In [1]:

```
#----------------------------------------------------------------------------------------------------------------
#   Tarea de regresion lineal
#   Alma Paulina Gonzalez Sandoval A01631256
#----------------------------------------------------------------------------------------------------------------
```

In [130]:

```
import sys
!{sys.executable} -m pip install pandas
import sys
!{sys.executable} -m pip install seaborn
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn import linear_model
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.model_selection import KFold
from sklearn.linear_model import Ridge
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.feature_selection import RFE
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import Lasso
from sklearn.model_selection import StratifiedKFold, GridSearchCV, cross_val_predict
```

```
Requirement already satisfied: pandas in /opt/anaconda3/lib/python3.12/site-packages (2.2.2)
Requirement already satisfied: numpy>=1.26.0 in /opt/anaconda3/lib/python3.12/site-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/anaconda3/lib/python3.12/site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /opt/anaconda3/lib/python3.12/site-packages (from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in /opt/anaconda3/lib/python3.12/site-packages (from pandas) (2023.3)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/lib/python3.12/site-packages (from python-dateutil>=2.8.2->pandas) (1.16.0)
Requirement already satisfied: seaborn in /opt/anaconda3/lib/python3.12/site-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in /opt/anaconda3/lib/python3.12/site-packages (from seaborn) (1.26.4)
Requirement already satisfied: pandas>=1.2 in /opt/anaconda3/lib/python3.12/site-packages (from seaborn) (2.2.2)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in /opt/anaconda3/lib/python3.12/site-packages (from seaborn) (3.8.4)
Requirement already satisfied: contourpy>=1.0.1 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (4.51.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4.4)
Requirement already satisfied: packaging>=20.0 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (23.2)
Requirement already satisfied: pillow>=8 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (10.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in /opt/anaconda3/lib/python3.12/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /opt/anaconda3/lib/python3.12/site-packages (from pandas>=1.2->seaborn) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in /opt/anaconda3/lib/python3.12/site-packages (from pandas>=1.2->seaborn) (2023.3)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/lib/python3.12/site-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
```

In [126]:

```
file_path = 'life_expectancy_data.csv'
df = pd.read_csv(file_path)
df.head()
```

Out[126]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	...	Polio	ex
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0	1154	...	6.0	
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0	492	...	58.0	
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0	430	...	62.0	
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0	2787	...	67.0	
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0	3013	...	68.0	

5 rows × 22 columns

In [5]:

```
print(df.columns)
```

```
Index(['Country', 'Year', 'Status', 'Life expectancy ', 'Adult Mortality',
       'infant deaths', 'Alcohol', 'percentage expenditure', 'Hepatitis B',
       'Measles ', ' BMI ', 'under-five deaths ', 'Polio', 'Total expenditure',
       'Diphtheria ', ' HIV/AIDS', 'GDP', 'Population',
       ' thinness  1-19 years', ' thinness 5-9 years',
       'Income composition of resources', 'Schooling'],
      dtype='object')
```

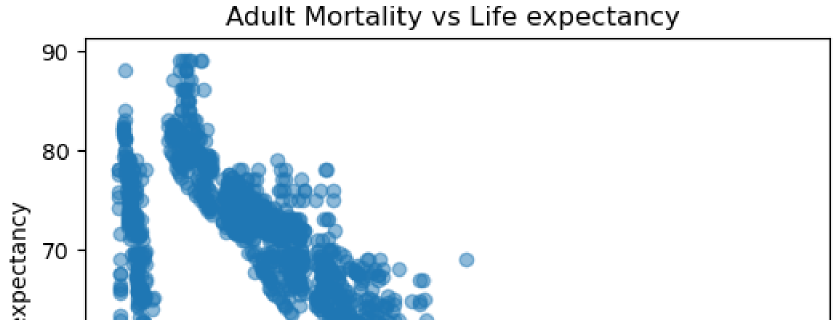
In [9]:

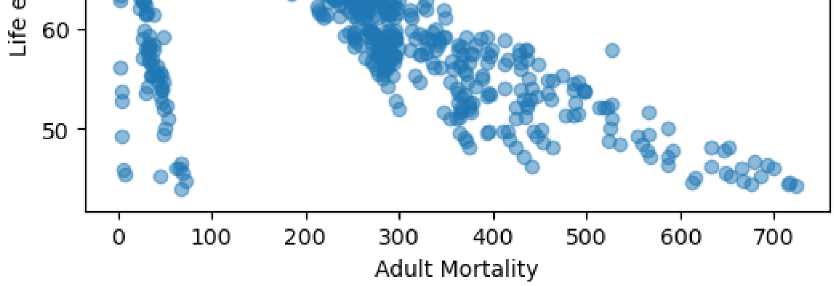
```
#Variables
var_independientes = [ 'Adult Mortality', 'infant deaths', 'percentage expenditure', 'Hepatitis B', 'Measles ',
                      'under-five deaths ','Polio', 'Total expenditure', ' HIV/AIDS', 'GDP', 'Population',
                 ' thinness 5-9 years', 'Income composition of resources','Schooling']
var_dependiente = 'Life expectancy '

data = df[var_independientes + [var_dependiente]]

data_cleaned = data.dropna()

x = data_cleaned[var_independientes].values
y = data_cleaned[var_dependiente].values

print(data_cleaned.head())
print(f"Variables independientes (X): {x.shape}")
print(f"Variable dependiente (y): {y.shape}")
print(df.head())
```

```
   Adult Mortality  infant deaths  percentage expenditure  Hepatitis B  \
0            263.0             62               71.279624         65.0
1            271.0             64               73.523582         62.0
2            268.0             66               73.219243         64.0
3            272.0             69               78.184215         67.0
4            275.0             71                7.097109         68.0

   Measles   under-five deaths   Polio  Total expenditure   HIV/AIDS  \
0     1154                  83     6.0               8.16        0.1
1      492                  86    58.0               8.18        0.1
2      430                  89    62.0               8.13        0.1
3     2787                  93    67.0               8.52        0.1
4     3013                  97    68.0               7.87        0.1

          GDP  Population   thinness 5-9 years  \
0  584.259210  33736494.0                 17.3
1  612.696514    327582.0                 17.5
2  631.744976  31731688.0                 17.7
3  669.959000   3696958.0                 18.0
4   63.537231   2978599.0                 18.2

   Income composition of resources  Schooling  Life expectancy
0                            0.479       10.1             65.0
1                            0.476       10.0             59.9
2                            0.470        9.9             59.9
3                            0.463        9.8             59.5
4                            0.454        9.5             59.2
Variables independientes (X): (1649, 14)
Variable dependiente (y): (1649,)
       Country  Year      Status  Life expectancy   Adult Mortality  \
0  Afghanistan  2015  Developing              65.0             263.0
1  Afghanistan  2014  Developing              59.9             271.0
2  Afghanistan  2013  Developing              59.9             268.0
3  Afghanistan  2012  Developing              59.5             272.0
4  Afghanistan  2011  Developing              59.2             275.0

   infant deaths  Alcohol  percentage expenditure  Hepatitis B  Measles   ...  \
0             62     0.01               71.279624         65.0      1154  ...
1             64     0.01               73.523582         62.0       492  ...
2             66     0.01               73.219243         64.0       430  ...
3             69     0.01               78.184215         67.0      2787  ...
4             71     0.01                7.097109         68.0      3013  ...

   Polio  Total expenditure  Diphtheria    HIV/AIDS         GDP  Population  \
0    6.0               8.16        65.0         0.1  584.259210  33736494.0
1   58.0               8.18        62.0         0.1  612.696514    327582.0
2   62.0               8.13        64.0         0.1  631.744976  31731688.0
3   67.0               8.52        67.0         0.1  669.959000   3696958.0
4   68.0               7.87        68.0         0.1   63.537231   2978599.0

    thinness  1-19 years   thinness 5-9 years  \
0                   17.2                 17.3
1                   17.5                 17.5
2                   17.7                 17.7
3                   17.9                 18.0
4                   18.2                 18.2

   Income composition of resources  Schooling
0                            0.479       10.1
1                            0.476       10.0
2                            0.470        9.9
3                            0.463        9.8
4                            0.454        9.5

[5 rows x 22 columns]
```

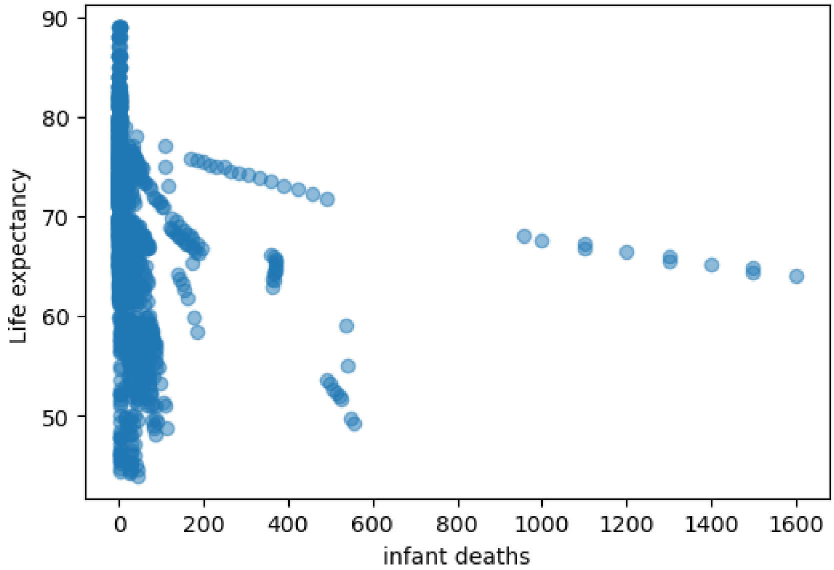
In [11]:

```python
for variable in var_independientes:
    plt.figure(figsize=(6, 4))
    plt.scatter(data_cleaned[variable], data_cleaned[var_dependiente], alpha=0.5)
    plt.title(f'{variable} vs {var_dependiente}')
    plt.xlabel(variable)
    plt.ylabel(var_dependiente)
    plt.show()
```

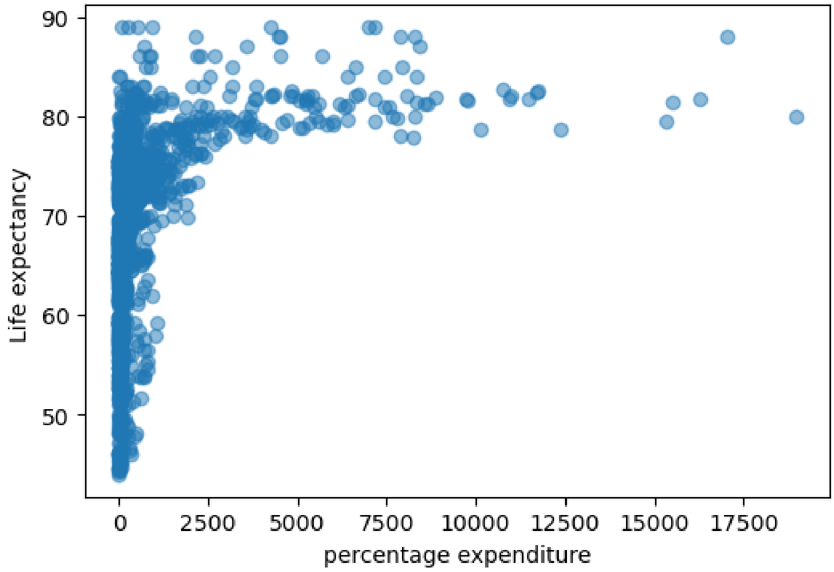




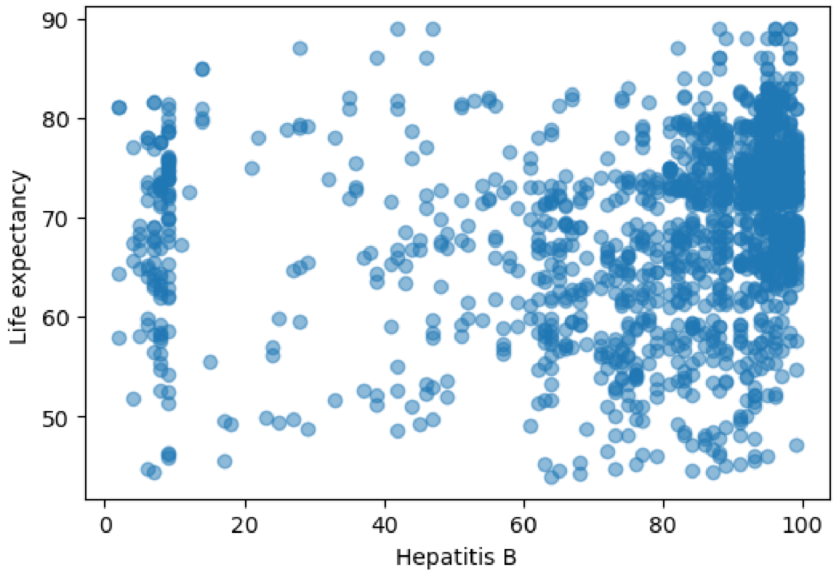
infant deaths vs Life expectancy



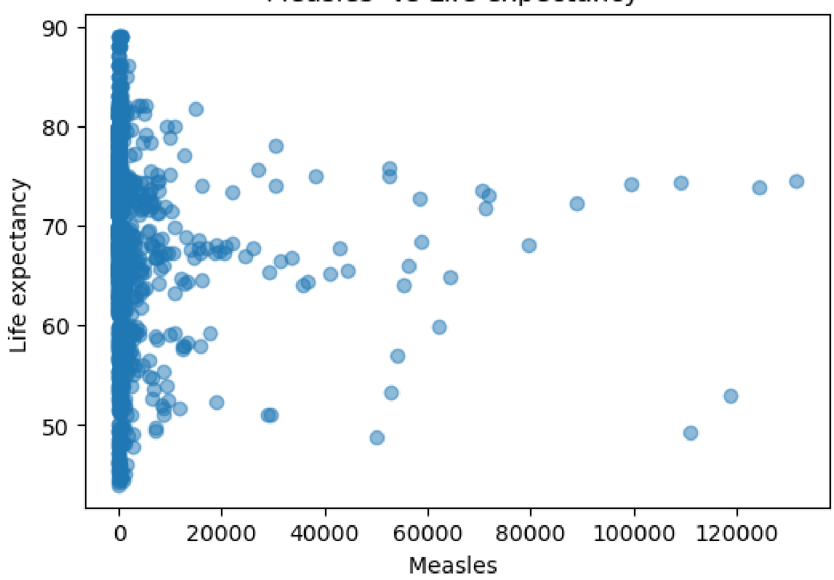
percentage expenditure vs Life expectancy

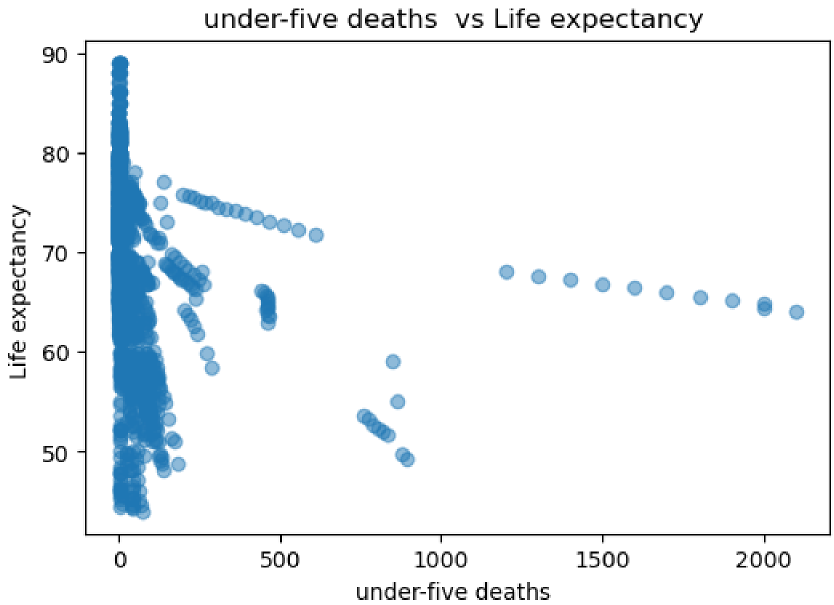


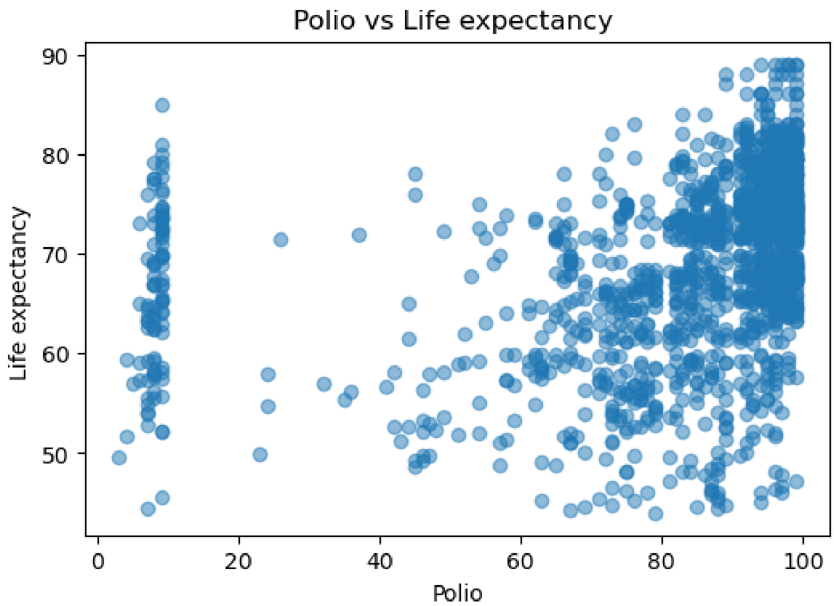
Hepatitis B vs Life expectancy

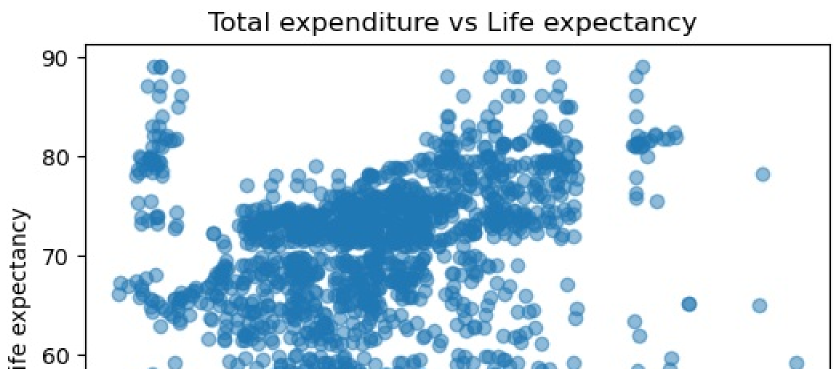


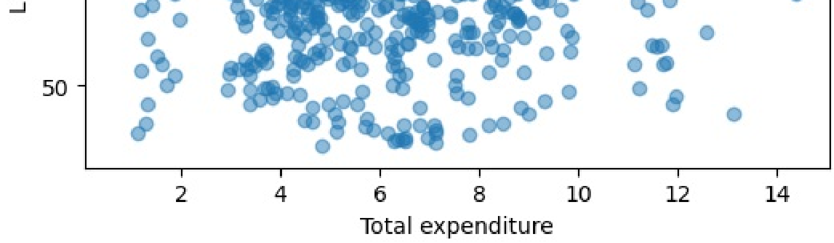
Measles vs Life expectancy


Life expectancy
Measles

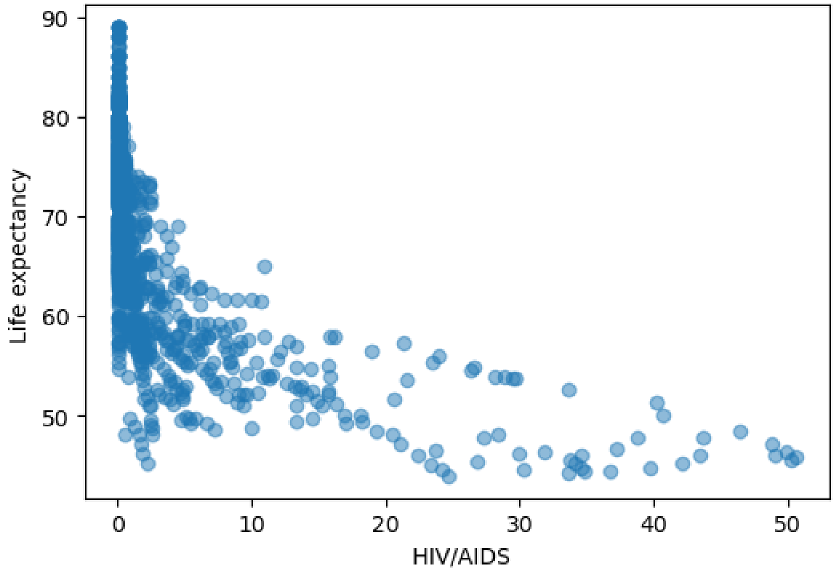

under-five deaths vs Life expectancy
Life expectancy
under-five deaths


Polio vs Life expectancy
Life expectancy
Polio

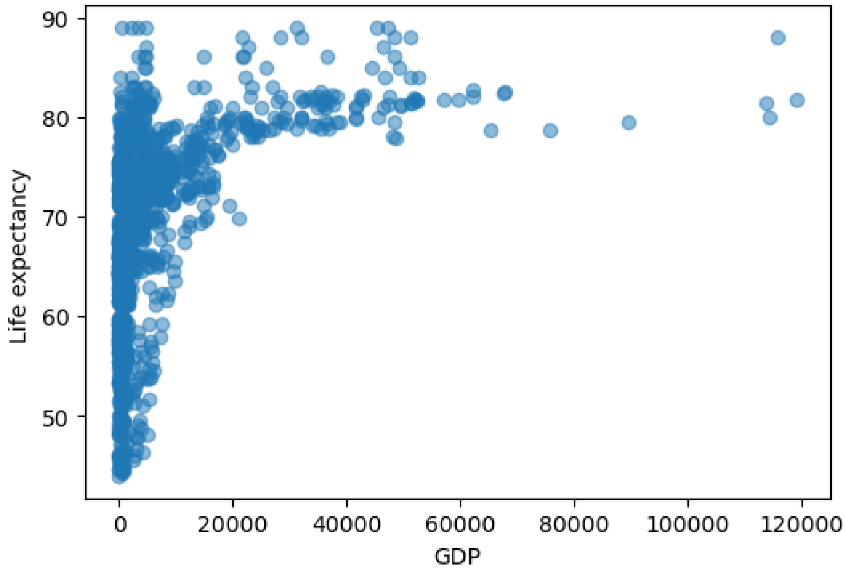

Total expenditure vs Life expectancy



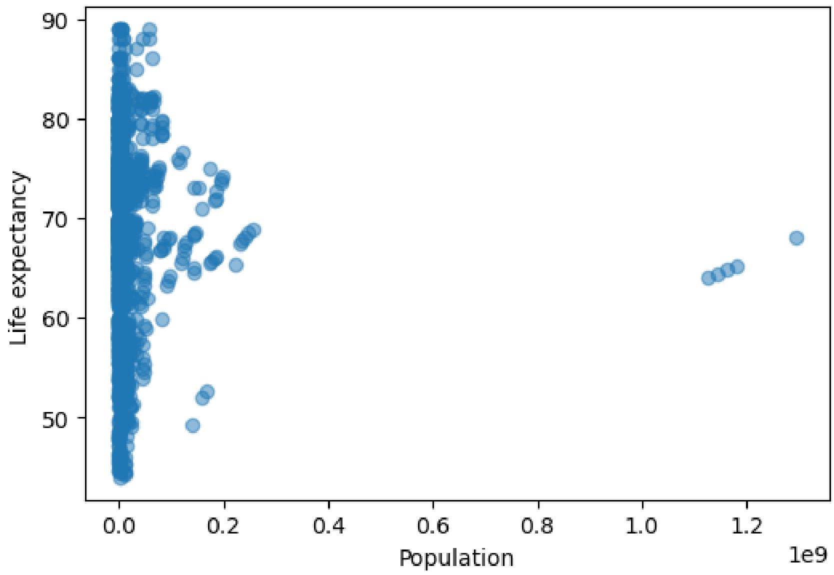
HIV/AIDS vs Life expectancy



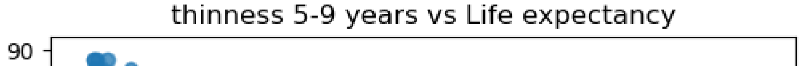
GDP vs Life expectancy

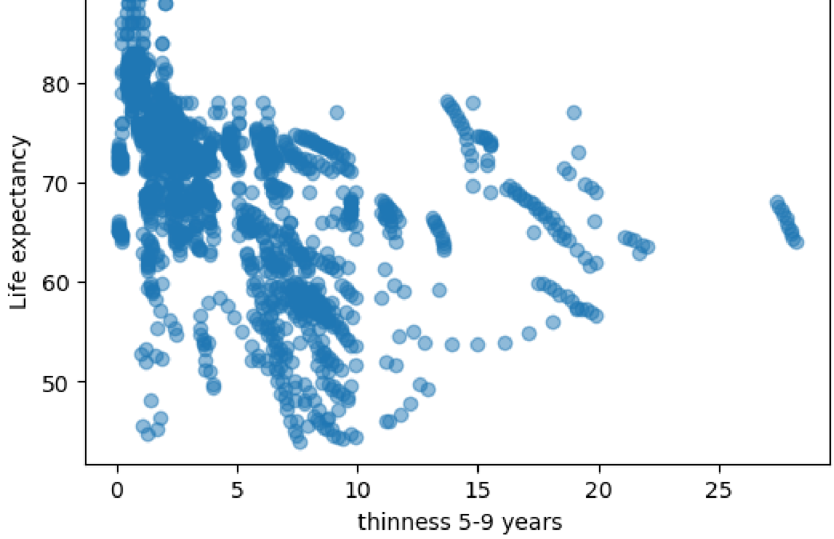


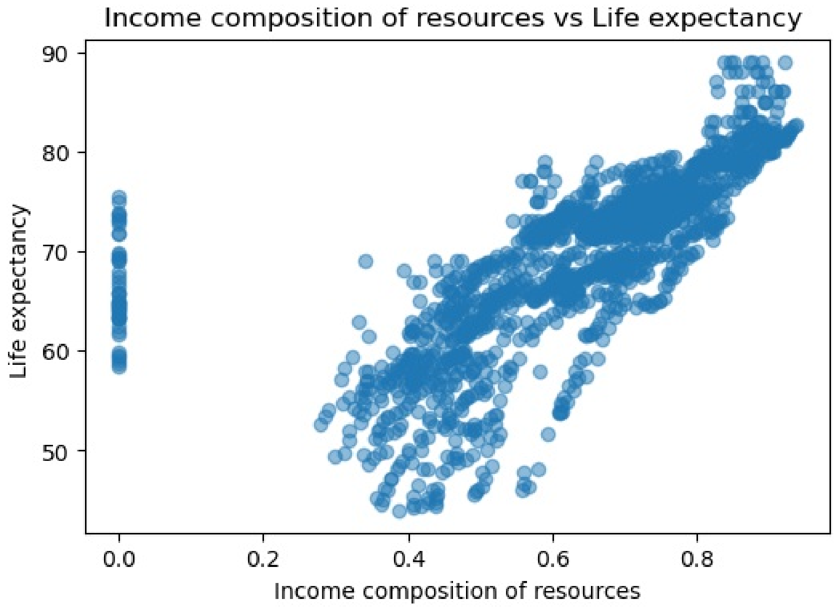
Population vs Life expectancy

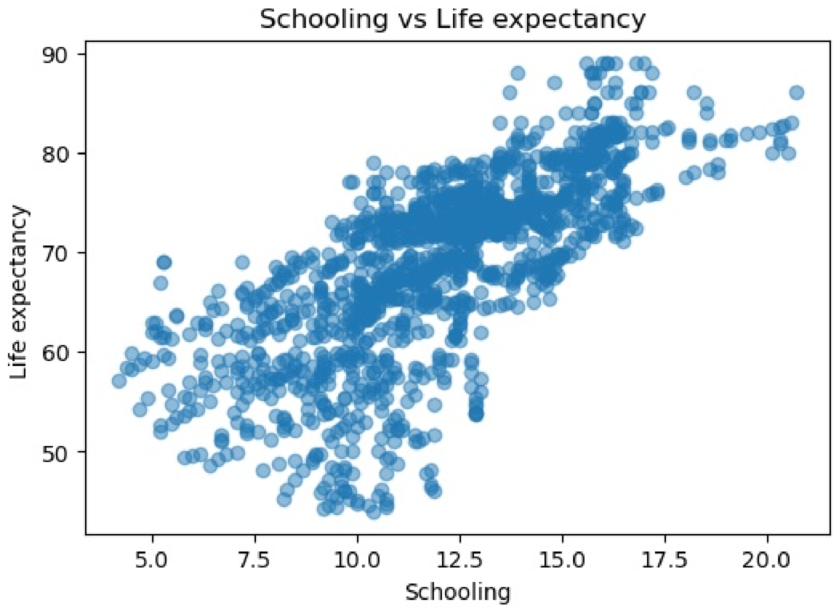


thinness 5-9 years vs Life expectancy





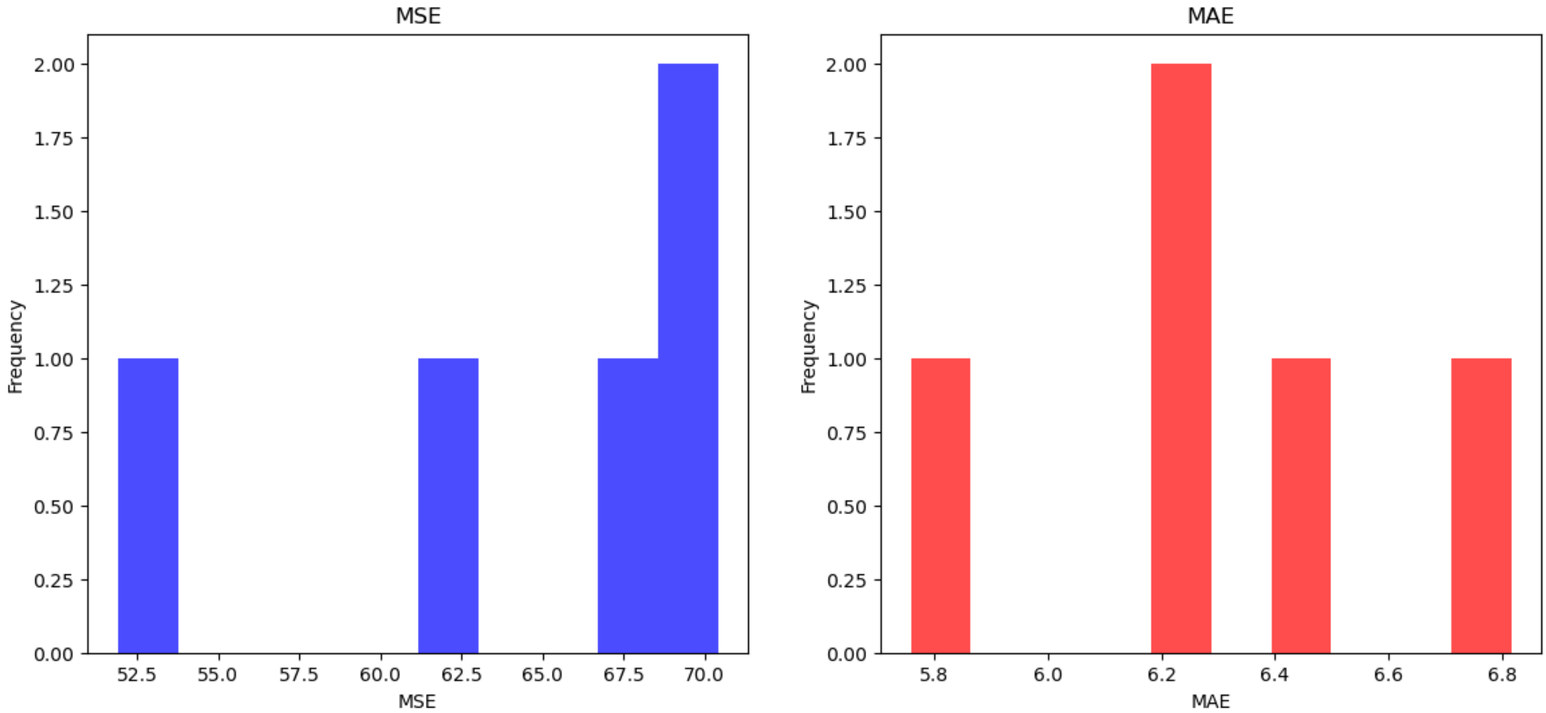




In [13]:
```
def fit_model(X, y):
    return np.linalg.inv(X.transpose() @ X) @ X.transpose() @ y
```
In [15]:
```
def predict(X, beta):
    return X @ beta
```
In [17]:
```
X = np.column_stack((np.ones(x.shape[0]), x))
```
In [19]:
```
beta = fit_model(X, y)
print ("Model coefficients: ", beta)
```

```
Model coefficients:  [ 5.44673903e+01 -1.74467926e-02  1.01728685e-01  3.85466290e-04
 -3.89612598e-04 -1.46642920e-05 -7.64450476e-02  1.12953878e-02
  8.49144621e-02 -4.42841446e-01  7.84321035e-06 -2.66698604e-10
 -1.04752262e-01  1.02002926e+01  9.15343265e-01]
```
In [21]:
```
y_pred = predict(X, beta)
r = y - y_pred

print('Residuals:', r)
```
```
Residuals: [ 2.14297995 -3.25841546 -3.14391398 ... -4.97345118  7.38990468
  9.28169265]
```
In [23]:
```
print('MSE: ', mean_squared_error(y, y_pred))
print("MAE: ", mean_absolute_error(y, y_pred))
print("R^2: ", r2_score(y, y_pred))
```
```
MSE:  13.085328110145221
MAE:  2.7737939474393274
R^2:  0.8308019870625327
```
In [25]:
```
n_folds = 5
kf = KFold(n_splits=n_folds, shuffle = True)
```
In [27]:
```
mse_cv = []
mae_cv = []
r2_cv = []
for train_index, test_index in kf.split(x):
    x_train = x[train_index, :]
    y_train = y[train_index]

    beta_cv = fit_model(x_train, y_train)

    x_test = x[test_index, :]
    y_test = y[test_index]

    y_pred = predict(x_test, beta_cv)

    mse_i = mean_squared_error(y_test, y_pred)
    print('mse = ', mse_i)
    mse_cv.append(mse_i)

    mae_i = mean_absolute_error(y_test, y_pred)
    print('mae = ', mae_i)
    mae_cv.append(mae_i)

    r2_i = r2_score(y_test, y_pred)
    print('r^2= ', r2_i)
    r2_cv.append(r2_i)

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.hist(mse_cv, bins=10, color='blue', alpha=0.7)
plt.title('MSE')
plt.xlabel('MSE')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
plt.hist(mae_cv, bins=10, color='red', alpha=0.7)
plt.title('MAE')
plt.xlabel('MAE')
plt.ylabel('Frequency')

plt.show()
```

mse = 62.71526278875913
mae = 6.399037997012488
r^2= 0.2438472020728888
mse = 70.42606002951949
mae = 6.816789452681232
r^2= 0.15018617888346253
mse = 69.82867815825111
mae = 6.261484757665297
r^2= 0.01823617099221364
mse = 68.54498901158516
mae = 6.272773176228941
r^2= 0.13585543819759227
mse = 51.89498967684502
mae = 5.758063007517762
r^2= 0.254431912245368



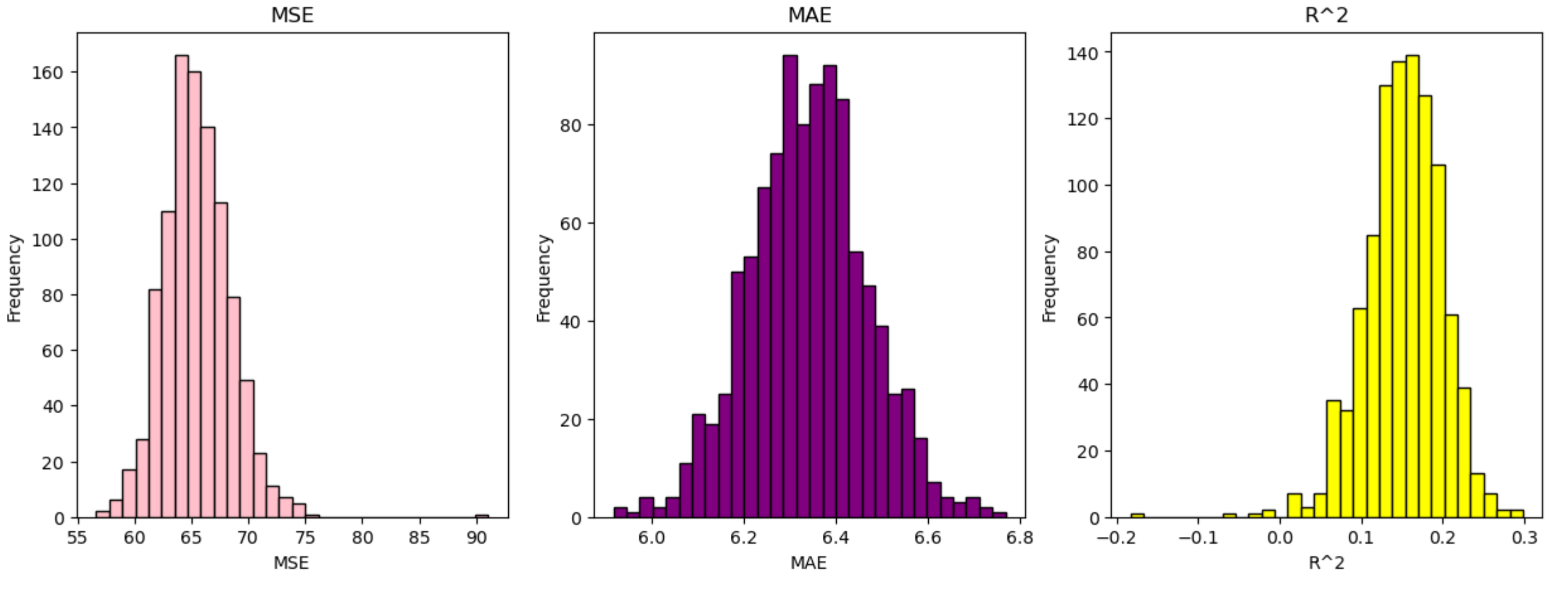
In [15]:

```
print('MSE:', np.average(mse_cv), '  MAE:', np.average(mae_cv),'  R^2:', np.average(r2_cv))
```

MSE: 64.12781997591098   MAE: 6.29194715023703   R^2: 0.16773528816377217

In [29]:

```
mse_mc = []
mae_mc = []
r2_mc = []

iterations = 1000
train_size = 0.5

for i in range(iterations):
    i = np.random.permutation(len(x))
    train_size = int(len(x) * 0.5)
    train_index = i[:train_size]
    test_index = i[train_size:]

    x_train = x[train_index, :]
    y_train = y[train_index]

    beta_mc = fit_model(x_train, y_train)

    x_test = x[test_index, :]
    y_test = y[test_index]

    y_pred = predict(x_test, beta_mc)

    mse_i = mean_squared_error(y_test, y_pred)
    mse_mc.append(mse_i)

    mae_i = mean_absolute_error(y_test, y_pred)
    mae_mc.append(mae_i)

    r2_i = r2_score(y_test, y_pred)
    r2_mc.append(r2_i)

plt.figure(figsize=(15, 5))

plt.subplot(1, 3, 1)
plt.hist(mse_mc, bins=30, color='pink', edgecolor='black')
plt.title('MSE')
plt.xlabel('MSE')
plt.ylabel('Frequency')

plt.subplot(1, 3, 2)
plt.hist(mae_mc, bins=30, color='purple', edgecolor='black')
plt.title('MAE')
plt.xlabel('MAE')
plt.ylabel('Frequency')

plt.subplot(1, 3, 3)
plt.hist(r2_mc, bins=30, color='yellow', edgecolor='black')
plt.title('R^2')
plt.xlabel('R^2')
plt.ylabel('Frequency')

plt.show()
```



In [31]:

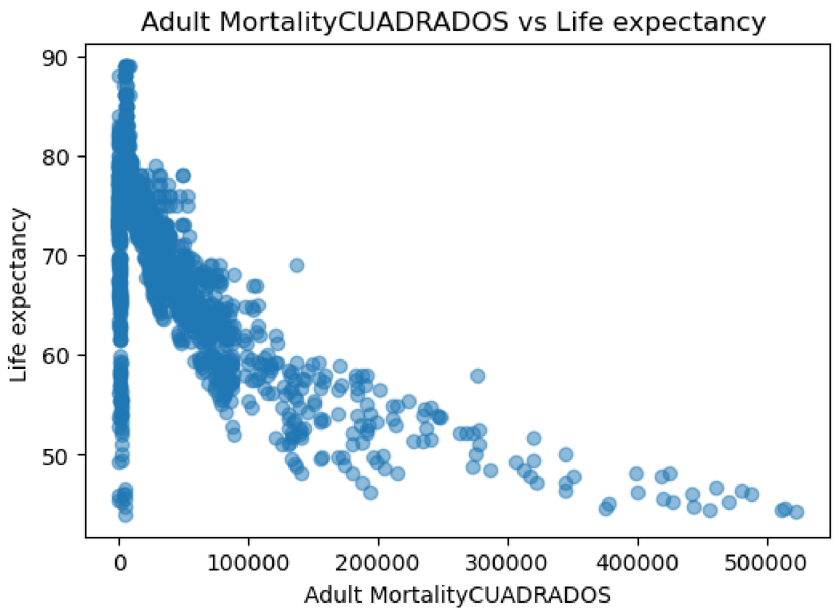
```
cuadrados = {column + 'CUADRADOS': data_cleaned[column] ** 2 for column in data_cleaned.columns}
print(pd.DataFrame(cuadrados).head())

productos = {}
columnas = data_cleaned.columns

for i in range(len(columnas)):
    for j in range(i + 1, len(columnas)):
        productos[columnas[i] + ' X ' + columnas[j]] = data_cleaned[columnas[i]] * data_cleaned[columnas[j]]

data_extended = pd.concat([data_cleaned, pd.DataFrame(cuadrados), pd.DataFrame(productos)], axis=1)
print(data_extended.head())
```

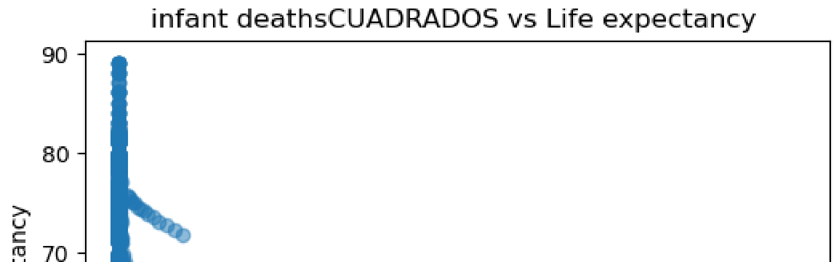
```
   Adult MortalityCUADRADOS  infant deathsCUADRADOS  \
0                   69169.0                    3844
1                   73441.0                    4096
2                   71824.0                    4356
3                   73984.0                    4761
4                   75625.0                    5041

   percentage expenditureCUADRADOS  Hepatitis BCUADRADOS  Measles CUADRADOS  \
0                      5080.784743                4225.0            1331716
1                      5405.717063                3844.0             242064
2                      5361.057504                4096.0             184900
3                      6112.771522                4489.0            7767369
4                        50.368952                4624.0            9078169

   under-five deaths CUADRADOS  PolioCUADRADOS  Total expenditureCUADRADOS  \
0                         6889            36.0                     66.5856
1                         7396          3364.0                     66.9124
2                         7921          3844.0                     66.0969
3                         8649          4489.0                     72.5904
4                         9409          4624.0                     61.9369

   HIV/AIDSCUADRADOS   GDPCUADRADOS  PopulationCUADRADOS  \
0               0.01  341358.824470         1.138151e+15
1               0.01  375397.018268         1.073100e+11
2               0.01  399101.714701         1.006900e+15
3               0.01  448845.061681         1.366750e+13
4               0.01    4036.979723         8.872052e+12

   thinness 5-9 yearsCUADRADOS  Income composition of resourcesCUADRADOS  \
0                       299.29                                  0.229441
1                       306.25                                  0.226576
2                       313.29                                  0.220900
3                       324.00                                  0.214369
4                       331.24                                  0.206116

   SchoolingCUADRADOS  Life expectancy CUADRADOS
0              102.01                    4225.00
1              100.00                    3588.01
2               98.01                    3588.01
3               96.04                    3540.25
4               90.25                    3504.64
   Adult Mortality  infant deaths  percentage expenditure  Hepatitis B  \
0            263.0             62               71.279624         65.0
1            271.0             64               73.523582         62.0
2            268.0             66               73.219243         64.0
3            272.0             69               78.184215         67.0
4            275.0             71                7.097109         68.0

   Measles   under-five deaths   Polio  Total expenditure   HIV/AIDS  \
0     1154                  83    6.0               8.16        0.1
1      492                  86   58.0               8.18        0.1
2      430                  89   62.0               8.13        0.1
3     2787                  93   67.0               8.52        0.1
4     3013                  97   68.0               7.87        0.1

          GDP  ...  Population X  thinness 5-9 years  \
0  584.259210  ...                       583641346.2
1  612.696514  ...                         5732685.0
2  631.744976  ...                       561650877.6
3  669.959000  ...                        66545244.0
4   63.537231  ...                        54210501.8

   Population X Income composition of resources  Population X Schooling  \
0                                  1.615978e+07             340738589.4
1                                  1.559290e+05               3275820.0
2                                  1.491389e+07             314143711.2
3                                  1.711692e+06              36230188.4
4                                  1.352284e+06              28296690.5

   Population X Life expectancy   \
0                  2.192872e+09
1                  1.962216e+07
```

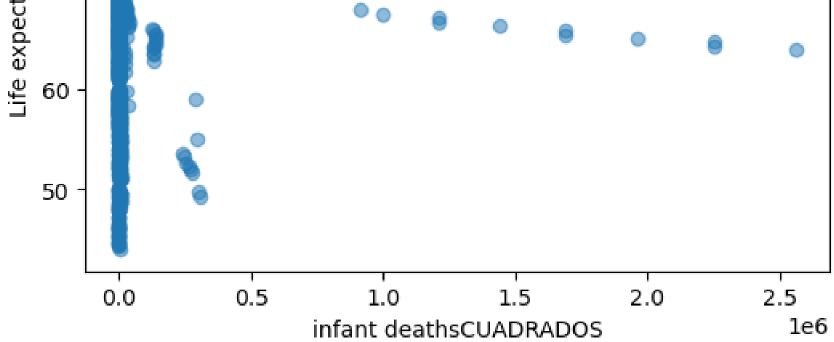
```
2              1.900728e+09
3              2.199690e+08
4              1.763331e+08

   thinness 5-9 years X Income composition of resources  \
0                                   8.2867
1                                   8.3300
2                                   8.3190
3                                   8.3340
4                                   8.2628

   thinness 5-9 years X Schooling  thinness 5-9 years X Life expectancy  \
0                        174.73                               1124.50
1                        175.00                               1048.25
2                        175.23                               1060.23
3                        176.40                               1071.00
4                        172.90                               1077.44

   Income composition of resources X Schooling  \
0                                     4.8379
1                                     4.7600
2                                     4.6530
3                                     4.5374
4                                     4.3130

   Income composition of resources X Life expectancy  \
0                                           31.1350
1                                           28.5124
2                                           28.1530
3                                           27.5485
4                                           26.8768

   Schooling X Life expectancy
0                      656.50
1                      599.00
2                      593.01
3                      583.10
4                      562.40

[5 rows x 135 columns]
```

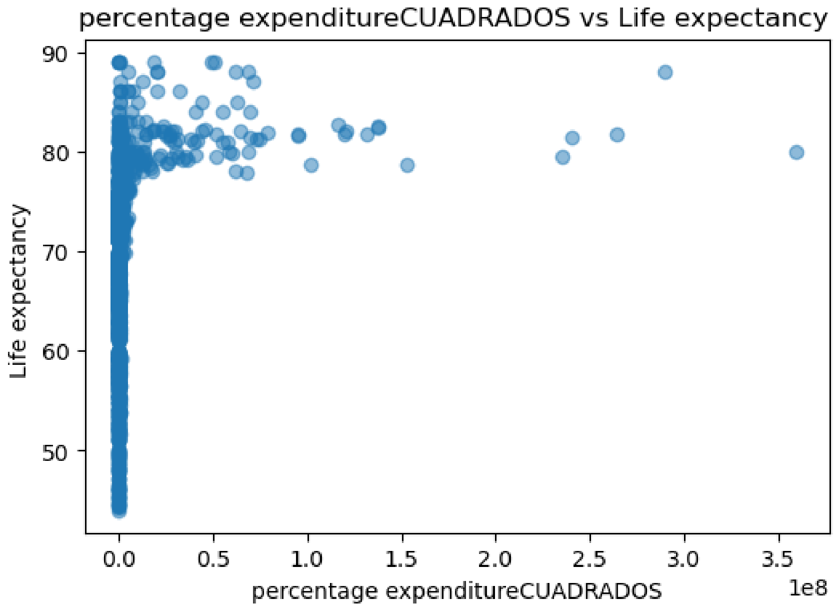
In [33]:

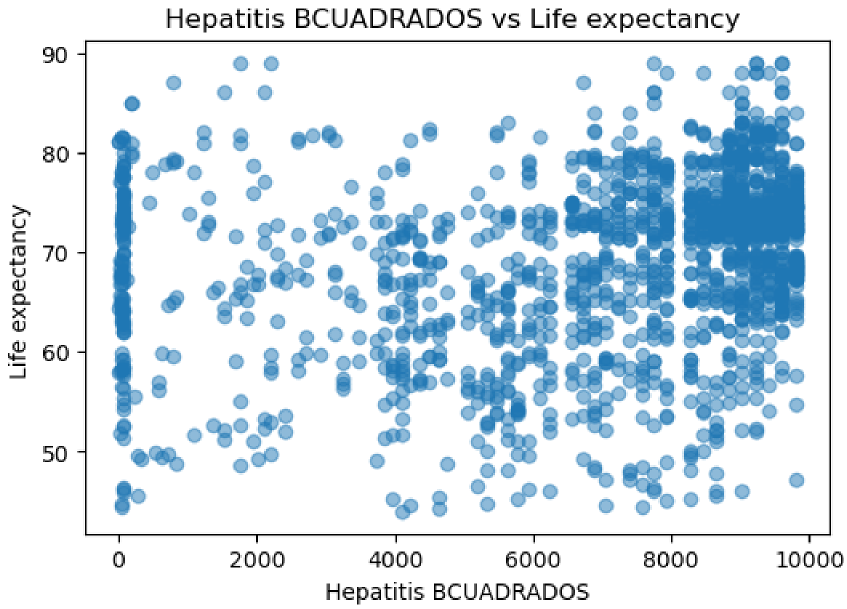
```
var_cuadrados = [col for col in data_extended.columns if 'CUADRADOS' in col]

for variable in var_cuadrados:
    plt.figure(figsize=(6, 4))
    plt.scatter(data_extended[variable], data_extended[var_dependiente], alpha=0.5)
    plt.title(f'{variable} vs {var_dependiente}')
    plt.xlabel(variable)
    plt.ylabel(var_dependiente)
    plt.show()
```

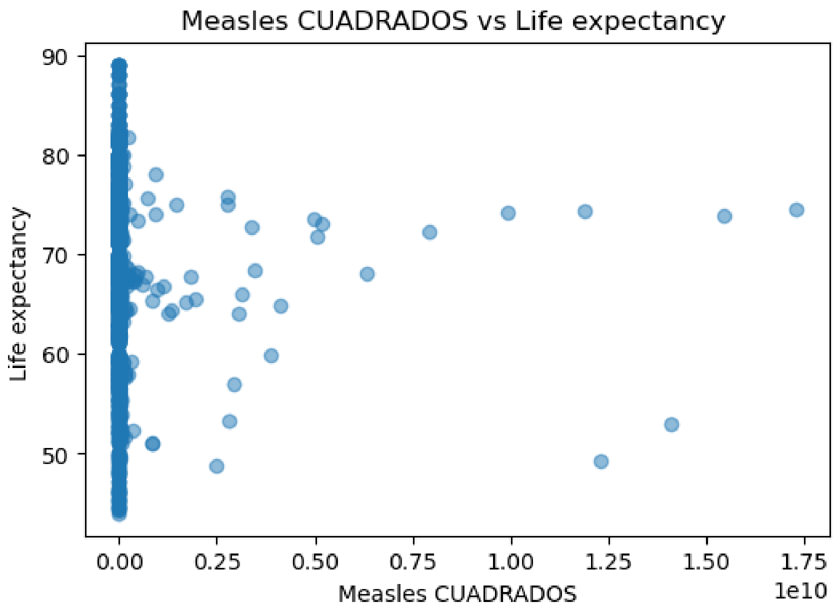


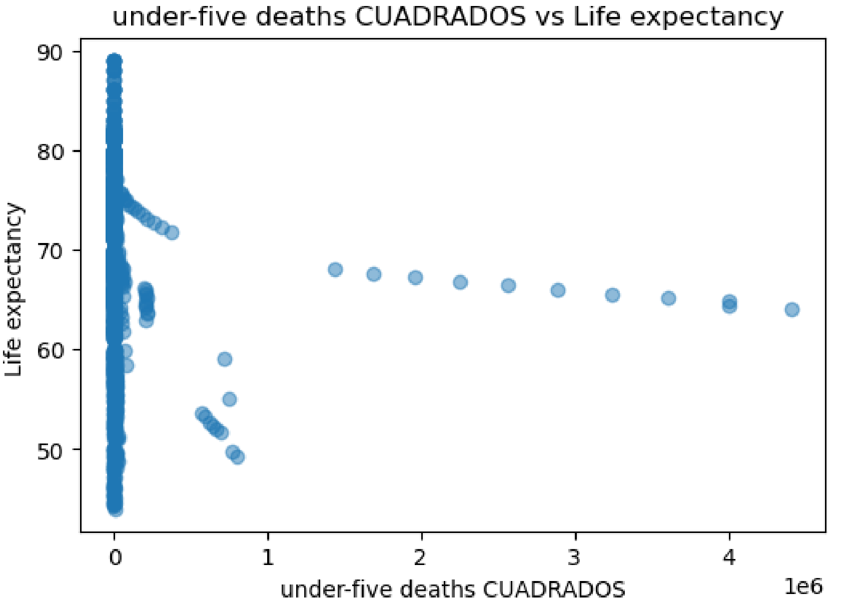


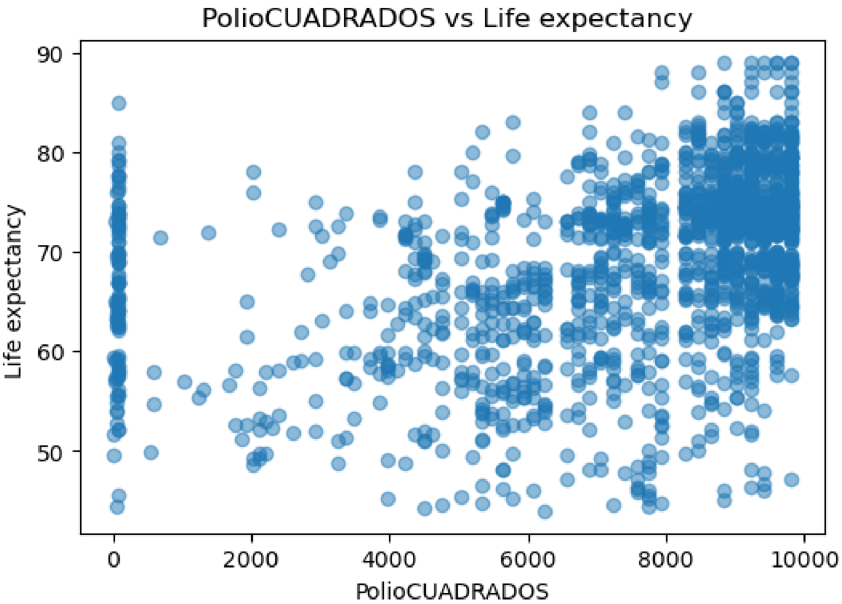

Life expect
infant deathsCUADRADOS
1e6

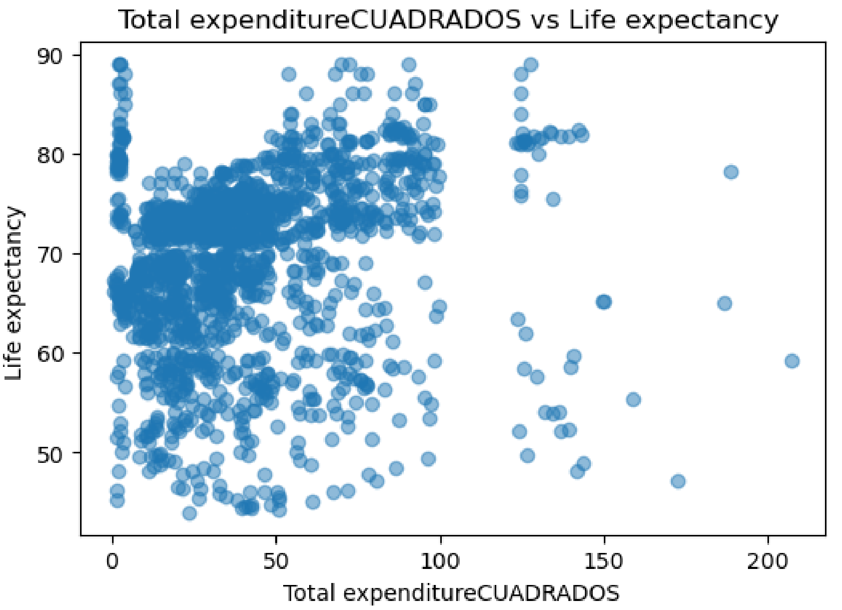

percentage expenditureCUADRADOS vs Life expectancy
Life expectancy
percentage expenditureCUADRADOS
1e8

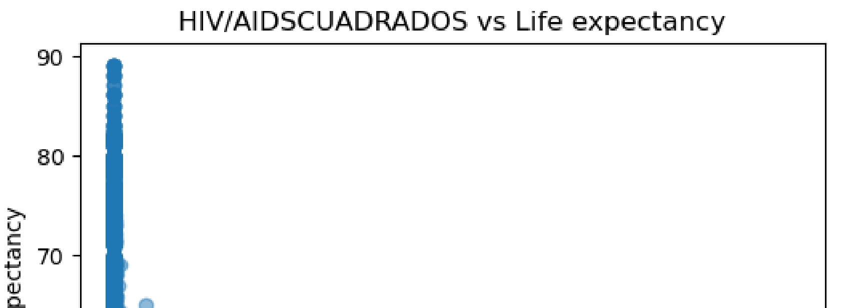

Hepatitis BCUADRADOS vs Life expectancy
Life expectancy
Hepatitis BCUADRADOS

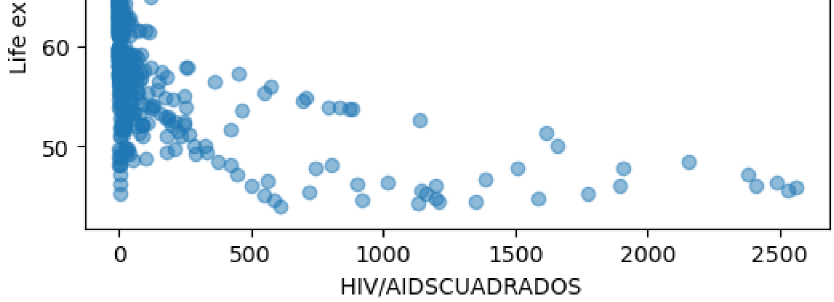

Measles CUADRADOS vs Life expectancy
Life expectancy
Measles CUADRADOS
1e10

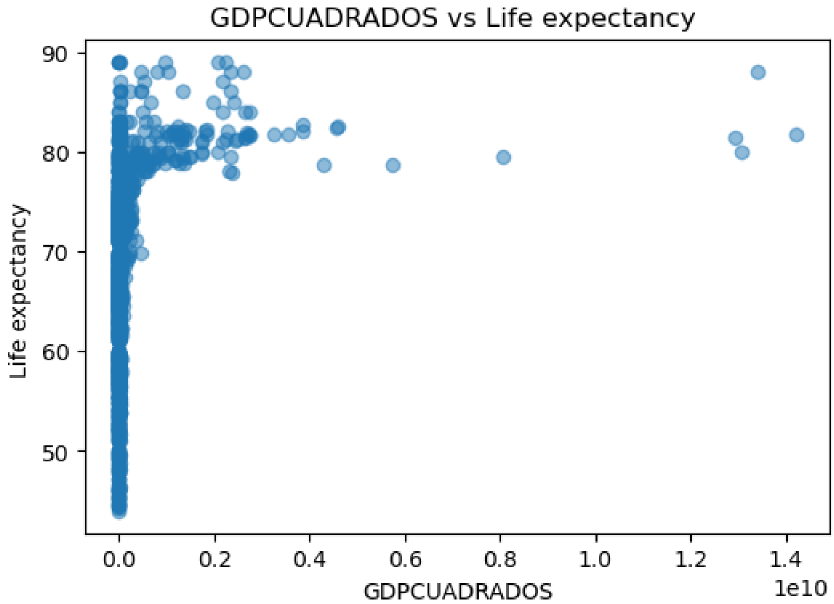

under-five deaths CUADRADOS vs Life expectancy
Life expectancy
under-five deaths CUADRADOS
1e6

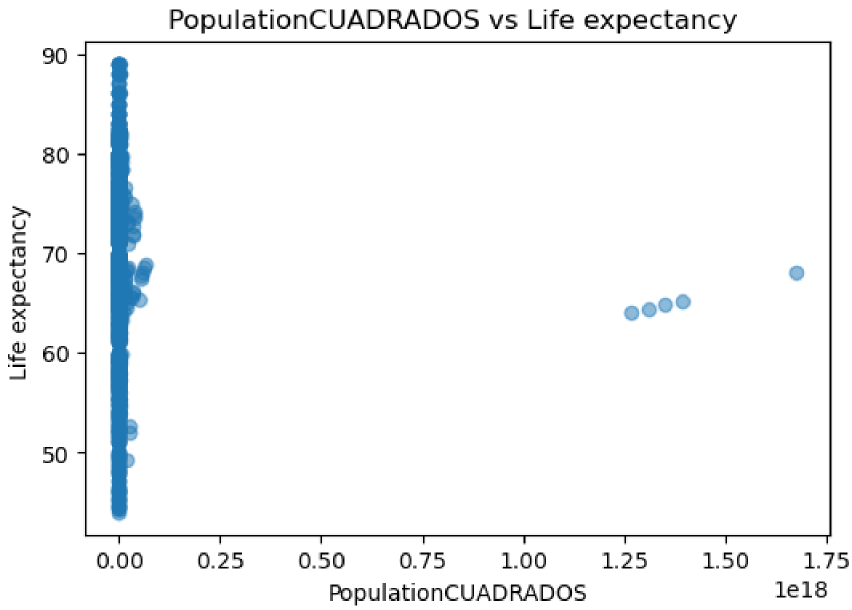

PolioCUADRADOS vs Life expectancy
Life expectancy
PolioCUADRADOS

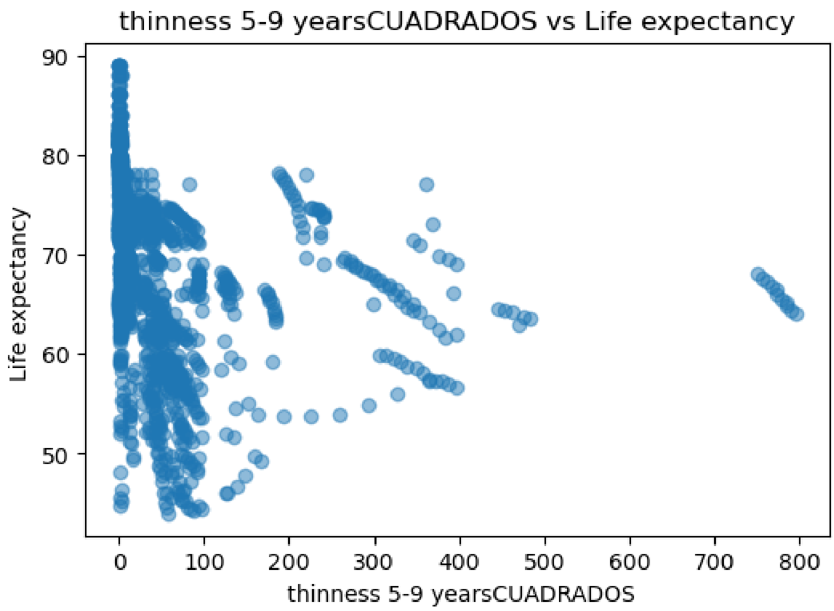

Total expenditureCUADRADOS vs Life expectancy
Life expectancy
Total expenditureCUADRADOS

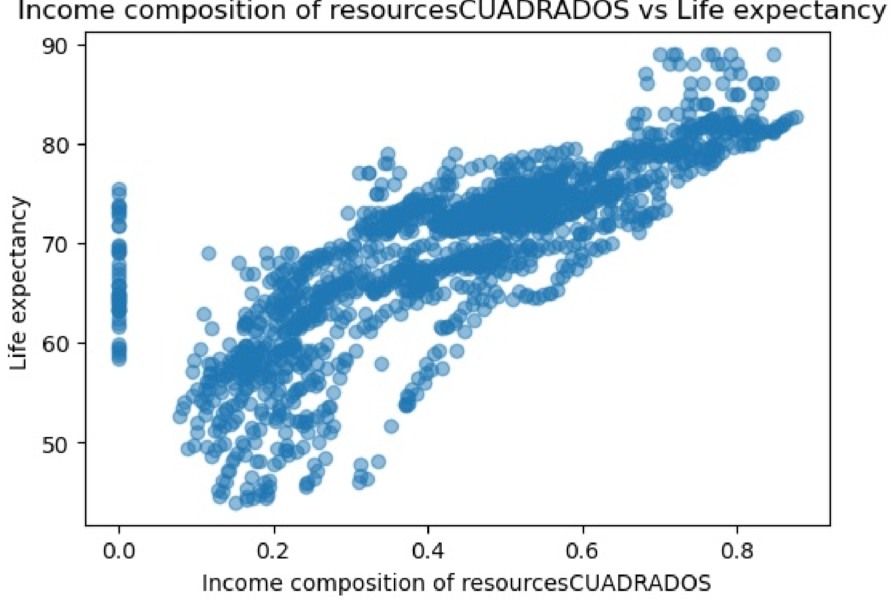

HIV/AIDSCUADRADOS vs Life expectancy

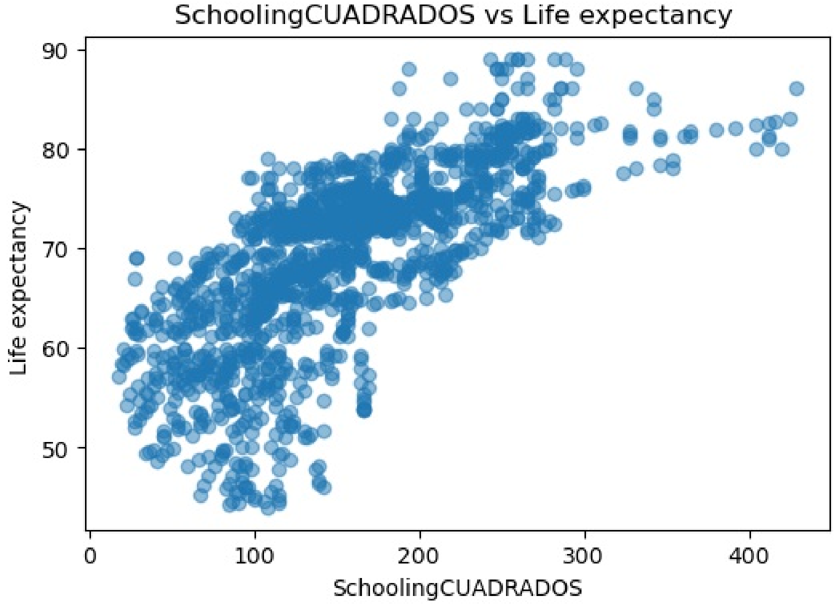

Life ex
60
50
0
500
1000
1500
2000
2500
HIV/AIDSCUADRADOS

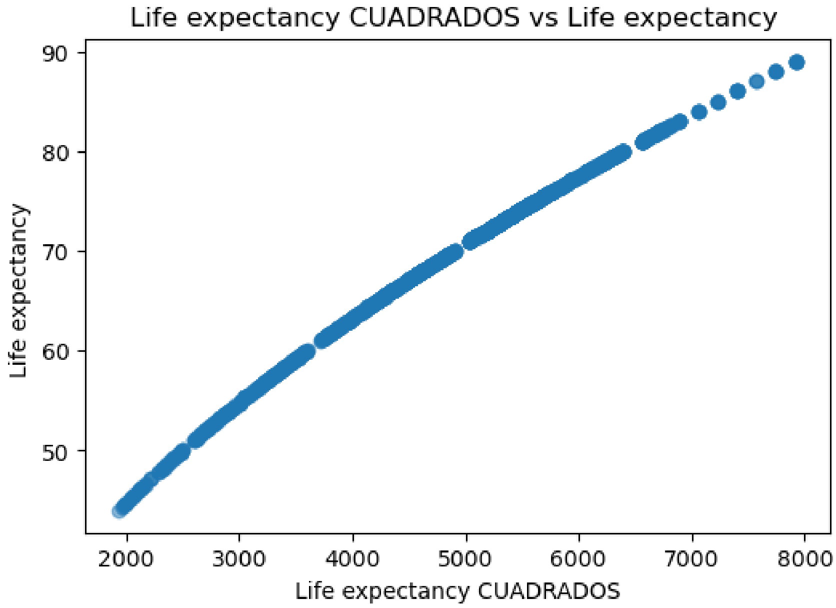

GDPCUADRADOS vs Life expectancy
Life expectancy
90
80
70
60
50
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
GDPCUADRADOS
1e10


PopulationCUADRADOS vs Life expectancy
Life expectancy
90
80
70
60
50
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
PopulationCUADRADOS
1e18


thinness 5-9 yearsCUADRADOS vs Life expectancy
Life expectancy
90
80
70
60
50
0
100
200
300
400
500
600
700
800
thinness 5-9 yearsCUADRADOS


Income composition of resourcesCUADRADOS vs Life expectancy
Life expectancy
Income composition of resourcesCUADRADOS


SchoolingCUADRADOS vs Life expectancy
Life expectancy
SchoolingCUADRADOS


Life expectancy CUADRADOS vs Life expectancy
Life expectancy
Life expectancy CUADRADOS

In [35]:

```
x_extended = data_extended.drop(columns=['Life expectancy ']).values
y = data_extended['Life expectancy '].values

x_extended = np.column_stack((np.ones(x_extended.shape[0]), x_extended))

beta = np.linalg.inv(x_extended.T @ x_extended) @ x_extended.T @ y

print("Model coefficients: ", beta)

y_pred = x_extended @ beta

from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

mse = mean_squared_error(y, y_pred)
mae = mean_absolute_error(y, y_pred)
r2 = r2_score(y, y_pred)

print("MSE: ", mse)
print("MAE: ", mae)
print("R^2: ", r2)
```

```
Model coefficients:  [ 3.04249624e+01 -1.55173134e-02  1.72664927e-01  5.04061025e-04
 -1.60697111e-02 -7.29581322e-05 -1.29036031e-01 -6.86873500e-03
  9.36664564e-02 -4.80745504e-01  4.69678138e-05  5.54756812e-09
 -3.08046548e-01  1.52666739e+01  3.80176683e-01  8.90215418e-07
  1.72214678e-04 -7.91410712e-10 -4.43906505e-06  2.85153798e-11
  9.76829853e-05  6.56388729e-06 -4.17637223e-03  1.46978133e-03
  1.05723667e-10 -4.45314074e-19  1.84019315e-04  1.07835512e+00
 -1.03775814e-03  7.79151874e-03 -6.79235684e-05  3.21455002e-07
  7.10035269e-06  2.59809751e-09  5.29535204e-05 -2.29934491e-06
 -2.59148494e-05  1.22932901e-04 -8.19183934e-08 -1.39582946e-12
  7.26480076e-05 -6.14420884e-03 -2.80267902e-05  2.75273626e-04
 -2.19543565e-05  1.03528198e-05 -2.18093496e-07 -2.58891711e-04
 -1.40452307e-04 -7.57384591e-04 -1.31091792e-03  3.16862643e-06
 -2.02054206e-11 -1.70841179e-04 -6.01645181e-02  5.04466238e-03
 -2.34278869e-03 -4.55476281e-07  5.25343197e-09  1.78049376e-05
  2.41898176e-07 -1.23385321e-06 -2.17965222e-05 -4.32816430e-10
  3.73936592e-13 -1.76337788e-05  1.57993814e-04  3.74095299e-06
 -8.18623382e-06  2.80414333e-09 -1.23777229e-05 -2.75853332e-06
 -4.19629312e-05  1.00466962e-04  2.66336930e-08  1.33329910e-11
 -6.87529140e-05 -2.07528696e-03 -4.10593429e-04  3.17314355e-04
  1.67144564e-07  3.16962670e-08  3.67131613e-07  7.50445054e-07
 -8.49185254e-10  1.21080880e-14  4.73962474e-07 -3.77105587e-05
  3.61656435e-07  1.22818797e-06  1.09589956e-04  5.30986564e-04
  9.38896827e-04 -2.52058405e-06  1.45355665e-11  9.17144779e-05
  4.23487244e-02 -3.75974491e-03  1.76864478e-03 -1.95599938e-04
  2.29229012e-04 -1.17716268e-07  1.60977511e-12 -1.16591127e-04
  1.40850071e-03 -4.76067702e-04  1.82794007e-04  1.25884518e-03
  2.35633362e-07  3.55334608e-11  6.59814241e-05  4.03826412e-02
 -3.35721164e-03 -3.45064549e-05  1.49113995e-06 -5.58099421e-11
  2.38077107e-03 -1.39454407e-01  2.60454068e-03  6.75558830e-03
 -4.64054991e-14  1.48607461e-06  1.45788788e-05 -3.82908989e-08
 -6.39146110e-07  3.92096949e-11  8.40334147e-10  6.41712740e-11
 -1.13011195e-10 -5.63740933e-03 -7.37230320e-03  5.71613403e-03
  1.02592862e-01 -2.39317650e-01 -4.25285653e-03]
MSE:  0.02613667553247974
MAE:  0.09675893322855132
R^2:  0.9996620433566769
```

In [37]:

```
print('MSE: ', mean_squared_error(y, y_pred))
print("MAE: ", mean_absolute_error(y, y_pred))
print("R^2: ", r2_score(y, y_pred))
```

```
MSE:  0.02613667553247974
MAE:  0.09675893322855132
R^2:  0.9996620433566769
```

In [39]:

```
print(data_extended.columns)
```

```
Index(['Adult Mortality', 'infant deaths', 'percentage expenditure',
       'Hepatitis B', 'Measles ', 'under-five deaths ', 'Polio',
       'Total expenditure', ' HIV/AIDS', 'GDP',
       ...
       'Population X  thinness 5-9 years',
       'Population X Income composition of resources',
       'Population X Schooling', 'Population X Life expectancy ',
       ' thinness 5-9 years X Income composition of resources',
       ' thinness 5-9 years X Schooling',
       ' thinness 5-9 years X Life expectancy ',
       'Income composition of resources X Schooling',
       'Income composition of resources X Life expectancy ',
       'Schooling X Life expectancy '],
      dtype='object', length=135)
```

In [41]:

```
x_extended = data_extended.drop(columns=['Life expectancy '])
y = data_extended['Life expectancy '].values
```

In [43]:

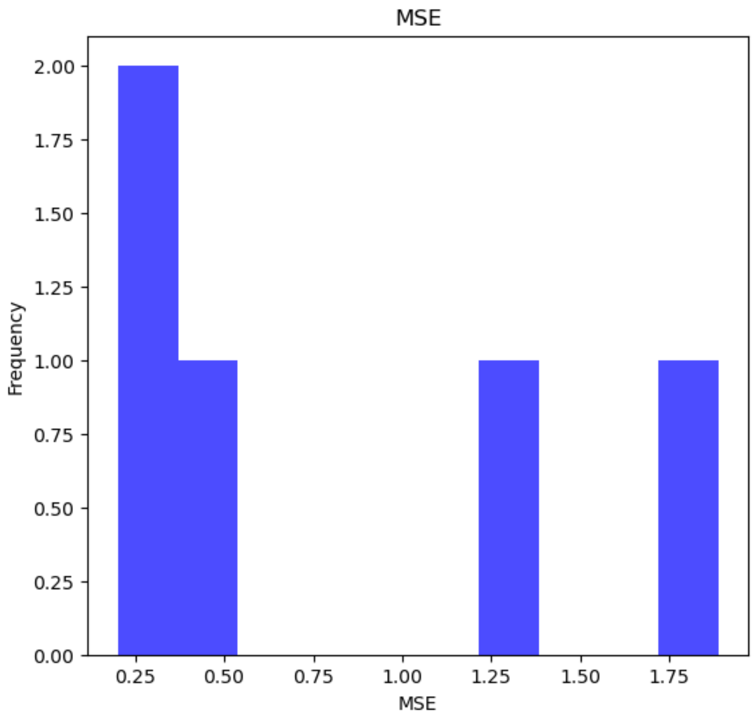
```
x_extended = x_extended.values
```

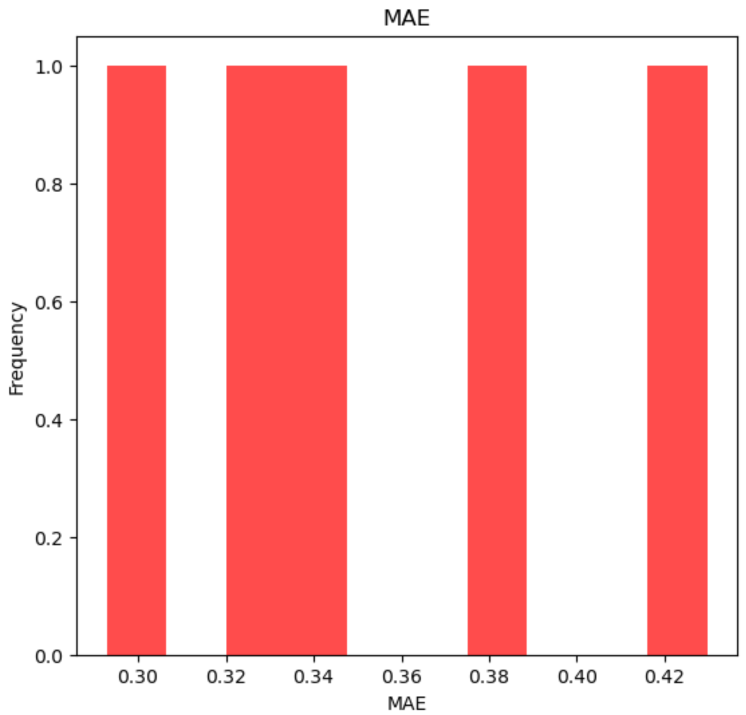
In [45]:

```
n_folds = 5
kf = KFold(n_splits=n_folds, shuffle=True)
```

In [47]:

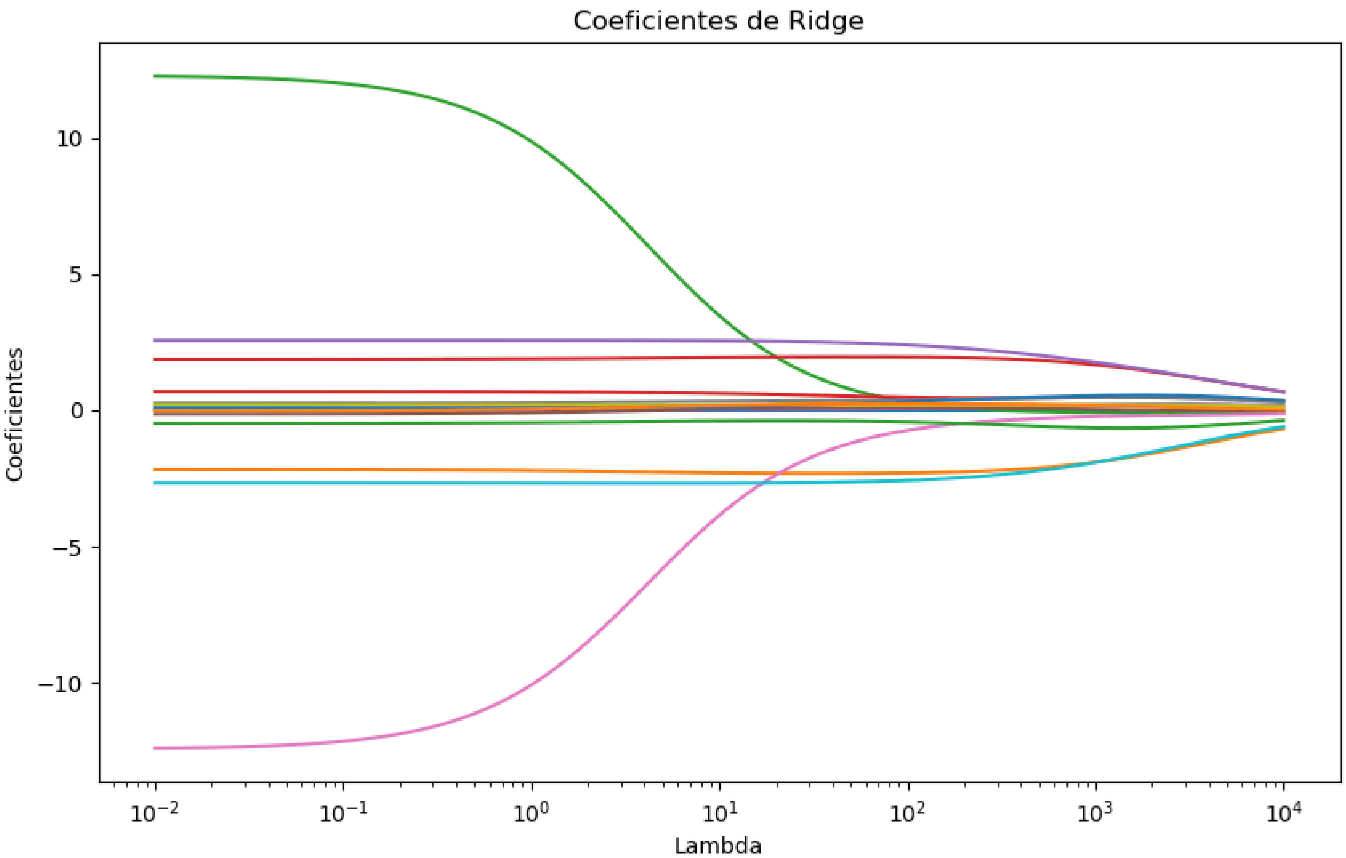
```
mse_cv = []
mae_cv = []
r2_cv = []

for train_index, test_index in kf.split(x_extended):
    x_train, y_train = x_extended[train_index, :], y[train_index]

    beta_cv = fit_model(x_train, y_train)

    x_test, y_test = x_extended[test_index, :], y[test_index]
    y_pred = predict(x_test, beta_cv)

    mse_i = mean_squared_error(y_test, y_pred)
    mae_i = mean_absolute_error(y_test, y_pred)
    r2_i = r2_score(y_test, y_pred)

    mse_cv.append(mse_i)
    mae_cv.append(mae_i)
    r2_cv.append(r2_i)

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.hist(mse_cv, bins=10, color='blue', alpha=0.7)
plt.title('MSE')
plt.xlabel('MSE')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
plt.hist(mae_cv, bins=10, color='red', alpha=0.7)
plt.title('MAE')
plt.xlabel('MAE')
plt.ylabel('Frequency')

plt.show()
```





In [49]:

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

lambdas = np.logspace(-2, 4, 100)

coefs = []

for lambd in lambdas:
    ridge = Ridge(alpha=lambd, fit_intercept=False)
    ridge.fit(X_scaled, y)
    coefs.append(ridge.coef_)

coefs = np.array(coefs)

plt.figure(figsize=(10,6))
plt.plot(lambdas, coefs)
plt.xscale('log')
plt.xlabel('Lambda')
plt.ylabel('Coeficientes')
plt.title('Coeficientes de Ridge')
plt.show()

y_pred = ridge.predict(X_scaled)
print('MSE:', mean_squared_error(y, y_pred))
print('R^2:', r2_score(y, y_pred))
```




```
MSE: 4844.549820042791
R^2: -61.641776822721795
```

In [51]:

```
lasso = Lasso(alpha=0.1)
lasso.fit(X_scaled, y)

lasso_coef = lasso.coef_

columns = data_cleaned.drop(columns=['Life expectancy ']).columns

for coef, col in zip(lasso_coef, columns):
    if coef != 0:
        print(f"Variable: {col}, Coeficiente: {coef}")
```

```
Variable: infant deaths, Coeficiente: -2.335771112418577
Variable: Hepatitis B, Coeficiente: 0.5752392840701521
Variable: Polio, Coeficiente: -0.23994671420767893
Variable: Total expenditure, Coeficiente: 0.30481402845668343
Variable:  HIV/AIDS, Coeficiente: 0.09294009887574015
Variable: GDP, Coeficiente: -2.6274899510797987
Variable: Population, Coeficiente: 0.07672752805465814
Variable: Income composition of resources, Coeficiente: -0.3323614264737169
Variable: Schooling, Coeficiente: 1.9449242881704207
```

In [53]:

```python
print(len(columns))
print(len(lasso_coef))
```

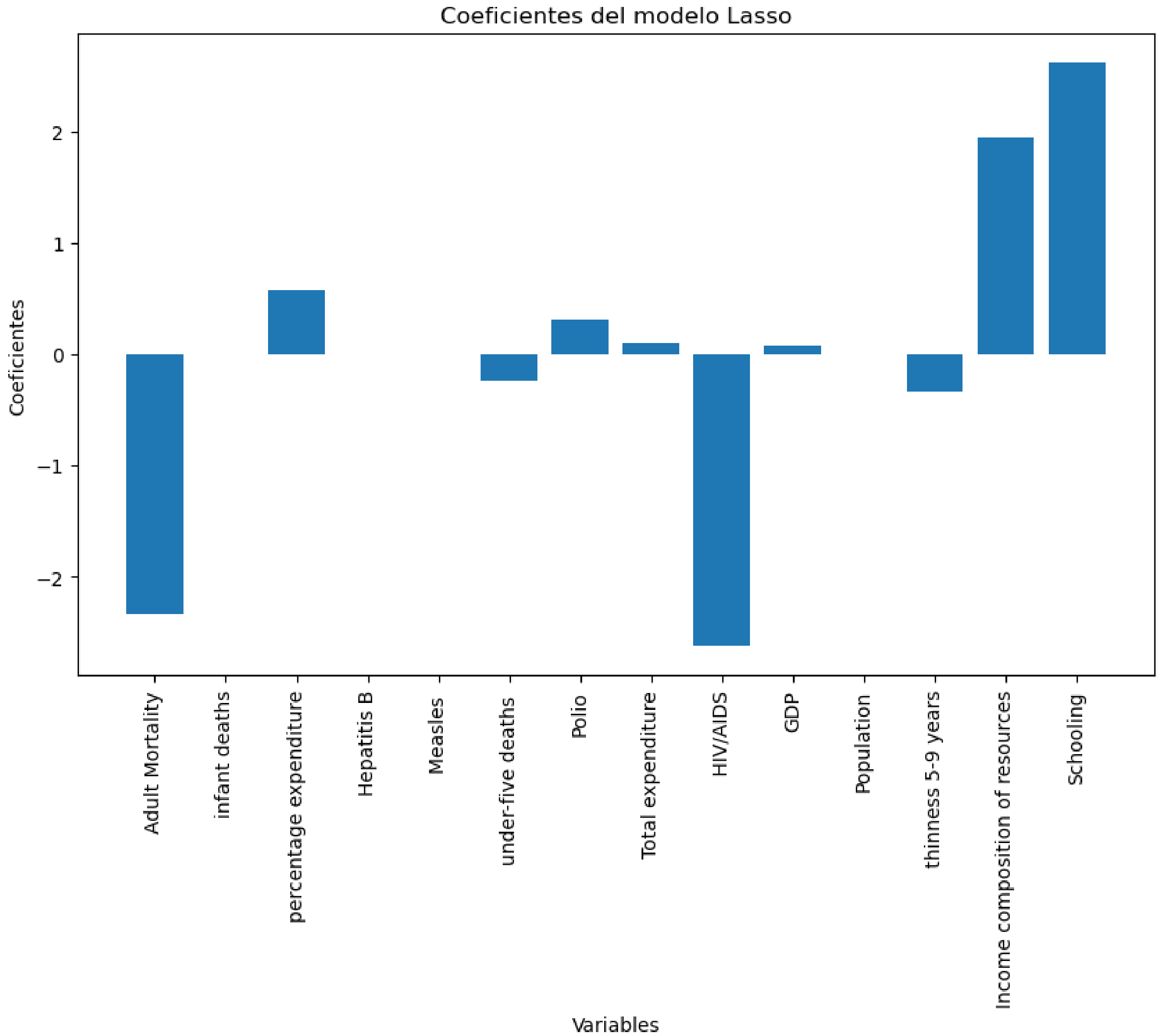
```
14
15
```

In [55]:

```python
if len(lasso_coef) != len(columns):
    lasso_coef = lasso_coef[1:]
```

In [30]:

```python
plt.figure(figsize=(10, 6))
plt.bar(columns, lasso_coef)
plt.xticks(rotation=90)
plt.xlabel('Variables')
plt.ylabel('Coeficientes')
plt.title('Coeficientes del modelo Lasso')
plt.show()
```



In [57]:

```
#-----------------------------------------------------------------------------------------------------------------
#                  9.  P R E G U N T A S
#-----------------------------------------------------------------------------------------------------------------


# a. ¿Consideras que el modelo de regresión lineal es efectivo para modelar los datos del problema? ¿Por qué?
# No, ya que el r^2 tiene un valor bajo y los valores algo altos de MSE Y MAE. Podría ser porque la relación entre las variables independi
# y la dependiente no es lineal o existen datos irrelevantes.

# b. ¿Observas una variabilidad importante en los valores de R2, MSE y MAE cuando aplicas validación cruzada? Detalla tu respuesta.
# Sí, hay una variabilidad importante en estos valores al aplicar cv. Los valores de r^2 van desde un min de -0.0431 hasta 0.2593, lo que
# el modelo no siempre explica la variación de los datos.
# Los valores de MSE van entre 61.22 y 69.90, por lo que el el error cuadrático medio también cambia entre dif subconjuntos. Los valores
# MAE también indican variabilidad, desde 6.0379 hasta 6.6880, esto demuestra que el error prom abs del modelo también cambia entre

# c. Qué modelo es mejor para los datos del problema, el lineal o el cuadrático? ¿Por qué?
# El cuadrático, el r^2 es más alto, ahora es de 0.99, también MSE Y MAE son valores más bajos en comparación al lineal.

# d. ¿Qué variables son más relevantes para el modelo según Ridge y Lasso?
# Los dos modelos muestran que Adult mortality y HIV/AIDS son variables importantes, ya que tienen coeficientes significativos.

# e. ¿Encuentras alguna relación interesante entre la variable de respuesta y los predictores?
#
```

In [59]:

```
#-----------------------------------------------------------------------------------------------------------------
#   Ejercicio 2
#---------------------------------------------------------
```

In [61]:

```
#Las características de este conjunto de datos son las siguientes:

# X1 - age
# X2 - test_time
# X3 - Jitter (%)
# X4 - Jitter (Abs)
# X5 - Jitter: RAP
# X6 - Jitter: PPQ5
# X7 - Jitter: DDP
# X8 - Shimmer
# X9- Shimmer (dB)
# X10 - Shimmer: APQ3
# X11 - Shimmer: APQ5
# X12 - Shimmer: APQ11
# X13 - Shimmer: DDA
# X14 - NHR
# X15 - HNR
# X16 - RPDE
# X17 - DFA
# X18 - PPE
# X19 - sex

# Variables dependientes:  motor_UPDRS
# Variables predictoras: Todas las variables predictoras, menos X2, X6, X10, X14

# X1 - age
# X3 - Jitter (%)
# X4 - Jitter (Abs)
# X5 - Jitter: RAP
# X7 - Jitter: DDP
# X8 - Shimmer
# X9- Shimmer (dB)
# X11 - Shimmer: APQ5
# X12 - Shimmer: APQ11
# X13 - Shimmer: DDA
# X15 - HNR
# X16 - RPDE
# X17 - DFA
# X18 - PPE
# X19 - sex
```

In [69]:

```
column_names = ['subject#', 'age', 'sex', 'test_time', 'motor_UPDRS', 'total_UPDRS', 'Jitter(%)', 'Jitter(Abs)',
                'Jitter:RAP', 'Jitter:PPQ5', 'Jitter:DDP', 'Shimmer', 'Shimmer(dB)', 'Shimmer:APQ3', 'Shimmer:APQ5',
                'Shimmer:APQ11', 'Shimmer:DDA', 'NHR', 'HNR', 'RPDE', 'DFA', 'PPE']

file_path = '/Users/snvpau/Documents/parkinsons_updrs.data'
df = pd.read_csv(file_path, names=column_names)
print(df.head())
```

```
  subject#  age  sex  test_time  motor_UPDRS  total_UPDRS  Jitter(%)  \
0  subject#  age  sex  test_time  motor_UPDRS  total_UPDRS  Jitter(%)
1        1   72    0     5.6431       28.199       34.398    0.00662
2        1   72    0     12.666       28.447       34.894      0.003
3        1   72    0     19.681       28.695       35.389    0.00481
4        1   72    0     25.647       28.905        35.81    0.00528

  Jitter(Abs)  Jitter:RAP  Jitter:PPQ5  ...  Shimmer(dB)  Shimmer:APQ3  \
0  Jitter(Abs)  Jitter:RAP  Jitter:PPQ5  ...  Shimmer(dB)  Shimmer:APQ3
1    3.38e-005     0.00401      0.00317  ...         0.23       0.01438
2    1.68e-005     0.00132       0.0015  ...        0.179       0.00994
3   2.462e-005     0.00205      0.00208  ...        0.181       0.00734
4   2.657e-005     0.00191      0.00264  ...        0.327       0.01106

  Shimmer:APQ5  Shimmer:APQ11  Shimmer:DDA       NHR     HNR     RPDE  \
0  Shimmer:APQ5  Shimmer:APQ11  Shimmer:DDA       NHR     HNR     RPDE
1      0.01309        0.01662      0.04314   0.01429   21.64  0.41888
2      0.01072        0.01689      0.02982  0.011112  27.183  0.43493
3      0.00844        0.01458      0.02202   0.02022  23.047  0.46222
4      0.01265        0.01963      0.03317  0.027837  24.445   0.4873

      DFA      PPE
0     DFA      PPE
1  0.54842  0.16006
2  0.56477   0.1081
3  0.54405  0.21014
4  0.57794  0.33277

[5 rows x 22 columns]
```

In [71]:

```
predictoras = ['age', 'Jitter(%)', 'Jitter(Abs)', 'Jitter:RAP', 'Jitter:DDP', 'Shimmer', 'Shimmer(dB)',
       'Shimmer:APQ5', 'Shimmer:APQ11', 'Shimmer:DDA', 'HNR', 'RPDE', 'DFA', 'PPE', 'sex']
dependiente = 'motor_UPDRS'

data = df[predictoras + [dependiente]]

data_cleaned = data.dropna()

x = data_cleaned[predictoras].values
y = data_cleaned[dependiente].values

print(data_cleaned.head())
print(f"Variables predictoras (X): {x.shape}")
print(f"Variable dependiente (y): {y.shape}")
print(df.head())
```

```
  age  Jitter(%)  Jitter(Abs)  Jitter:RAP  Jitter:DDP  Shimmer  Shimmer(dB)  \
0  age  Jitter(%)  Jitter(Abs)  Jitter:RAP  Jitter:DDP  Shimmer  Shimmer(dB)
1   72    0.00662    3.38e-005     0.00401     0.01204  0.02565        0.23
2   72      0.003    1.68e-005     0.00132     0.00395  0.02024       0.179
3   72    0.00481  2.462e-005     0.00205     0.00616  0.01675       0.181
4   72    0.00528  2.657e-005     0.00191     0.00573  0.02309       0.327

  Shimmer:APQ5  Shimmer:APQ11  Shimmer:DDA     HNR     RPDE      DFA  \
0  Shimmer:APQ5  Shimmer:APQ11  Shimmer:DDA     HNR     RPDE      DFA
1      0.01309       0.01662      0.04314   21.64  0.41888  0.54842
2      0.01072       0.01689      0.02982  27.183  0.43493  0.56477
3      0.00844       0.01458      0.02202  23.047  0.46222  0.54405
4      0.01265       0.01963      0.03317  24.445   0.4873  0.57794

      PPE  sex  motor_UPDRS
0      PPE  sex  motor_UPDRS
1  0.16006    0       28.199
2   0.1081    0       28.447
3  0.21014    0       28.695
4  0.33277    0       28.905
Variables predictoras (X): (5876, 15)
Variable dependiente (y): (5876,)
  subject#  age  sex  test_time  motor_UPDRS  total_UPDRS  Jitter(%)  \
0  subject#  age  sex  test_time  motor_UPDRS  total_UPDRS  Jitter(%)
1        1   72    0     5.6431       28.199       34.398    0.00662
2        1   72    0     12.666       28.447       34.894      0.003
3        1   72    0     19.681       28.695       35.389    0.00481
4        1   72    0     25.647       28.905        35.81    0.00528

  Jitter(Abs)  Jitter:RAP  Jitter:PPQ5  ...  Shimmer(dB)  Shimmer:APQ3  \
0  Jitter(Abs)  Jitter:RAP  Jitter:PPQ5  ...  Shimmer(dB)  Shimmer:APQ3
1    3.38e-005     0.00401      0.00317  ...         0.23       0.01438
2    1.68e-005     0.00132       0.0015  ...        0.179       0.00994
3   2.462e-005     0.00205      0.00208  ...        0.181       0.00734
4   2.657e-005     0.00191      0.00264  ...        0.327       0.01106

  Shimmer:APQ5  Shimmer:APQ11  Shimmer:DDA       NHR     HNR     RPDE  \
0  Shimmer:APQ5  Shimmer:APQ11  Shimmer:DDA       NHR     HNR     RPDE
1      0.01309       0.01662      0.04314   0.01429   21.64  0.41888
2      0.01072       0.01689      0.02982  0.011112  27.183  0.43493
3      0.00844       0.01458      0.02202   0.02022  23.047  0.46222
4      0.01265       0.01963      0.03317  0.027837  24.445   0.4873

      DFA      PPE
0      DFA      PPE
1  0.54842  0.16006
2  0.56477   0.1081
3  0.54405  0.21014
4  0.57794  0.33277

[5 rows x 22 columns]
```

In [73]:

```python
n_folds = 5
kf = KFold(n_splits=n_folds, shuffle=True)
```

In [75]:

```python
for column in predictoras + [dependiente]:
    df[column] = pd.to_numeric(df[column], errors='coerce')

print(df.dtypes)

data_cleaned = df.dropna(subset = predictoras + [dependiente])

x = data_cleaned[predictoras].values
y = data_cleaned[dependiente].values

print(data_cleaned.head())
print(f"Variables predictoras (X): {x.shape}")
print(f"Variable dependiente (y): {y.shape}")

mse_list = []
mae_list = []
r2_list = []

for train_index, test_index in kf.split(x):
    X_train, X_test = x[train_index], x[test_index]
    y_train, y_test = y[train_index], y[test_index]

    model = LinearRegression()
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    mse_list.append(mean_squared_error(y_test, y_pred))
    mae_list.append(mean_absolute_error(y_test, y_pred))
    r2_list.append(r2_score(y_test, y_pred))

print('MSE promedio:', np.mean(mse_list))
print('MAE promedio:', np.mean(mae_list))
print('R^2 promedio:', np.mean(r2_list))
```

```
subject#          object
age              float64
sex              float64
test_time         object
motor_UPDRS      float64
total_UPDRS       object
Jitter(%)        float64
Jitter(Abs)      float64
Jitter:RAP       float64
Jitter:PPQ5       object
Jitter:DDP       float64
Shimmer          float64
Shimmer(dB)      float64
Shimmer:APQ3      object
Shimmer:APQ5     float64
Shimmer:APQ11    float64
Shimmer:DDA      float64
NHR               object
HNR              float64
RPDE             float64
DFA              float64
PPE              float64
dtype: object
  subject#   age  sex test_time  motor_UPDRS total_UPDRS  Jitter(%)  \
1        1  72.0  0.0    5.6431       28.199      34.398    0.00662
2        1  72.0  0.0    12.666       28.447      34.894    0.00300
3        1  72.0  0.0    19.681       28.695      35.389    0.00481
4        1  72.0  0.0    25.647       28.905       35.81    0.00528
5        1  72.0  0.0    33.642       29.187      36.375    0.00335

   Jitter(Abs)  Jitter:RAP Jitter:PPQ5  ...  Shimmer(dB)  Shimmer:APQ3  \
1     0.000034     0.00401     0.00317  ...        0.230       0.01438
2     0.000017     0.00132      0.0015  ...        0.179       0.00994
3     0.000025     0.00205     0.00208  ...        0.181       0.00734
4     0.000027     0.00191     0.00264  ...        0.327       0.01106
5     0.000020     0.00093      0.0013  ...        0.176       0.00679

   Shimmer:APQ5 Shimmer:APQ11  Shimmer:DDA       NHR     HNR     RPDE  \
1       0.01309       0.01662      0.04314   0.01429  21.640  0.41888
2       0.01072       0.01689      0.02982  0.011112  27.183  0.43493
3       0.00844       0.01458      0.02202   0.02022  23.047  0.46222
4       0.01265       0.01963      0.03317  0.027837  24.445  0.48730
5       0.00929       0.01819      0.02036  0.011625  26.126  0.47188

       DFA      PPE
1  0.54842  0.16006
2  0.56477  0.10810
3  0.54405  0.21014
4  0.57794  0.33277
5  0.56122  0.19361

[5 rows x 22 columns]
Variables predictoras (X): (5875, 15)
Variable dependiente (y): (5875,)
MSE promedio: 56.48972795584008
MAE promedio: 6.347300376805391
R^2 promedio: 0.14493986447572405
```

In [77]:

```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

In [79]:

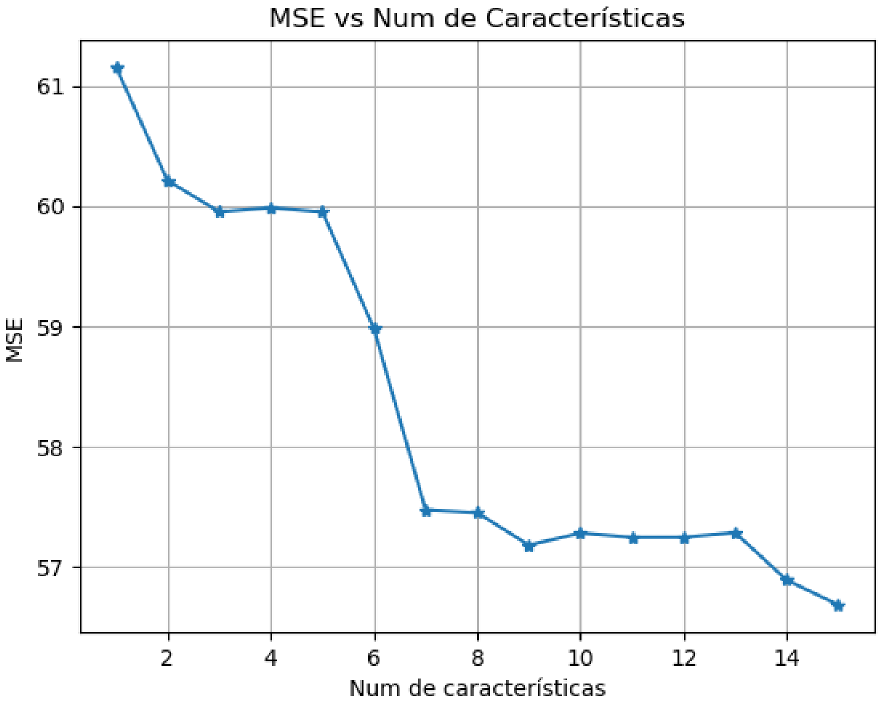
```python
mse_nfeat = []

n_feats = range(1, len(predictoras) + 1)

for n_feat in n_feats:
    print(f'---- n features = {n_feat} ----')

    mse_cv = []

    kf = KFold(n_splits=5, shuffle=True)

    for train_index, test_index in kf.split(x_scaled):

        x_train, x_test = x_scaled[train_index], x_scaled[test_index]
        y_train, y_test = y[train_index], y[test_index]

        fselection_cv = SelectKBest(f_regression, k=n_feat)
        x_train_kbest = fselection_cv.fit_transform(x_train, y_train)
        x_test_kbest = fselection_cv.transform(x_test)

        model_cv = LinearRegression()
        model_cv.fit(x_train_kbest, y_train)

        y_pred = model_cv.predict(x_test_kbest)
        mse_i = mean_squared_error(y_test, y_pred)
        mse_cv.append(mse_i)

    mse_avg = np.mean(mse_cv)
    mse_nfeat.append(mse_avg)
    print(f'MSE promedio para {n_feat} características: {mse_avg}')
```

```
---- n features = 1 ----
MSE promedio para 1 características: 61.15404761534212
---- n features = 2 ----
MSE promedio para 2 características: 60.21165390277007
---- n features = 3 ----
MSE promedio para 3 características: 59.95307855359145
---- n features = 4 ----
MSE promedio para 4 características: 59.98596831415936
---- n features = 5 ----
MSE promedio para 5 características: 59.95177346709304
---- n features = 6 ----
MSE promedio para 6 características: 58.98009062072386
---- n features = 7 ----
MSE promedio para 7 características: 57.475337432630894
---- n features = 8 ----
MSE promedio para 8 características: 57.45274080830036
---- n features = 9 ----
MSE promedio para 9 características: 57.183163646282864
---- n features = 10 ----
MSE promedio para 10 características: 57.282914492190244
---- n features = 11 ----
MSE promedio para 11 características: 57.24809416582938
---- n features = 12 ----
MSE promedio para 12 características: 57.248505750997694
---- n features = 13 ----
MSE promedio para 13 características: 57.28615984470806
---- n features = 14 ----
MSE promedio para 14 características: 56.892696931345974
---- n features = 15 ----
MSE promedio para 15 características: 56.68728615417505
```

In [81]:

```
opt_index = np.argmin(mse_nfeat)
opt_features = n_feats[opt_index]
print(f"Número óptimo de características: {opt_features}")

plt.plot(n_feats, mse_nfeat, marker ='*')
plt.xlabel("Num de características")
plt.ylabel("MSE")
plt.title("MSE vs Num de Características")
plt.grid(True)
plt.show()

fselection_opt = SelectKBest(f_regression, k=opt_features)
x_transformed = fselection_opt.fit_transform(x_scaled, y)

print("Características seleccionadas: ", np.array(predictoras)[fselection_opt.get_support()])

model_ = LinearRegression()
model_.fit(x_transformed, y)
print("Coeficientes del modelo final:", model_.coef_)
```

```
Número óptimo de características: 15
```




```
Características seleccionadas:  ['age' 'Jitter(%)' 'Jitter(Abs)' 'Jitter:RAP' 'Jitter:DDP' 'Shimmer'
 'Shimmer(dB)' 'Shimmer:APQ5' 'Shimmer:APQ11' 'Shimmer:DDA' 'HNR' 'RPDE'
 'DFA' 'PPE' 'sex']
Coeficientes del modelo final: [ 1.73347153e+00  2.45153211e-01 -2.26168988e+00 -1.15444749e+02
  1.16478662e+02  2.62810850e+00 -1.34889780e+00 -3.21650200e+00
  1.90794995e+00 -8.81354751e-01 -1.67084658e+00  7.75876209e-02
 -1.53505641e+00  1.72627249e+00 -5.65044687e-01]
```

In [87]:

```
for column in data_cleaned.columns:
    data_cleaned[column] = pd.to_numeric(data_cleaned[column], errors='coerce')

print(data_cleaned.dtypes)

data_cleaned = data_cleaned.dropna()

print(data_cleaned.isna().sum())

X = data_cleaned[predictoras].values
y = data_cleaned[dependiente].values

print("----- Selección de características usando el 50% de los predictores -----")
modelo = LinearRegression()
selector_secuencial = SequentialFeatureSelector(modelo, n_features_to_select=int(len(predictoras) * 0.5), direction='forward')
selector_secuencial.fit(X, y)
selected_features = np.array(predictoras)[selector_secuencial.get_support()]
print("Características seleccionadas:", selected_features)
```

```
age              float64
Jitter(%)        float64
Jitter(Abs)      float64
Jitter:RAP       float64
Jitter:DDP       float64
Shimmer          float64
Shimmer(dB)      float64
Shimmer:APQ5     float64
Shimmer:APQ11    float64
Shimmer:DDA      float64
HNR              float64
RPDE             float64
DFA              float64
PPE              float64
sex              float64
motor_UPDRS      float64
dtype: object
age              0
Jitter(%)        0
Jitter(Abs)      0
Jitter:RAP       0
Jitter:DDP       0
Shimmer          0
Shimmer(dB)      0
Shimmer:APQ5     0
Shimmer:APQ11    0
Shimmer:DDA      0
HNR              0
RPDE             0
DFA              0
PPE              0
sex              0
motor_UPDRS      0
dtype: int64
----- Selección de características usando el 50% de los predictores -----
Características seleccionadas: ['age' 'Jitter(%)' 'Jitter(Abs)' 'Jitter:RAP' 'Jitter:DDP' 'Shimmer:APQ11'
 'PPE']
```

In [89]:

```python
n_feats = list(range(1, len(predictoras)))

mse_nfeat = []

for n_feat in n_feats:
    print('---- Número de características =', n_feat)

    mse_cv = []

    kf = KFold(n_splits=5, shuffle=True)

    for train_index, test_index in kf.split(X):
        X_train = X[train_index]
        y_train = y[train_index]

        modelo_cv = LinearRegression()

        selector_secuencial_cv = SequentialFeatureSelector(modelo_cv, n_features_to_select=n_feat, direction ='forward')
        selector_secuencial_cv.fit(X_train, y_train)
        X_train_transformed = selector_secuencial_cv.transform(X_train)

        modelo_cv.fit(X_train_transformed, y_train)

        X_test_transformed = selector_secuencial_cv.transform(X[test_index])
        y_test = y[test_index]
        y_pred = modelo_cv.predict(X_test_transformed)

        mse_i = mean_squared_error(y_test, y_pred)
        mse_cv.append(mse_i)

    mse_promedio = np.mean(mse_cv)
    mse_nfeat.append(mse_promedio)

    print('MSE Promedio:', mse_promedio)
```

```
---- Número de características = 1
MSE Promedio: 61.14297343339306
---- Número de características = 2
MSE Promedio: 60.039784362329485
---- Número de características = 3
MSE Promedio: 59.880406201675896
---- Número de características = 4
MSE Promedio: 59.27171168539455
---- Número de características = 5
MSE Promedio: 59.245264752324616
---- Número de características = 6
MSE Promedio: 59.42831893399366
---- Número de características = 7
MSE Promedio: 59.10301995015766
---- Número de características = 8
MSE Promedio: 58.76815659033126
---- Número de características = 9
MSE Promedio: 59.01328307540823
---- Número de características = 10
MSE Promedio: 58.93912362549448
---- Número de características = 11
MSE Promedio: 58.94576966821128
---- Número de características = 12
MSE Promedio: 58.431073831778875
---- Número de características = 13
MSE Promedio: 58.02391221305337
---- Número de características = 14
MSE Promedio: 56.73276505598725
```

In [91]:

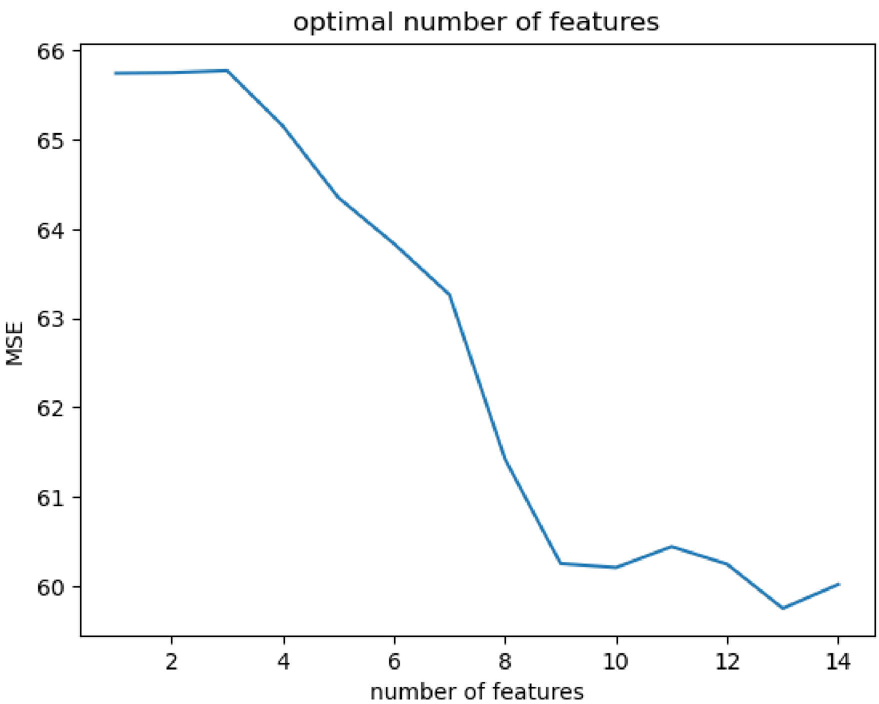
```
n_feats = list(range(1, len(predictoras)))

mse_nfeat = []

for n_feat in n_feats:
    print('---- Número de características =', n_feat)

    mse_cv = []

    kf = KFold(n_splits=5, shuffle=True)

    for train_index, test_index in kf.split(X):
        X_train = X[train_index]
        y_train = y[train_index]

        modelo_cv = LinearRegression()

        selector_rfe_cv = RFE(modelo_cv, n_features_to_select=n_feat)
        selector_rfe_cv.fit(X_train, y_train)
        X_train_transformed = selector_rfe_cv.transform(X_train)

        modelo_cv.fit(X_train_transformed, y_train)

        X_test_transformed = selector_rfe_cv.transform(X[test_index])
        y_test = y[test_index]
        y_pred = modelo_cv.predict(X_test_transformed)

        mse_i = mean_squared_error(y_test, y_pred)
        mse_cv.append(mse_i)

    mse_promedio = np.mean(mse_cv)
    mse_nfeat.append(mse_promedio)

    print('MSE Promedio:', mse_promedio)
```

---- Número de características = 1
MSE Promedio: 65.74719229887924
---- Número de características = 2
MSE Promedio: 65.75293860683848
---- Número de características = 3
MSE Promedio: 65.7758396639804
---- Número de características = 4
MSE Promedio: 65.15623864032064
---- Número de características = 5
MSE Promedio: 64.35289272030916
---- Número de características = 6
MSE Promedio: 63.83668519799615
---- Número de características = 7
MSE Promedio: 63.264524858731065
---- Número de características = 8
MSE Promedio: 61.421750757096525
---- Número de características = 9
MSE Promedio: 60.24940754441788
---- Número de características = 10
MSE Promedio: 60.20500441210478
---- Número de características = 11
MSE Promedio: 60.43865300824827
---- Número de características = 12
MSE Promedio: 60.24133087146917
---- Número de características = 13
MSE Promedio: 59.747173066022164
---- Número de características = 14
MSE Promedio: 60.01626786533259

In [93]:

```
opt_index = np.argmin(mse_nfeat)
opt_features = n_feats[opt_index]
print("optimal number of features ", opt_features)

plt.plot(n_feats, mse_nfeat)
plt.xlabel("number of features")
plt.ylabel("MSE")
plt.title("optimal number of features")
plt.show()

modelo = LinearRegression()
selector_rfe_opt = RFE(modelo, n_features_to_select=opt_features)
selector_rfe_opt.fit(X, y)

selected_features_opt = np.array(predictoras)[selector_rfe_opt.get_support()]
print("optimal number of features:", selected_features_opt)
```

optimal number of features 13



optimal number of features: ['Jitter(%)' 'Jitter(Abs)' 'Jitter:RAP' 'Jitter:DDP' 'Shimmer'
 'Shimmer(dB)' 'Shimmer:APQ5' 'Shimmer:APQ11' 'Shimmer:DDA' 'RPDE' 'DFA'
 'PPE' 'sex']

In [122]:

```python
x = data_cleaned[predictoras].values
y = data_cleaned[dependiente].values

kf = KFold(n_splits=5, shuffle=True)

parameters = {'n_neighbors': np.arange(1, 100)}
knn_cv = GridSearchCV(KNeighborsRegressor(), parameters, cv=5)

y_pred = cross_val_predict(knn_cv, X, y, cv=kf)

mse = mean_squared_error(y, y_pred)
mae = mean_absolute_error(y, y_pred)
r2 = r2_score(y, y_pred)

print(f"MSE: {mse}")
print(f"MAE: {mae}")
print(f"R^2: {r2}")
```

```
MSE: 15.367967539662143
MAE: 2.7469988684031805
R^2: 0.7674126793891374
```

In [ ]:

```python
#------------------------------------------------------------------------------------------------------------------
#                    7.  P R E G U N T A S
#------------------------------------------------------------------------------------------------------------------


# a. Consideras que el modelo de regresión lineal es adecuado para los datos. ¿Por qué?
# No, no es el más adecuado. Tenemos un r^2 (0.14) bajo y un alto MSE

# b. ¿Qué método de selección de características consideras que funciona bien con los datos? ¿Por qué?
# WRAPPER puede ser un bueb método, puesto que ayuda a encontrar el num óptimo de características que minimizan el error.
# y es un método que nos sirve para maximizar el rendimiento de nuestro modelo.

# d. KNN funcionó mejor que los lineales. Esto porque los modelos no lineales son más indicados para capturar patrones
# más complejos y no lineales, lo que resulta en un mejor rendimiento, un MSE bajo y un r^2 alto, y para mis datos que
# parecen tener relaciones no lineales, resulta más efectivo.

# e. ¿Se puede concluir algo interesante sobre los resultados de modelar estos datos con regresión? Argumenta tu respuesta.
# Después de modelar los datos pude darme cuenta de la importancia que tiene el probar distintos modelos de regresión y
# selección de características. Para los datos con relaciones no lineales, los modelos como KNN son más efectivos.
# Sin embargo, la regresión lineal sigue siendo útil para comenzar y entender las relaciones en los datos. La selección del
ortante para el rendimiento.
```