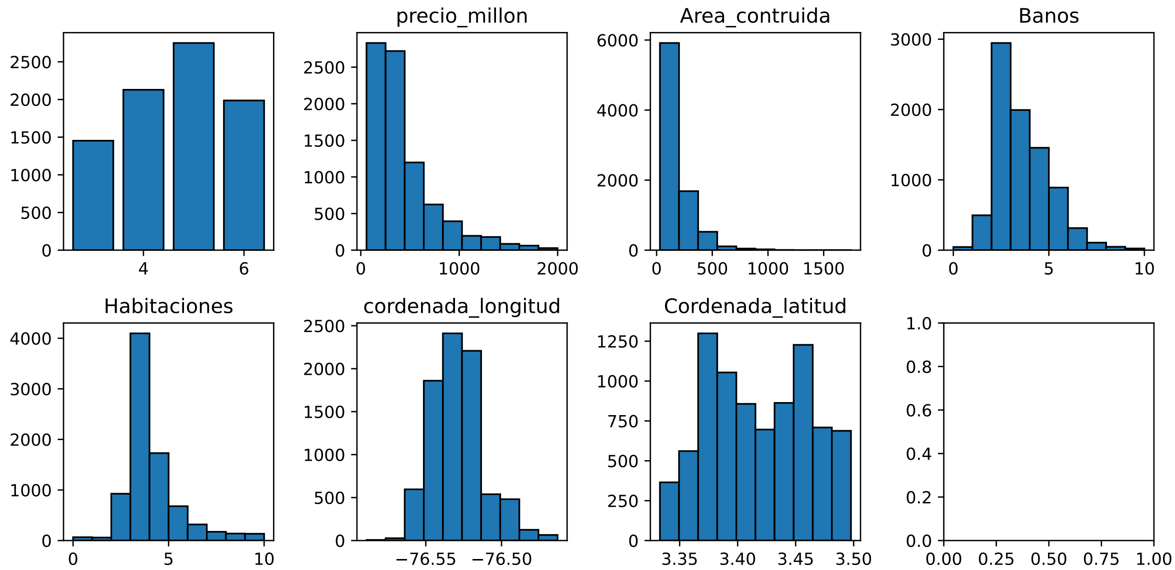
```
from matplotlib.colors import ListedColormap

# Obtain the housing count by neighborhood
count_by_barrio = df['Barrio'].value_counts()

# Create labels
labels_ = count_by_barrio.index[:10].tolist()

# Calculate the sum of the smallest values and add it to the list of labels
sum_low_values = count_by_barrio.iloc[10:].sum()
labels_.append('Otros')

# Create pie chart
fig = plt.figure(facecolor='white')
colores = sns.color_palette("Set3", n_colors=11)
paleta_colores = ListedColormap(colores)
plt.pie(count_by_barrio[:10].tolist() + [sum_low_values], labels=labels_, autopct='%1.1f%%
plt.axis('equal')
```

```
plt.title('Distribución por barrio')
plt.show()
```



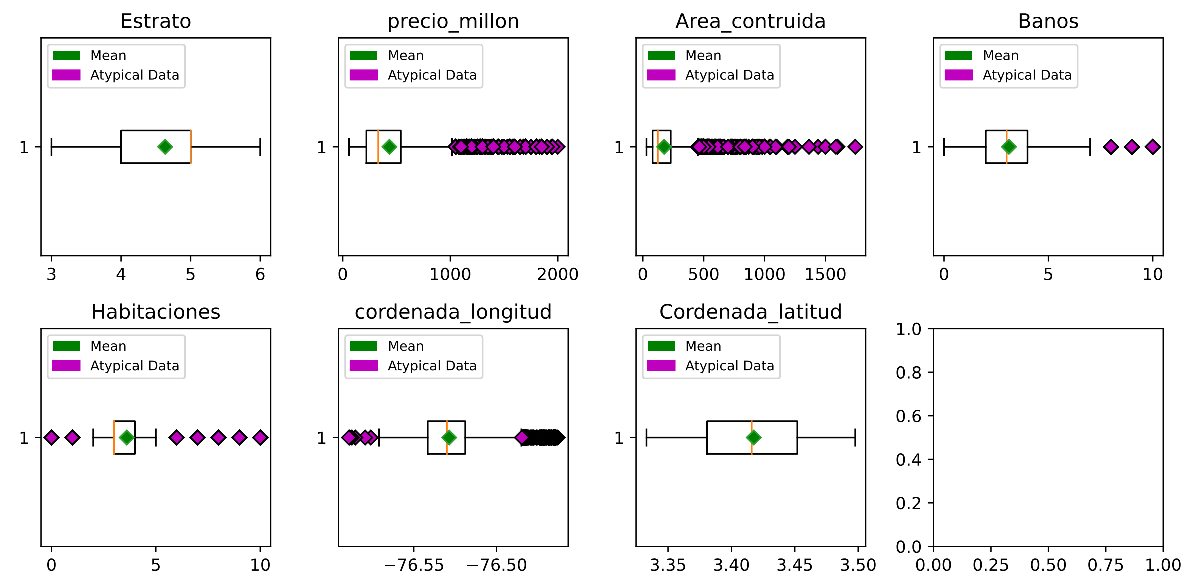
Histograms

```
fig, axs = plt.subplots(2, 4, figsize=(10,5))
axs = axs[:8].ravel()

for i, col in enumerate(float_attributes):
    if col != 'Estrato':
        axs[i].hist(df[col], edgecolor='black')
        axs[i].set_title(col)
    else:
        axs[i].bar(df[col].value_counts().index, df[col].value_counts().values, edgecolor=

plt.tight_layout()
plt.show()
```



Box Plots

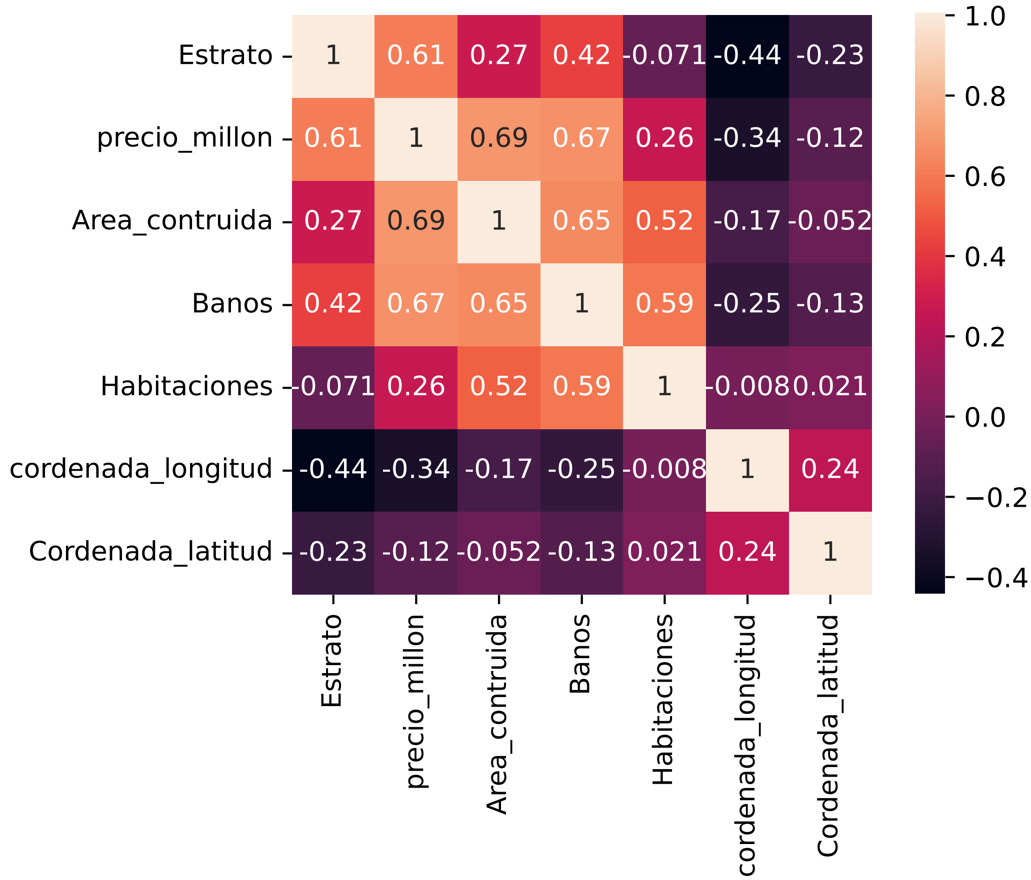
```
import matplotlib.patches as mpatches

fliers = dict(markerfacecolor='m', marker='D') #atypical data
mean_ = dict(markerfacecolor='green', marker='D')
mean_artist = mpatches.Patch(facecolor='green', label='Mean')
ad_artist = mpatches.Patch(color='m', label='Atypical Data')

fig, axs = plt.subplots(2, 4, figsize=(10,5))
axs = axs[:8].ravel()
for i, col in enumerate(float_attributes):
  bp = axs[i].boxplot(df[col], vert=False, flierprops=fliers, showmeans=True, meanprops=me
  axs[i].legend(handles=[mean_artist, ad_artist], loc='upper left', fontsize=8)
  axs[i].set_title(col)

plt.tight_layout()
plt.show()
```



Correlation

```
sns.heatmap(df.corr(), square=True, annot=True)
```

```
<Axes: >
```



As can be seen in the correlation table, the variables 'Area_contruida' and 'precio_millon' have a direct positive relationship, of approximately 0.7

Simple Linear Regression (precio_millon - Area_contruida)

```
df_el_ingenio = df[df['Barrio'] == 'el ingenio'][['precio_millon', 'Area_contruida']]
```

```
# Create the SLR model
modelo = smf.ols('precio_millon ~ Area_contruida', data=df_el_ingenio).fit()
print(modelo.summary())
```

```
                            OLS Regression Results
```

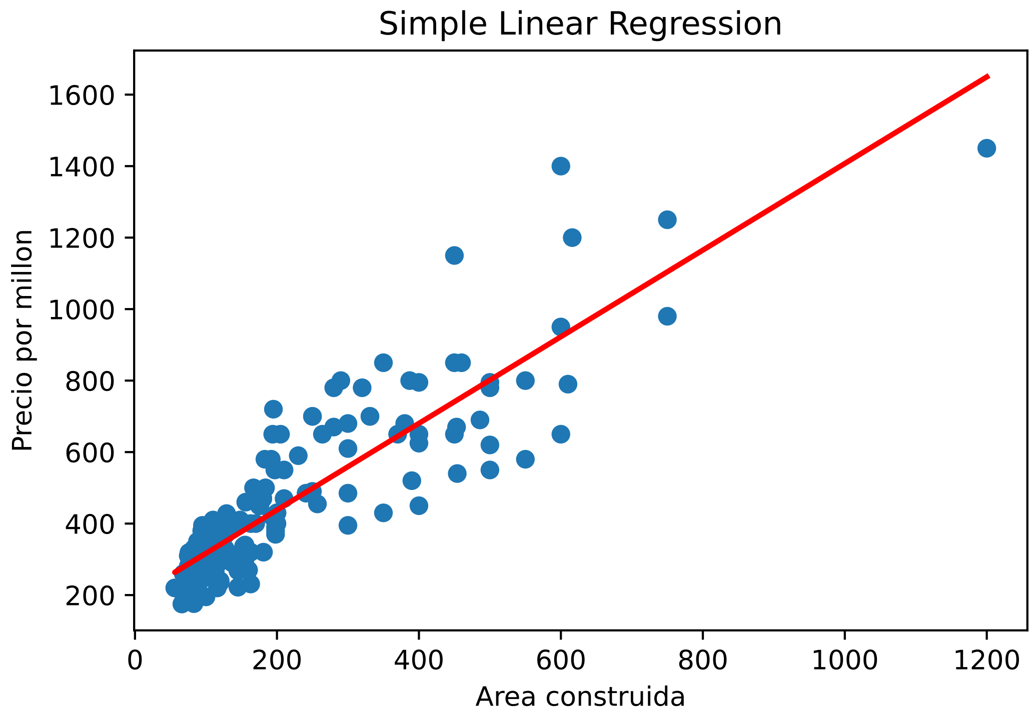
```
==============================================================================
Dep. Variable:          precio_millon   R-squared:                       0.774
Model:                            OLS   Adj. R-squared:                  0.773
Method:                 Least Squares   F-statistic:                     684.2
Date:                Tue, 04 Apr 2023   Prob (F-statistic):           1.80e-66
Time:                        21:25:00   Log-Likelihood:                -1226.1
No. Observations:                 202   AIC:                             2456.
Df Residuals:                     200   BIC:                             2463.
Df Model:                           1
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept        195.7150     11.639     16.816      0.000     172.765     218.665
Area_contruida     1.2116      0.046     26.157      0.000       1.120       1.303
==============================================================================
Omnibus:                       39.056   Durbin-Watson:                   1.924
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               98.633
Skew:                           0.836   Prob(JB):                     3.82e-22
Kurtosis:                       5.987   Cond. No.                         395.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The SLR model is given by:

$$Y = 1.21X + 195.71$$

Where Y is 'precio_millon' and 'X' is 'Area_contruida'. The R-squared value of the model is approximately 0.78, which indicates that the proportion of the variability in the dependent variable is well explained by the independent variable. We can see that the standard error for both the intercept and the slope are small so the coefficients are accurate.

```python
plt.scatter(df_el_ingenio.Area_contruida, df_el_ingenio.precio_millon)
plt.plot(df_el_ingenio.Area_contruida, modelo.predict(), color='red', linewidth=2)
plt.xlabel('Area construida')
plt.ylabel('Precio por millon')
plt.title('Simple Linear Regression')
plt.show()
```

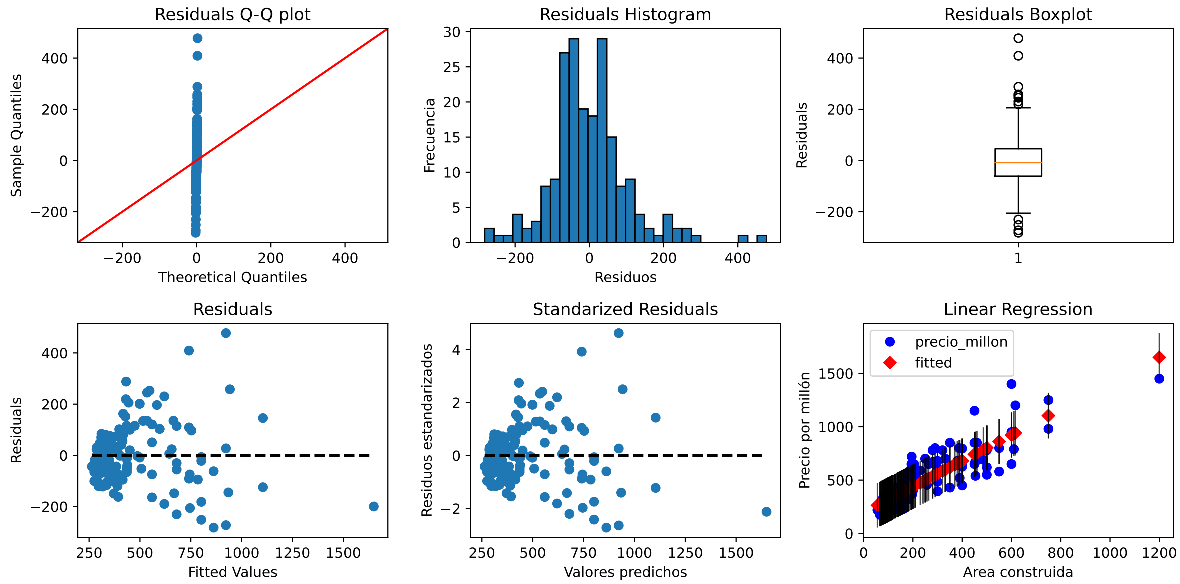


Check model assumptions

```
from scipy.stats import shapiro
from statsmodels.stats.diagnostic import het_breuschpagan

def checkModelAssumptions(model):
    residuos = model.resid
    fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(12, 6))
    #QQ plot
    sm.qqplot(residuos, line='45', ax=axs[0,0])
    axs[0,0].set_title('Residuals Q-Q plot')
    #Residuals Histogram
    axs[0,1].hist(residuos, bins=30, edgecolor='black')
    axs[0,1].set_xlabel('Residuos')
    axs[0,1].set_ylabel('Frecuencia')
    axs[0,1].set_title('Residuals Histogram')
    #Reiduals Boxplot
    axs[0,2].boxplot(residuos)
```

```
axs[0,2].set_ylabel('Residuals')
axs[0,2].set_title('Residuals Boxplot')
#Residuals
axs[1,0].scatter(model.fittedvalues, residuos)
axs[1,0].plot([min(model.fittedvalues), max(model.fittedvalues)], [0, 0], 'k--', lw=2)
axs[1,0].set_xlabel('Fitted Values')
axs[1,0].set_ylabel('Residuals')
axs[1,0].set_title('Residuals')
#Standarized residuals
predicciones = model.predict()
residuos_estandarizados = model.get_influence().resid_studentized_internal
axs[1,1].scatter(predicciones, residuos_estandarizados)
axs[1,1].plot([min(predicciones), max(predicciones)], [0, 0], 'k--', lw=2)
axs[1,1].set_xlabel('Valores predichos')
axs[1,1].set_ylabel('Residuos estandarizados')
axs[1,1].set_title('Standarized Residuals')
#Plot fit
sm.graphics.plot_fit(model, 'Area_contruida', ax=axs[1,2])
axs[1,2].set_xlabel("Area construida")
axs[1,2].set_ylabel("Precio por millón")
axs[1,2].set_title("Linear Regression")

plt.tight_layout()
plt.show()

#Normality test
print('================= Normality test =================')
stat, p = shapiro(residuos)
print('Estadística de prueba:', stat)
print('Valor p:', p)
if p <= 0.05: print("Se rechaza H0")
else: print("No se rechaza H0")
#Homoscedasticity test
print('================= Homoscedasticity test =================')
lm, lm_pvalue, fvalue, f_pvalue = het_breuschpagan(residuos, model.model.exog)
print('Lagrange multiplier statistic:', lm)
print('p-value', lm_pvalue)
print('F value:', fvalue)
print('F p-value', f_pvalue)
if lm_pvalue <= 0.05: print("Se rechaza H0")
else: print("No se rechaza H0")
```

```
checkModelAssumptions(modelo)
```

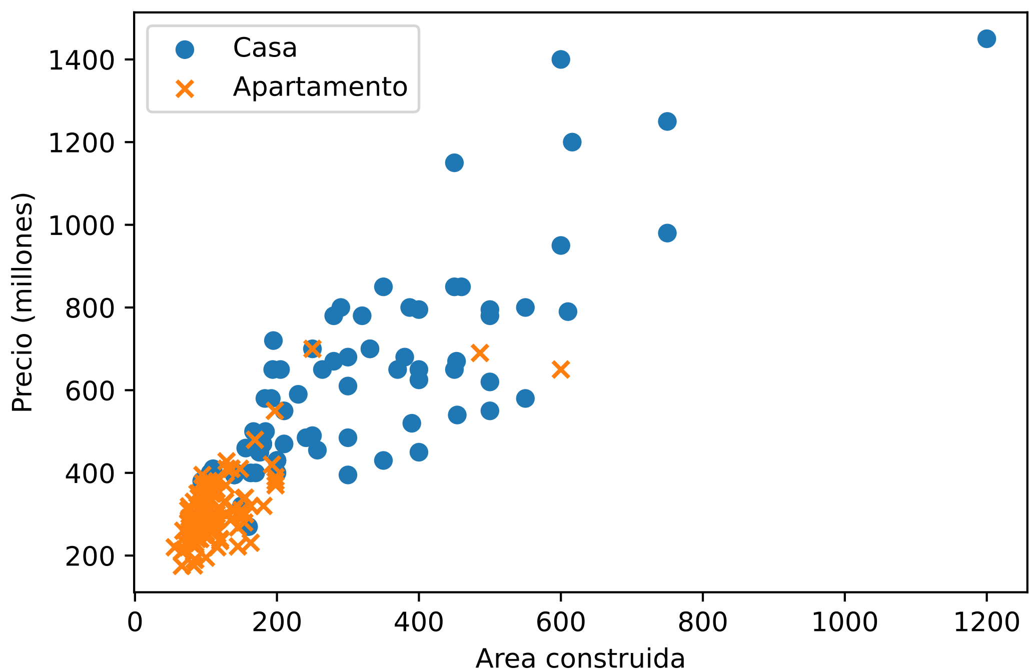



```
================= Normality test =================
Estadística de prueba: 0.9449506402015686
Valor p: 5.659239832311869e-07
Se rechaza H0
================= Homoscedasticity test =================
Lagrange multiplier statistic: 46.49553687988353
p-value 9.18273677648706e-12
F value: 59.79961725467512
F p-value 5.035974457263909e-13
Se rechaza H0
```

Analysis: - Normality test: Since the null hypothesis is rejected, the residuals are not from a normal distribution. It can also be verified that the QQ plot does not conform to a normal distribution. - Homoscedasticity test: Since H0 is rejected, it means that there is sufficient evidence to conclude that the variance of the errors is not constant and, therefore, that there is heteroscedasticity in the model. - Independecy and lineality: In both residual plots we can see that the residuals follow a tendency to cluster to the left, so the model variables are not linear.

Categorical Regression

```
df2 = df[df['Barrio'] == 'el ingenio'][['precio_millon', 'Area_contruida', 'Tipo']]

df_casa = df2[df2['Tipo'] == 'Casa']
df_apto = df2[df2['Tipo'] == 'Apartamento']
plt.scatter(df_casa['Area_contruida'], df_casa['precio_millon'], marker='o', label='Casa')
plt.scatter(df_apto['Area_contruida'], df_apto['precio_millon'], marker='x', label='Aparta
# Configurar la gráfica
plt.xlabel('Area construida')
plt.ylabel('Precio (millones)')
plt.legend()
plt.show()
```



In this case, a model could have the following structure:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

where X_2 can take the values of zero or one, according to the type of housing. For example:

$$X_2 = \begin{cases} 0, & \text{si la vivienda es una casa.} \\ 1, & \text{si la vivienda es un apartamento.} \end{cases}$$

```python
#Create the dummy column
df_el_ingenio['Tipo_Dummy'] = df2["Tipo"].map({"Casa": 0, "Apartamento": 1})
```

```python
#df_dummies = pd.get_dummies(df2['Tipo'], prefix='Tipo')
#df_el_ingenio = pd.concat([df_el_ingenio, df_dummies], axis=1)
```

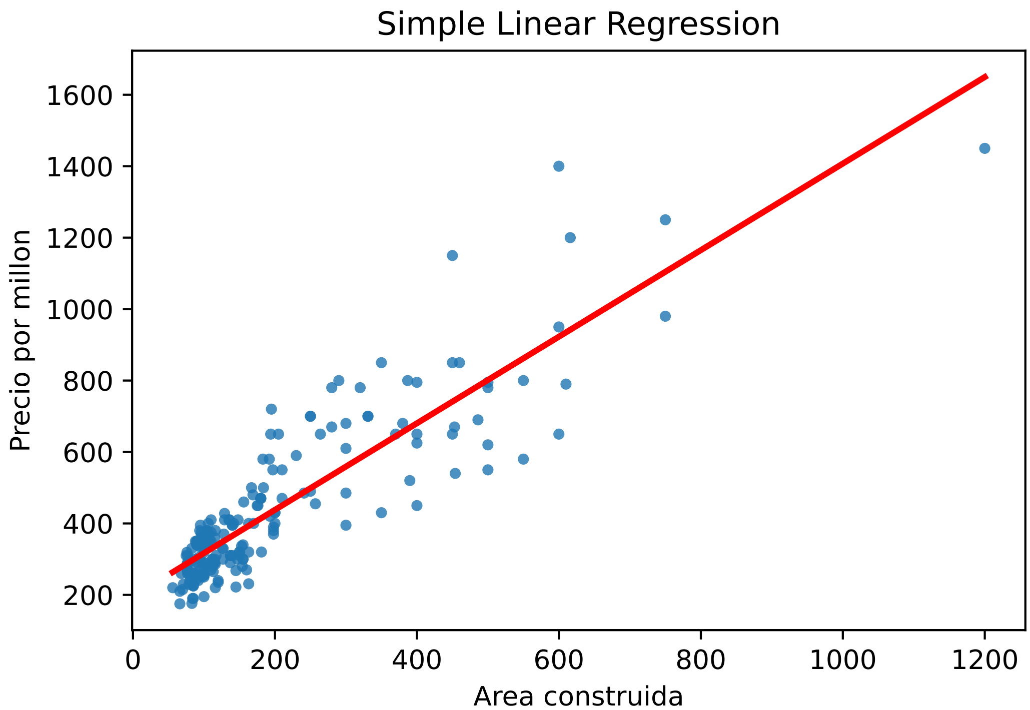
```python
# Ajustar el modelo de regresión lineal
modelo2 = smf.ols(formula='precio_millon ~ Area_contruida + Tipo_Dummy', data=df_el_ingeni
print(modelo2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          precio_millon   R-squared:                       0.802
Model:                            OLS   Adj. R-squared:                  0.800
Method:                 Least Squares   F-statistic:                     403.1
Date:                Tue, 04 Apr 2023   Prob (F-statistic):           1.02e-70
Time:                        21:25:02   Log-Likelihood:                -1212.7
No. Observations:                 202   AIC:                             2431.
Df Residuals:                     199   BIC:                             2441.
Df Model:                           2
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept        295.3695     21.659     13.637      0.000     252.659     338.080
Area_contruida     1.0220      0.056     18.196      0.000       0.911       1.133
Tipo_Dummy       -99.2499     18.631     -5.327      0.000    -135.990     -62.510
==============================================================================
Omnibus:                       45.694   Durbin-Watson:                   1.965
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              169.888
Skew:                           0.835   Prob(JB):                     1.29e-37
Kurtosis:                       7.171   Cond. No.                         999.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The model is given by:

$$Y = 1.02X_1 - 99.24X_2 + 295.36$$

```python
# Graficar el modelo
sns.regplot(x='Area_contruida', y='precio_millon', data=df_el_ingenio, ci=None, scatter_kw
plt.xlabel('Area construida')
plt.ylabel('Precio por millon')
plt.title('Simple Linear Regression')
plt.show()
```



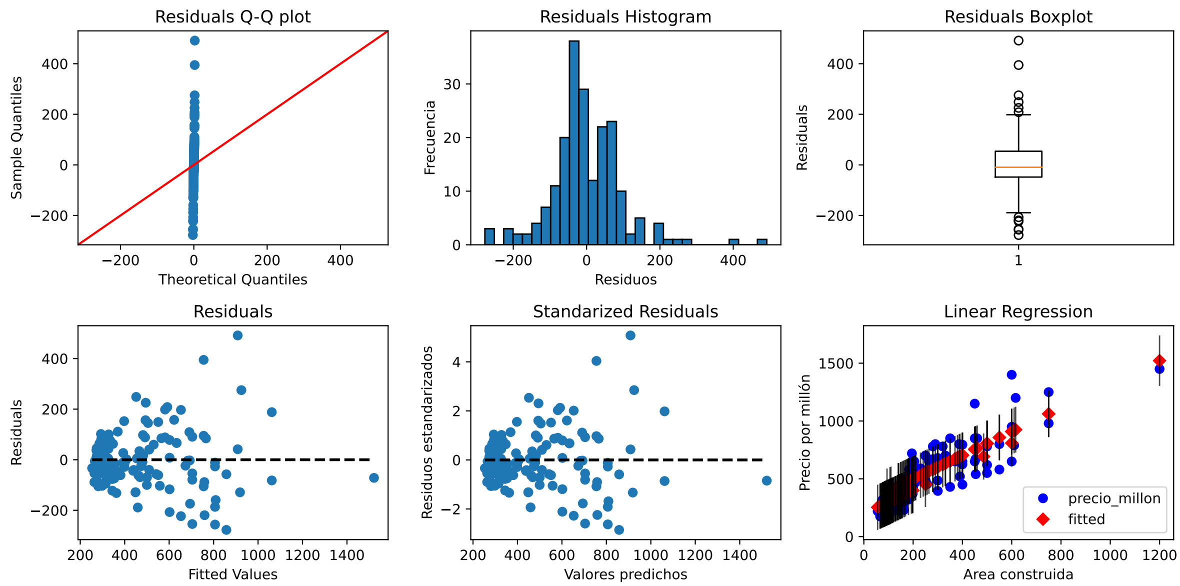
We performed the ANOVA of the model

```python
anova_results = sm.stats.anova_lm(modelo2, typ=2)
print(anova_results)
```

```
                      sum_sq     df           F        PR(>F)
Area_contruida  3.224499e+06    1.0  331.110433  3.268170e-44
Tipo_Dummy      2.763536e+05    1.0   28.377610  2.687289e-07
Residual        1.937949e+06  199.0         NaN           NaN
```

In particular, the variable "Area_contruida" has an F-value of 331.11 with a p-value of practically zero, suggesting that it is highly significant in explaining the variability in "Precio_millon". Similarly, the variable "Tipo_Dummy" has an F-value of 28.38 and a very low p-value, suggesting that it is also significant in explaining the variability in "Precio_millon".

```
checkModelAssumptions(modelo2)
```




```
================= Normality test =================
Estadística de prueba: 0.9320821762084961
Valor p: 4.378554052664185e-08
Se rechaza H0
================= Homoscedasticity test =================
Lagrange multiplier statistic: 38.517190513868876
p-value 4.326117895839744e-09
F value: 23.442589885605535
F p-value 7.21127318498435e-10
Se rechaza H0
```

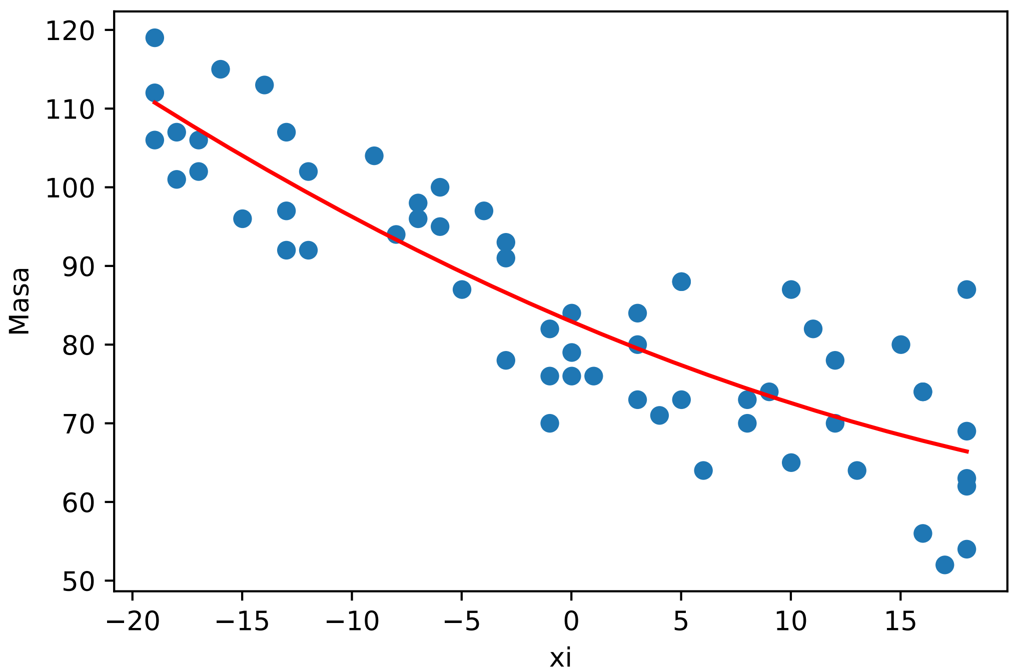
Punto 2

```
data = pd.read_csv('datosME.txt', header=None, delim_whitespace=True, names=['Masa', 'Edad
#Center the data
x_mean = data['Edad'].mean()
data['xi'] = data['Edad'] - x_mean
```

```
data['xi2'] = data['xi']**2
```

```
modelo = smf.ols(formula='Masa ~ xi + np.power(xi, 2)', data=data).fit()
```

```
xi_range = np.linspace(data['xi'].min(), data['xi'].max(), 500)
y_pred = modelo.predict(exog=dict(xi=xi_range, xi2=xi_range**2))
plt.scatter(data['xi'], data['Masa'])
plt.plot(xi_range, y_pred, color='red')
plt.xlabel('xi')
plt.ylabel('Masa')
plt.show()
```




```
print(modelo.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Masa   R-squared:                       0.763
Model:                            OLS   Adj. R-squared:                  0.755
```

```
Method:                 Least Squares   F-statistic:                     91.84
Date:                Tue, 04 Apr 2023   Prob (F-statistic):           1.48e-18
Time:                        21:25:04   Log-Likelihood:                -208.56
No. Observations:                  60   AIC:                             423.1
Df Residuals:                      57   BIC:                             429.4
Df Model:                           2
Covariance Type:            nonrobust
====================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept         82.9357      1.543     53.745      0.000      79.846      86.026
xi                -1.1840      0.089    -13.358      0.000      -1.361      -1.006
np.power(xi, 2)    0.0148      0.008      1.776      0.081      -0.002       0.032
==============================================================================
Omnibus:                        1.630   Durbin-Watson:                   2.459
Prob(Omnibus):                  0.443   Jarque-Bera (JB):                1.395
Skew:                           0.214   Prob(JB):                        0.498
Kurtosis:                       2.387   Cond. No.                         275.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The parameter xi is the coefficient associated with the independent variable xi, which is the centered age. The negative value of -1.1840 indicates that there is a negative relationship between age and mass. That is, as age increases, mass is expected to decrease by 1.1840 kg.

The parameter np.power(xi, 2) is the coefficient associated with the independent variable xi squared, which is age centered and squared. The value of 0.0148 indicates that there is a positive relationship between age and mass, but its p-value is 0.081, suggesting that it is not significant at the 0.05 significance level.

Let

$$H_0 : \text{the quadratic term of the model is 0}$$

$$H_1 : \text{the quadratic term of the model is different from 0}$$

If the p-value associated with the F-test is less than the chosen significance level ($\alpha = 0.05$), then we reject the null hypothesis.

```python
# Hypothesis test to eliminate the quadratic term
p_val = modelo.f_test("np.power(xi, 2) = 0").pvalue
print(p_val)
if p_val <= 0.05: print("Se rechaza H0")
```

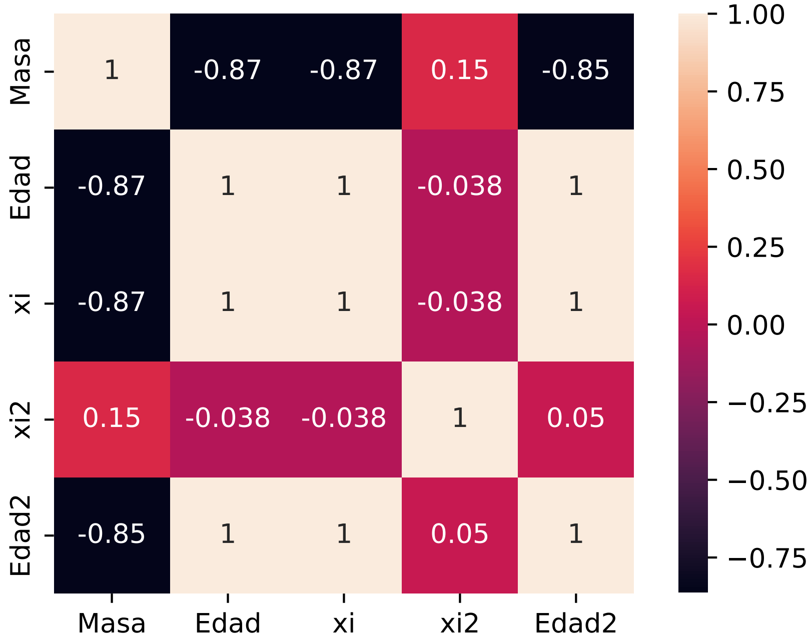
```python
else: print("No se rechaza H0")
```

```
0.08108689981613854
No se rechaza H0
```

It is concluded that there is not enough statistical evidence to claim that the quadratic term is important in the model. This means that the option of eliminating the quadratic term from the model can be considered.

```python
data['Edad2'] = data['Edad']**2
sns.heatmap(data.corr(), square=True, annot=True)
```

```
<Axes: >
```



As can be seen in the correlation table, the variable Edad and Edad**2 are highly positively related. While centering the data and their respective square have a correlation close to zero (-0.038) indicating that there is no strong relationship between the two variables. Therefore, the transformation of the initial variable (centering the variable) is justified to eliminate the multicollinearity between the variable and its quadratic form.