Linear Models

- In supervised learning, the training data fed to the algorithm includes the desired solutions, called labels.
- In **regression**, the labels are continuous quantities.
- Linear models predict by computing a weighted sum of input features plus a bias term.

```
import numpy as np
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
np.random.seed(42)
```

```
5-2
```

```
3
```

Simple Linear Regression

Simple linear regression equation:

$y = ax + b$

a: slope

b: intercept

Generate linear-looking data with the equation:

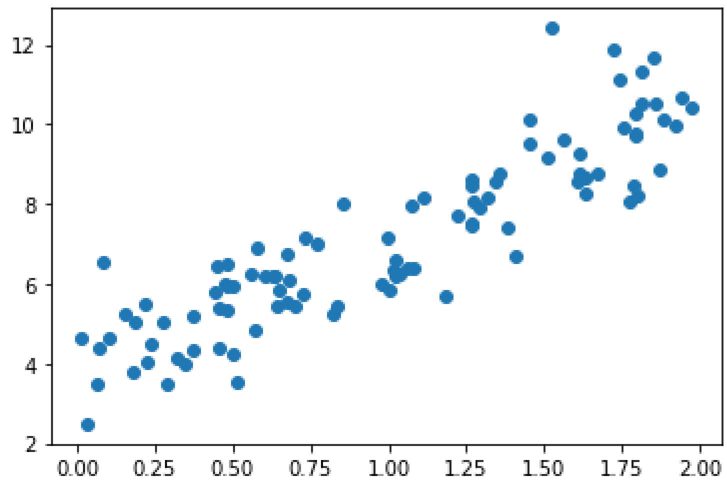
$$y = 3X + 4 + noise$$

```
np.random.rand(100, 1)
```

```
array([[0.37454012],
       [0.95071431],
       [0.73199394],
       [0.59865848],
       [0.15601864],
       [0.15599452],
       [0.05808361],
```

```
       [0.86617615],
       [0.60111501],
       [0.70807258],
       [0.02058449],
       [0.96990985],
       [0.83244264],
       [0.21233911],
       [0.18182497],
       [0.18340451],
       [0.30424224],
       [0.52475643],
       [0.43194502],
       [0.29122914],
       [0.61185289],
       [0.13949386],
       [0.29214465],
       [0.36636184],
       [0.45606998],
       [0.78517596],
       [0.19967378],
       [0.51423444],
       [0.59241457],
       [0.04645041],
       [0.60754485],
       [0.17052412],
       [0.06505159],
       [0.94888554],
       [0.96563203],
       [0.80839735],
       [0.30461377],
       [0.09767211],
       [0.68423303],
       [0.44015249],
       [0.12203823],
       [0.49517691],
       [0.03438852],
       [0.9093204 ],
       [0.25877998],
       [0.66252228],
       [0.31171108],
       [0.52006802],
       [0.54671028],
       [0.18485446],
       [0.96958463],
       [0.77513282],
       [0.93949894],
       [0.89482735],
       [0.59789998],
       [0.92187424],
       [0.0884925 ],
```

```
X = 2*np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)
plt.scatter(X, y);
```



```
import pandas as pd
pd.DataFrame(y)
```

	0
0	3.508550
1	8.050716
2	6.179208
3	6.337073
4	11.311173
...	...
95	5.441928
96	10.121188
97	9.787643
98	8.061635
99	9.597115

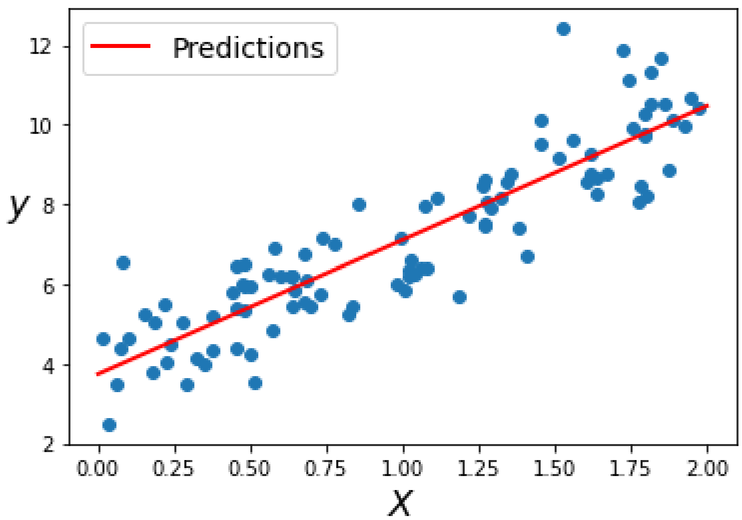
100 rows × 1 columns

```
from sklearn.linear_model import LinearRegression

linear_reg = LinearRegression(fit_intercept=True)
linear_reg.fit(X, y)
```

```
LinearRegression()
```

Plot the model's predictions:

```
#X_fit[]

# construct best fit line
X_fit = np.linspace(0, 2, 100)
y_fit = linear_reg.predict(X_fit[:, np.newaxis])

plt.scatter(X, y)
plt.plot(X_fit, y_fit, "r-", linewidth=2, label="Predictions")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper left", fontsize=14);
```



Predictions are a good fit.

Generate new data to make predictions with the model:

```
X_new = np.array([[0], [2]])
X_new
```

```
array([[0],
       [2]])
```

```
X_new.shape
```

```
(2, 1)
```

```
y_new = linear_reg.predict(X_new)
y_new
```

```
array([[ 3.74406122],
       [10.47517611]])
```

```
linear_reg.coef_, linear_reg.intercept_
```

```
(array([[3.36555744]]), array([3.74406122]))
```

The model estimates:

$\hat{y} = 3.36X + 3.74$

```
#|VENTAS|GANANCIAS|
#COEF*VENTAS+B
#|VENTAS|COMPRAS|GANANCIAS|
#COEF1*X1+COEF2*X2+B=Y
```

Polynomial Regression

If data is more complex than a straight line, you can use a linear model ti fit non-linear data adding powers of each feature as new features and then train a linear model on the extended set of features.

$$y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 + \ldots$$

to

$$y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + \ldots$$

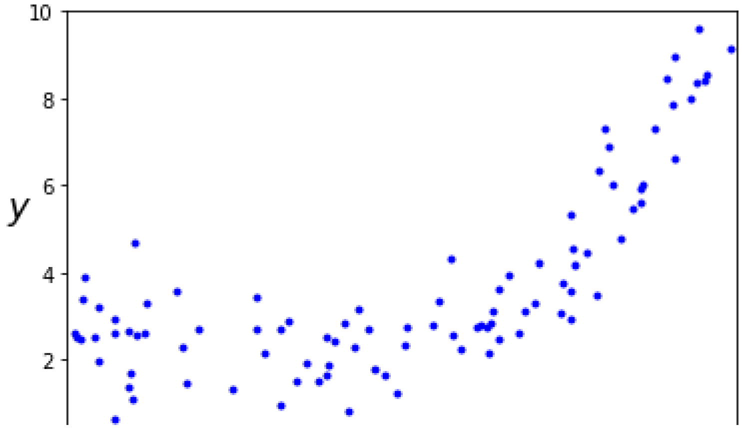
This is still a linear model, the linearity refers to the fact that the coefficients never multiply or divide each other.

To generate polynomial data we use the function:

$y = 0.50X^2 + X + 2 + noise$

```
# generate non-linear data e.g. quadratic equation
m = 100
X = 6 * np.random.rand(m, 1) - 3
y = 0.5 * X**2 + X + 2 + np.random.randn(m, 1)
```

```
plt.plot(X, y, "b.")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.axis([-3, 3, 0, 10]);
```




```
import pandas as pd
pd.DataFrame(y)
```

	0
0	8.529240
1	3.768929
2	3.354423
3	2.747935
4	0.808458
...	...
95	5.346771
96	6.338229
97	3.488785
98	1.372002
99	-0.072150

100 rows × 1 columns

Now we can use `PolynomialFeatues` to transform training data adding the square of each feature as new features.

```
from sklearn.preprocessing import PolynomialFeatures

poly_features = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly_features.fit_transform(X)
```

```
X_poly
```

```
array([[ 2.72919168e+00,  7.44848725e+00],
```

```
       [ 1.42738150e+00,  2.03741795e+00],
       [ 3.26124315e-01,  1.06357069e-01],
       [ 6.70324477e-01,  4.49334905e-01],
       [-4.82399625e-01,  2.32709399e-01],
       [-1.51361406e+00,  2.29102753e+00],
       [-8.64163928e-01,  7.46779295e-01],
       [ 1.54707666e+00,  2.39344620e+00],
       [-2.91363907e+00,  8.48929262e+00],
       [-2.30356416e+00,  5.30640783e+00],
       [-2.72398415e+00,  7.42008964e+00],
       [-2.75562719e+00,  7.59348119e+00],
       [ 2.13276350e+00,  4.54868016e+00],
       [ 1.22194716e+00,  1.49315485e+00],
       [-1.54957025e-01,  2.40116797e-02],
       [-2.41299504e+00,  5.82254504e+00],
       [-5.03047493e-02,  2.53056780e-03],
       [-1.59169375e-01,  2.53348900e-02],
       [-1.96078878e+00,  3.84469264e+00],
       [-3.96890105e-01,  1.57521755e-01],
       [-6.08971594e-01,  3.70846402e-01],
       [ 6.95100588e-01,  4.83164828e-01],
       [ 8.10561905e-01,  6.57010602e-01],
       [-2.72817594e+00,  7.44294397e+00],
       [-7.52324312e-01,  5.65991871e-01],
       [ 7.55159494e-01,  5.70265862e-01],
       [ 1.88175515e-02,  3.54100244e-04],
       [ 2.13893905e+00,  4.57506025e+00],
       [ 9.52161790e-01,  9.06612074e-01],
       [-2.02239344e+00,  4.09007522e+00],
       [-2.57658752e+00,  6.63880323e+00],
       [ 8.54515669e-01,  7.30197029e-01],
       [-2.84093214e+00,  8.07089541e+00],
       [ 5.14653488e-01,  2.64868212e-01],
       [ 2.64138145e+00,  6.97689596e+00],
       [ 4.52845067e-01,  2.05068655e-01],
       [-6.70980443e-01,  4.50214755e-01],
       [ 8.59729311e-01,  7.39134488e-01],
       [-2.50482657e-01,  6.27415615e-02],
       [ 2.73700736e-01,  7.49120928e-02],
       [ 2.64878885e+00,  7.01608239e+00],
       [-6.83384173e-01,  4.67013928e-01],
       [ 2.76714338e+00,  7.65708250e+00],
       [ 2.43210385e+00,  5.91512915e+00],
       [-1.82525319e+00,  3.33154921e+00],
       [-2.58383219e+00,  6.67618881e+00],
       [-2.39533199e+00,  5.73761535e+00],
       [-2.89066905e+00,  8.35596753e+00],
       [-2.43334224e+00,  5.92115443e+00],
       [ 1.09804064e+00,  1.20569325e+00],
       [-2.57286811e+00,  6.61965031e+00],
       [-1.08614622e+00,  1.17971361e+00],
       [ 2.06925187e+00,  4.28180328e+00],
       [-2.86036839e+00,  8.18170730e+00],
       [ 1.88681090e+00,  3.56005536e+00],
       [-1.30887135e+00,  1.71314421e+00],
       [-2.29101103e+00,  5.24873156e+00],
```

```
[-1.18042299e+00  1.39339844e+00]
```

`X_poly` now contains the original feature of X plus the square of the feature:

```
print(X[0])
print(X[0]*X[0])
```

```
[2.72919168]
[7.44848725]
```

```
X_poly[0]
```

```
array([2.72919168, 7.44848725])
```

Fit the model to this extended training data:

```
lin_reg = LinearRegression(fit_intercept=True)
lin_reg.fit(X_poly, y)
lin_reg.coef_, lin_reg.intercept_
```

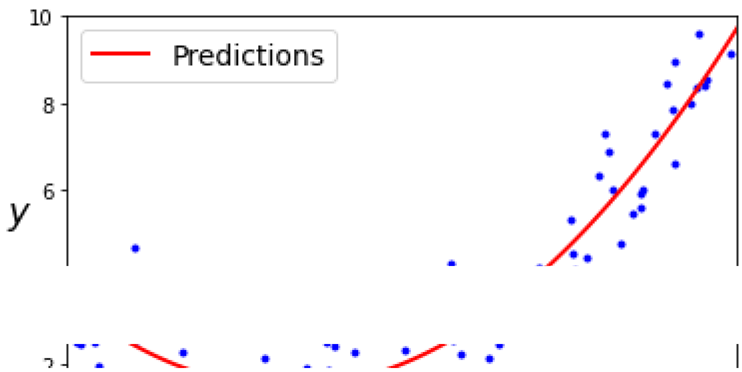
```
(array([[1.04271531, 0.50866711]]), array([2.01873554]))
```

The model estimates:

$$\hat{y} = 0.89X + 0.48X^2 + 2.09$$

Plot the data and the predictions:

```
X_new=np.linspace(-3, 3, 100).reshape(100, 1)
X_new_poly = poly_features.transform(X_new)
y_new = lin_reg.predict(X_new_poly)
plt.plot(X, y, "b.")
plt.plot(X_new, y_new, "r-", linewidth=2, label="Predictions")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper left", fontsize=14)
plt.axis([-3, 3, 0, 10]);
```



R square

R^2 es una medida estadística de qué tan cerca están los datos de la línea de regresión ajustada. También se conoce como el coeficiente de determinación o el coeficiente de determinación múltiple para la regresión múltiple. Para decirlo en un lenguaje más simple, R^2 es una medida de ajuste para los modelos de regresión lineal.

R^2 no indica si un modelo de regresión se ajusta adecuadamente a sus datos. Un buen modelo puede tener un valor R^2 bajo. Por otro lado, un modelo sesgado puede tener un valor alto de R^2.

SSres + SSreg = SStot, R^2 = Explained variation / Total Variation

Sum Squared Regression Error

$$R^2 = 1 - \frac{SS_{Regression}}{SS_{Total}}$$

Sum Squared Total Error

$$R^2 \equiv 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}} \equiv 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

$$R^2 = \frac{SS_{\mathrm{reg}}}{SS_{\mathrm{tot}}}$$

Ejercicio 1

Utiliza la base de datos de https://www.kaggle.com/vinicius150987/manufacturing-cost

Suponga que trabaja como consultor de una empresa de nueva creación que busca desarrollar un modelo para estimar el costo de los bienes vendidos a medida que varían el volumen de producción (número de unidades producidas). La startup recopiló datos y le pidió que desarrollara un modelo para predecir su costo frente a la cantidad de unidades vendidas.

```
import pandas as pd
df = pd.read_csv('https://raw.githubusercontent.com/marypazrf/bdd/main/EconomiesOfSca
df.sample(10)
```

	Number of Units	Manufacturing Cost
968	7.065653	27.804027
212	3.372115	41.127212
416	4.194513	43.832711
677	5.068888	41.225741
550	4.604122	37.569764
764	5.389522	31.191501
386	4.104190	42.988730
339	3.942214	46.291435
82	2.665856	48.578425
487	4.399514	37.567914

```
X = df[['Number of Units']]
y = df['Manufacturing Cost']
```

```
len(X)
```

```
1000
```

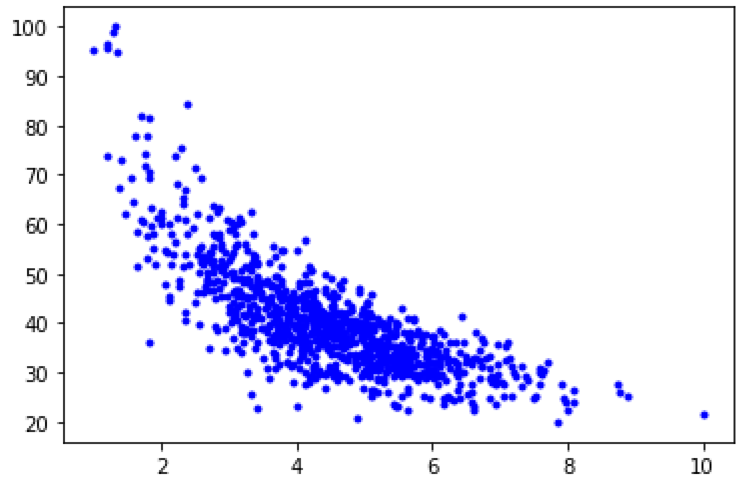
```
y.describe
```

```
<bound method NDFrame.describe of 0      95.066056
1      96.531750
2      73.661311
3      95.566843
4      98.777013
         ...
995    23.855067
996    27.536542
```

```
997    25.973787
998    25.138311
999    21.547777
Name: Manufacturing Cost, Length: 1000, dtype: float64>
```

```
plt.plot(X,y,'b.')
```

```
[<matplotlib.lines.Line2D at 0x7f72cce23110>]
```



```
#lineal
linear_reg = LinearRegression(fit_intercept=True)
linear_reg.fit(X,y)
```

```
LinearRegression()
```

```
linear_reg.coef_
```

```
array([-6.0333683])
```

```
linear_reg.intercept_
```

```
67.03904193389238
```

y' = -6.03X + 67.03

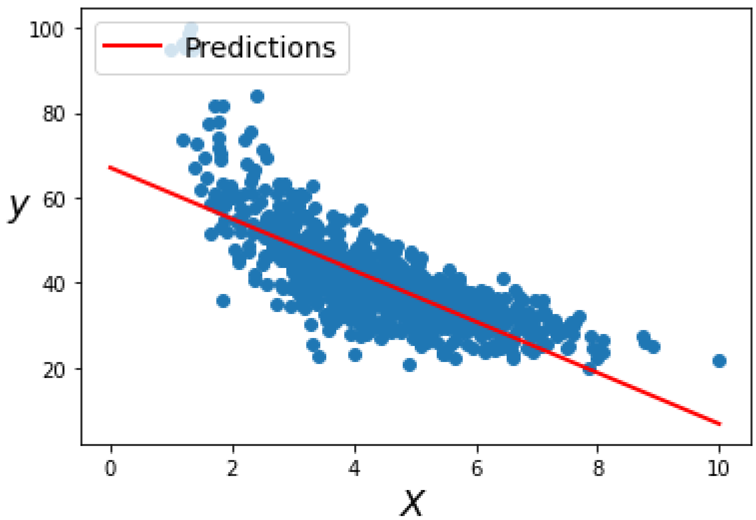
```
y_pred = linear_reg.predict(X)
```

```
from sklearn import metrics
from sklearn.metrics import r2_score

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y, y_pred)))
print('r2_score',r2_score(y, y_pred))
```

```
Error medio Absoluto (MAE): 4.921245677483368
Root Mean Squared Error: 6.871474273023592
r2_score 0.5789767558506287
```

```
X_fit = np.linspace(0, 10, 100)
y_fit = linear_reg.predict(X_fit[:, np.newaxis])

plt.scatter(X, y)
plt.plot(X_fit, y_fit, "r-", linewidth=2, label="Predictions")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper left", fontsize=14);
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does
  "X does not have valid feature names, but"
```




```
#polinomial
poly_transform = PolynomialFeatures(degree=2, include_bias = False)
polyX = poly_transform.fit_transform(X)

polyX
```

```
array([[  1.        ,   1.        ],
       [  1.18599365,   1.40658094],
       [  1.19149864,   1.41966901],
       ...,
       [  8.78088812,  77.10399623],
       [  8.89769971,  79.16906006],
       [ 10.        , 100.        ]])
```

```
poly_regression = LinearRegression(fit_intercept=True)
poly_regression.fit(polyX, y)
```

```
LinearRegression()
```

```
poly_regression.coef_
```

```
array([-16.82425278,   1.17336718])
```

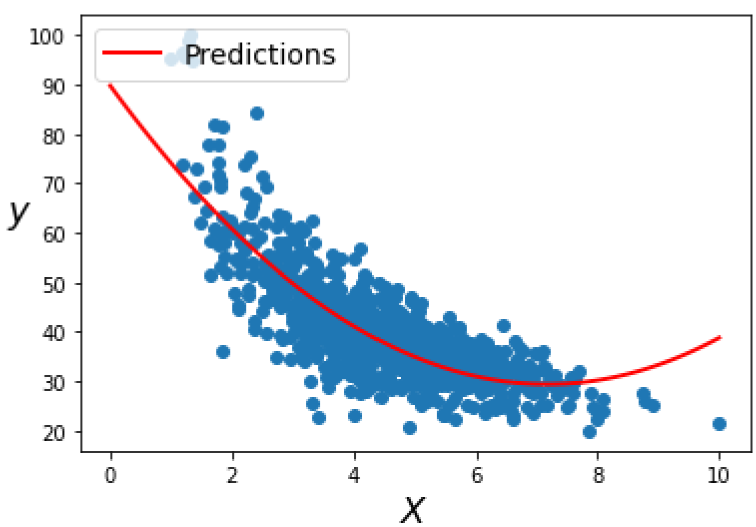
```
poly_regression.intercept_
```

```
89.73719677939121
```

y' = -16.82X + 1.17x^2 + 89.73

```
y_pred = poly_regression.predict(polyX)
```

```
X_fit = np.linspace(0, 10, 100).reshape(100,1)
polyX_fit = poly_transform.fit_transform(X_fit)
y_fit = poly_regression.predict(polyX_fit)

plt.scatter(X, y)
plt.plot(X_fit, y_fit, "r-", linewidth=2, label="Predictions")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper left", fontsize=14);
```




```
from sklearn import metrics
from sklearn.metrics import r2_score

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y, y_pred)))
print('r2_score',r2_score(y, y_pred))
```

```
Error medio Absoluto (MAE): 4.538765565228896
Root Mean Squared Error: 6.129173450227568
r2_score 0.6650268116056028
```

```
df = pd.read_csv('https://raw.githubusercontent.com/marypazrf/bdd/main/EconomiesOfSca
df.head()
```

	Number of Units	Manufacturing Cost
0	1.000000	95.066056
1	1.185994	96.531750
2	1.191499	73.661311
3	1.204771	95.566843
4	1.298773	98.777013

```
X = df[['Number of Units']]
y = df['Manufacturing Cost']
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
np.random.seed(42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

Lineal Regression

```
X_train.shape
```

```
(800, 1)
```

```
y_train.shape
```

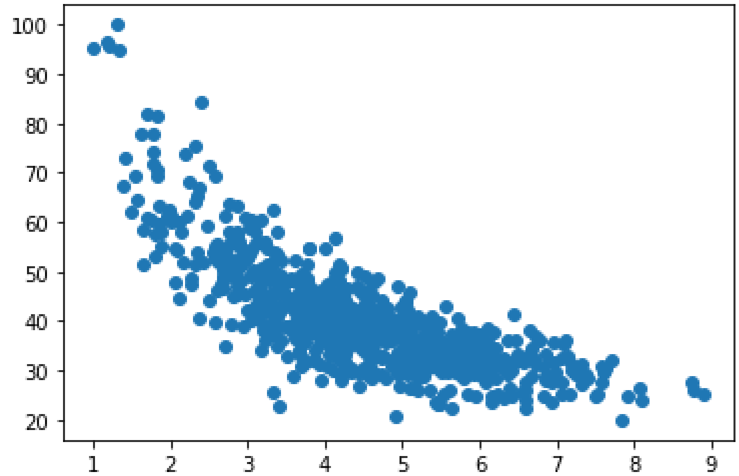
```
(800,)
```

```
y_test.shape
```

```
(200,)
```

```
plt.scatter(X_train, y_train)
```

```
<matplotlib.collections.PathCollection at 0x7f72ccd28a90>
```

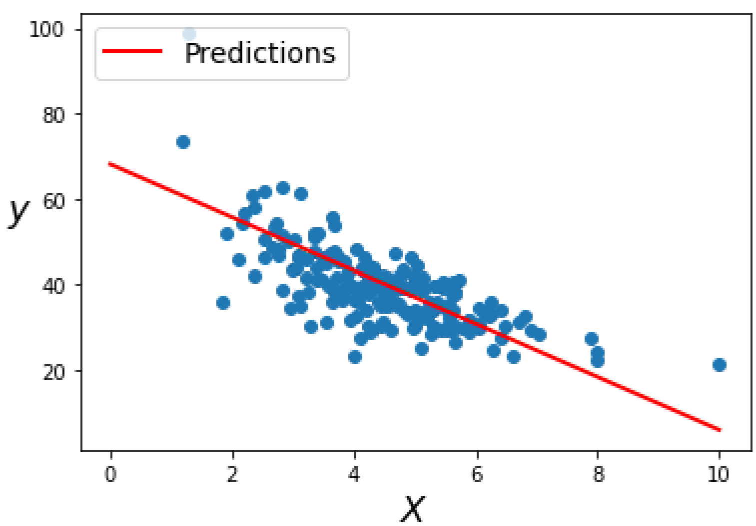



```
from sklearn.linear_model import LinearRegression

linear_reg = LinearRegression(fit_intercept=True)
linear_reg.fit(X_train, y_train)
```

```
LinearRegression()
```

```
X_fit = np.linspace(0, 10, 100)
y_fit = linear_reg.predict(X_fit[:, np.newaxis])

plt.scatter(X_test, y_test)
plt.plot(X_fit, y_fit, "r-", linewidth=2, label="Predictions")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper left", fontsize=14);
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does
  "X does not have valid feature names, but"
```




```
linear_reg.coef_
```

```
array([-6.22263745])
```

```
linear_reg.intercept_
```

```
68.08187672497846
```

```
y_pred = linear_reg.predict(X_train)
from sklearn import metrics
from sklearn.metrics import r2_score
linear_Mae_train=metrics.mean_absolute_error(y_train,y_pred)
linear_r2_train=r2_score(y_train,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_train, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_pred)
print('r2_score', r2_score(y_train, y_pred))
```

```
Error medio Absoluto (MAE): 4.983664639039784
Root Mean Squared Error: 6.930601695798021
r2_score 0.594243664202029
```

```
y_pred = linear_reg.predict(X_test)
from sklearn import metrics
from sklearn.metrics import r2_score
linear_Mae=metrics.mean_absolute_error(y_test,y_pred)
linear_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('r2_score', r2_score(y_test, y_pred))
```

```
Error medio Absoluto (MAE): 4.83324114398872
Root Mean Squared Error: 6.6682038827508405
r2_score 0.48439969577999376
```

Polynomical Regression

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

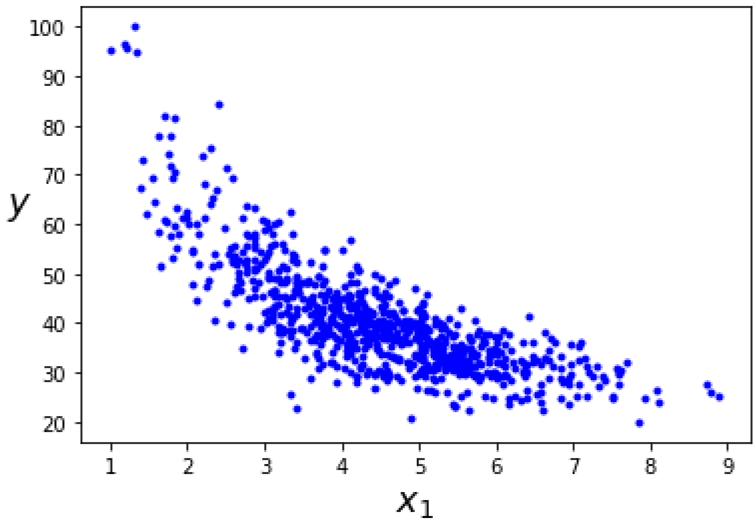
```
y_train.shape
```

```
(800,)
```

```
y_test.shape
```

```
(200,)
```

```
plt.plot(X_train, y_train, "b.")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.show()
```




```
from sklearn.preprocessing import PolynomialFeatures

poly_transform = PolynomialFeatures(degree=3, include_bias = False)
polyX = poly_transform.fit_transform(X_train)
polyX
```

```
array([[  5.65669179,  31.99816198, 181.00374013],
       [  5.53635996,  30.65128163, 169.69652839],
       [  2.25713058,   5.09463847,  11.49926431],
       ...,
       [  2.64655085,   7.00423138,  18.53705446],
       [  5.18000789,  26.83248172, 138.99246696],
       [  6.37652342,  40.66005096, 259.26976735]])
```

```
poly_regression = LinearRegression(fit_intercept=True)
poly_regression.fit(polyX, y_train)
```

```
LinearRegression()
```

```
poly_regression.coef_
```

```
array([-35.3746951 ,   5.28612952,  -0.28112892])
```

```
poly_regression.intercept_
```

```
115.22180379591046
```

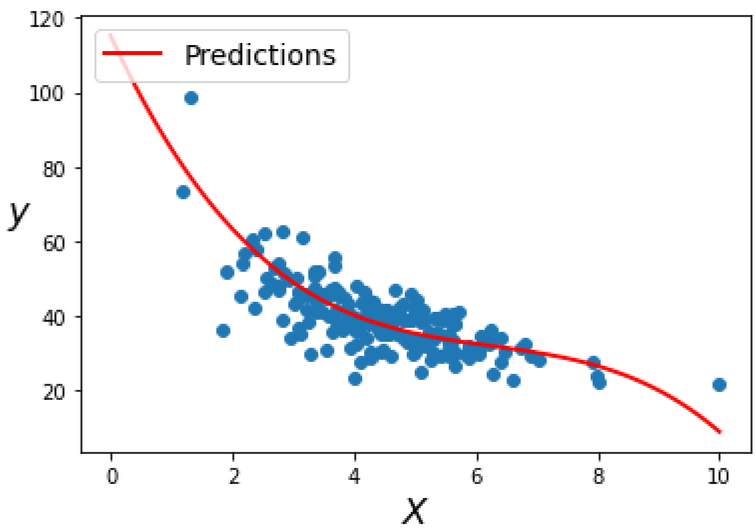
```
poly_transform = PolynomialFeatures(degree=3, include_bias = False)
polyX = poly_transform.fit_transform(X_train)
```

```
y_pred = poly_regression.predict(polyX)
```

```
from sklearn import metrics
from sklearn.metrics import r2_score
Poly_Mae_train=metrics.mean_absolute_error(y_train,y_pred)
Poly_r2_train=r2_score(y_train,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_train, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_pred)
print('r2_score',r2_score(y_train, y_pred ))
```

```
Error medio Absoluto (MAE): 4.462630935588183
Root Mean Squared Error: 5.858467673318268
r2_score 0.7100711021026239
```

```
X_fit = np.linspace(0, 10, 100).reshape(100,1)
polyX_fit = poly_transform.fit_transform(X_fit)

y_fit = poly_regression.predict(polyX_fit)

plt.scatter(X_test, y_test)
plt.plot(X_fit, y_fit, "r-", linewidth=2, label="Predictions")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper left", fontsize=14);
```




```
poly_transform = PolynomialFeatures(degree=3, include_bias = False)
polyX = poly_transform.fit_transform(X_test)
```

```
y_pred = poly_regression.predict(polyX)
```

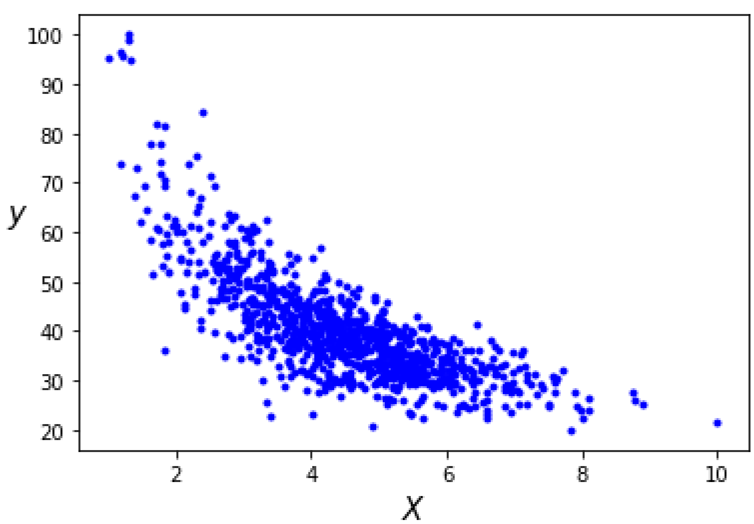
```
from sklearn import metrics
from sklearn.metrics import r2_score
Poly_Mae=metrics.mean_absolute_error(y_test,y_pred)
Poly_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('r2_score',r2_score(y_test, y_pred ))
```

```
Error medio Absoluto (MAE): 4.6058129615113925
Root Mean Squared Error: 6.209999522706177
r2_score 0.5528239263527293
```

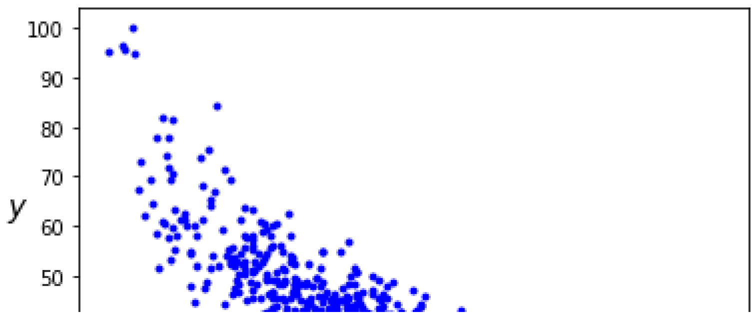
Ridge

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

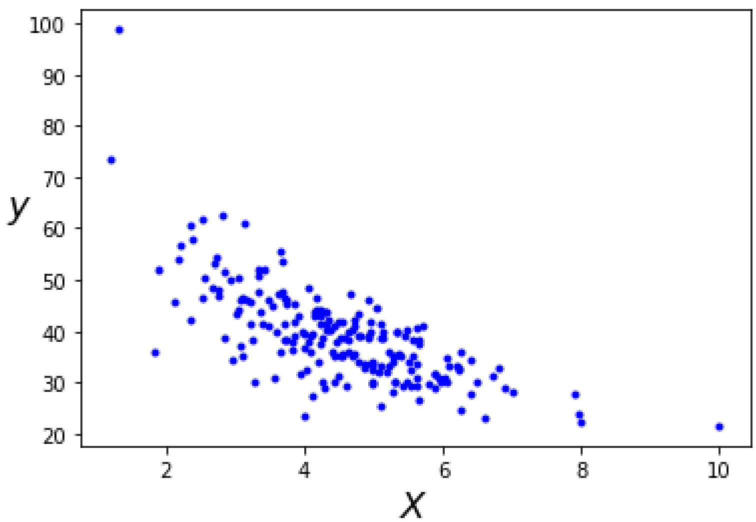
```
plt.plot(X, y,"b.")
plt.xlabel("$X$", fontsize=15)
plt.ylabel("$y$", rotation=0, fontsize=15);
```




```
plt.plot(X_train, y_train,"b.")
plt.xlabel("$X$", fontsize=15)
plt.ylabel("$y$", rotation=0, fontsize=15);
```



```
plt.plot(X_test, y_test,"b.")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18);
```



```
X_train2=X_train.to_numpy().reshape(-1,1)
```

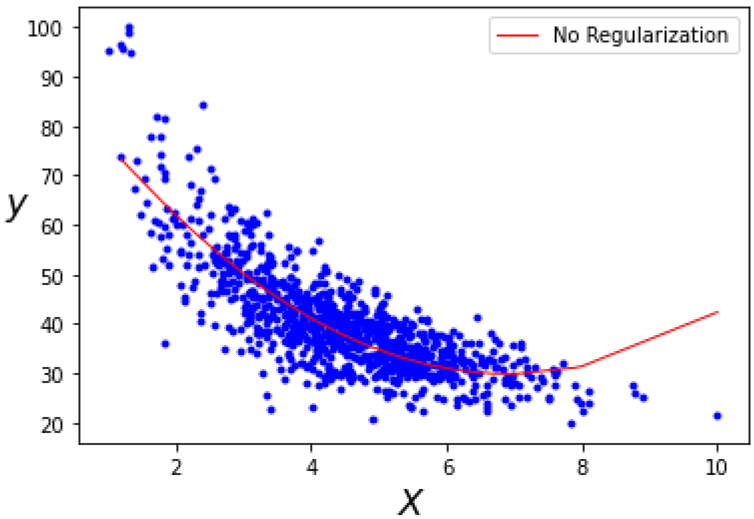
```
model = Pipeline([("poly_features", PolynomialFeatures(degree=2, include_bias=False))
                  ("scaler", StandardScaler()),
                  ("linear_reg", LinearRegression())])
model.fit(X_train, y_train)
```

```
Pipeline(steps=[('poly_features', PolynomialFeatures(include_bias=False)),
                ('scaler', StandardScaler()),
                ('linear_reg', LinearRegression())])
```

```
y_pred = model.predict(X_test)
```

```
order = np.argsort(X_test.values.ravel())
X_test2 = X_test.values.ravel()[order]
y_test2 = y_test.values[order]
y_pred2 = y_pred[order]
```

```
plt.plot(X, y, "b.")
plt.plot(X_test2, y_pred2, "r-", linewidth=1, label="No Regularization")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper right", fontsize=10);
```




```
from sklearn.linear_model import Ridge

model_ridge = Pipeline([("poly_features", PolynomialFeatures(degree=4, include_bias=F
                  ("scaler", StandardScaler()),
                  ("ridge", Ridge(alpha=1, solver = 'cholesky', random_state = 42,max
model_ridge.fit(X_train, y_train)
```

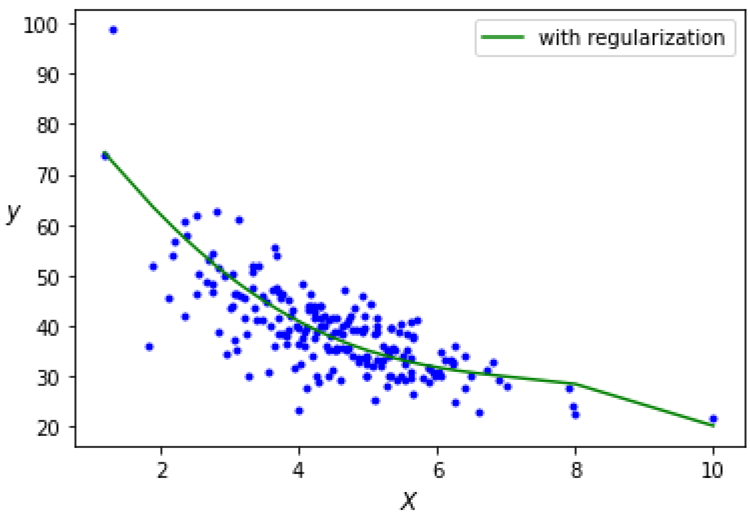
```
Pipeline(steps=[('poly_features',
                 PolynomialFeatures(degree=4, include_bias=False)),
                ('scaler', StandardScaler()),
                ('ridge',
                 Ridge(alpha=1, max_iter=1000, random_state=42,
                       solver='cholesky'))])
```

```
y_pred = model_ridge.predict(X_train)
Ridge_Mae_train=metrics.mean_absolute_error(y_train,y_pred)
Ridge_r2_train=r2_score(y_train,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_train, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_pred)
print('r2_score', r2_score(y_train, y_pred))
```

```
Error medio Absoluto (MAE): 4.453130806314608
Root Mean Squared Error: 5.948178018959322
r2_score 0.7011237920037103
```

```
y_pred = model_ridge.predict(X_test)

order = np.argsort(X_test.values.ravel())
```

```
X_test2 = X_test.values.ravel()[order]
y_test2 = y_test.values[order]
y_pred2 = y_pred[order]


plt.plot(X_test, y_test, "b.")
plt.plot(X_test2, y_pred2, "g-",label="with regularization")
plt.xlabel("$X$", fontsize=12)
plt.ylabel("$y$", rotation=0, fontsize=12)
plt.legend(loc="upper right", fontsize=10);
```




```
X_test=X_test.to_numpy().reshape(-1,1)
y_pred = model.predict(X_test)
from sklearn import metrics
from sklearn.metrics import r2_score
Ridge_Mae=metrics.mean_absolute_error(y_test,y_pred)
Ridge_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('r2_score',r2_score(y_test, y_pred ))
```

```
Error medio Absoluto (MAE): 4.762293483795133
Root Mean Squared Error: 6.513768934466413
r2_score 0.508005642552175
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does
  "X does not have valid feature names, but"
```

lasso

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

```
from sklearn.linear_model import Lasso
```

```
model_lasso = Pipeline([("poly_features", PolynomialFeatures(degree=15, include_bias=
                        ("scaler", StandardScaler()),
                        ("lasso", Lasso(alpha = .9,random_state = 10,tol=0.1,max_iter
model_lasso.fit(X_train, y_train)
```

```
Pipeline(steps=[('poly_features',
                 PolynomialFeatures(degree=15, include_bias=False)),
                ('scaler', StandardScaler()),
                ('lasso', Lasso(alpha=0.9, random_state=10, tol=0.1))])
```

```
y_pred = model_lasso.predict(X_train)
```

```
Lasso_MAE_train=metrics.mean_absolute_error(y_train,y_pred)
Lasso_r2_train=r2_score(y_train,y_pred)
```

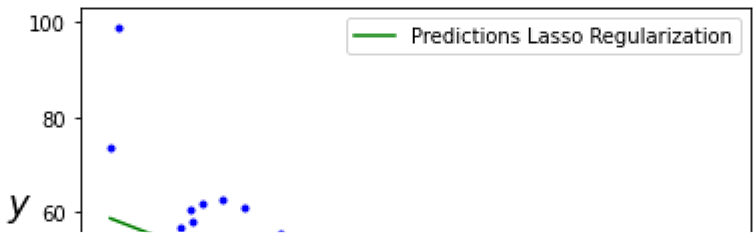
```
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_train, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_pred)
print('r2_score',r2_score(y_train, y_pred ))
```

```
Error medio Absoluto (MAE): 4.8969775859486955
Root Mean Squared Error: 6.935898287947112
r2_score 0.5936232427341488
```

```
y_pred = model_lasso.predict(X_test)
```

```
order = np.argsort(X_test.values.ravel())
X_test2 = X_test.values.ravel()[order]
y_test2 = y_test.values[order]
y_pred2 = y_pred[order]
```

```
plt.plot(X_test, y_test, "b.")
plt.plot(X_test2, y_pred2, "g-",label="Predictions Lasso Regularization")
plt.xlabel("$X$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper right", fontsize=10);
```




```
y_pred = model_lasso.predict(X_test)
from sklearn import metrics
from sklearn.metrics import r2_score
Lasso_MAE=metrics.mean_absolute_error(y_test,y_pred)
Lasso_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
print('r2_score',r2_score(y_test, y_pred ))
```

```
Error medio Absoluto (MAE): 4.646351122634725
Root Mean Squared Error: 6.486538755327113
r2_score 0.51211051393966
```

MAE

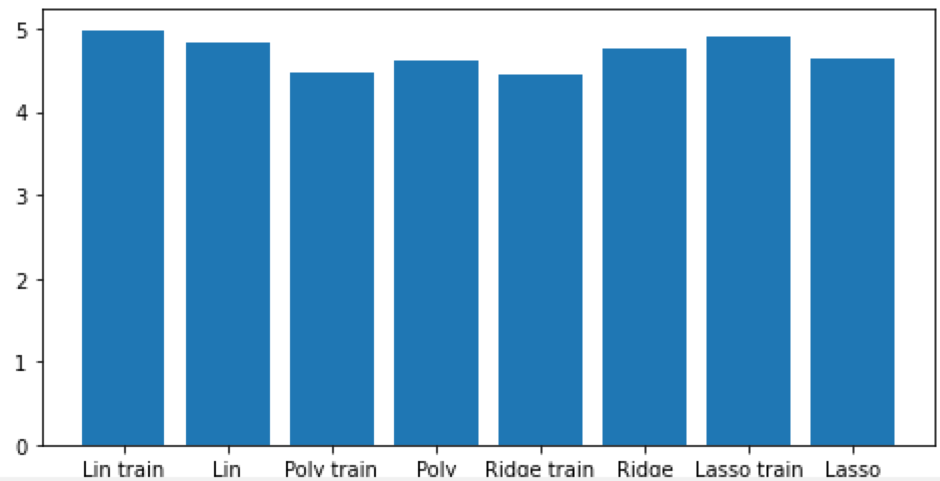
```
def diagramas(metricas):
    sumt=list()
    diagrama=metricas
    sumt.append(diagrama)
    return sumt
```

```
Metricas = list()
Metricas.append('Lin train')
Metricas.append('Lin')
Metricas.append('Poly train')
Metricas.append('Poly')
Metricas.append('Ridge train')
Metricas.append('Ridge')
Metricas.append('Lasso train')
Metricas.append('Lasso')
```

```
MAE_list = list()
MAE_list.append(linear_Mae_train)
MAE_list.append(linear_Mae)
MAE_list.append(Poly_Mae_train)
MAE_list.append(Poly_Mae)
MAE_list.append(Ridge_Mae_train)
MAE_list.append(Ridge_Mae)
MAE_list.append(Lasso_MAE_train)
MAE_list.append(Lasso_MAE)
```

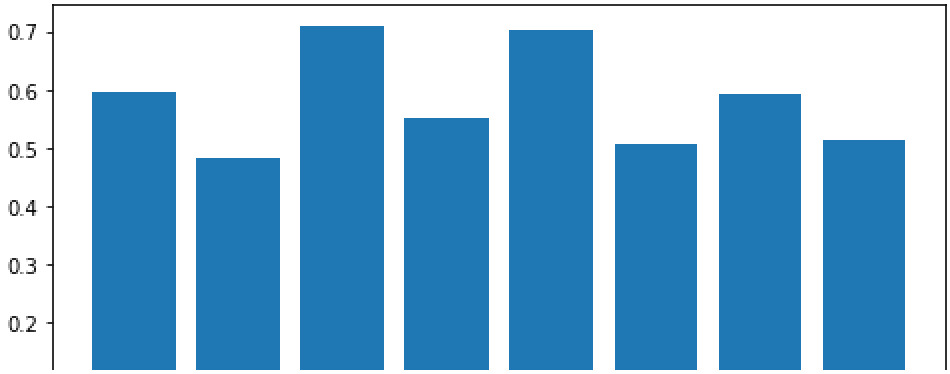
```
fig, ax = plt.subplots(figsize =(8, 4))
print("MAE")
print(MAE_list)
Metricas=list(Metricas)
plt.bar(Metricas,MAE_list)


plt.show()
```

```
MAE
[4.983664639039784, 4.83324114398872, 4.462630935588183, 4.6058129615113925, 4.4
```




```
R2_list = list()
R2_list.append(linear_r2_train)
R2_list.append(linear_r2)
R2_list.append(Poly_r2_train)
R2_list.append(Poly_r2)
R2_list.append(Ridge_r2_train)
R2_list.append(Ridge_r2)
R2_list.append(Lasso_r2_train)
R2_list.append(Lasso_r2)


fig, ax = plt.subplots(figsize =(8, 4))
print("r2")
print(R2_list)
R2=list(R2_list)
plt.bar(Metricas,R2_list)


plt.show()
```

```
r2
[0.594243664202029, 0.48439969577999376, 0.7100711021026239, 0.5528239263527293,
```



Conclusiones del ejercicio 1

La regression lineal no fue buena para los datos que se tienen. Mostro mejor comportamiento el modelo polinomial.

Para la empresa convendria usar el modelo MAE pero se requiere hacer mas pruebas.

Ejercicio 2

Realiza la regresión polinomial de los siguientes datos:

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.metrics import r2_score
import numpy as np
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
np.random.seed(42)
df = pd.read_csv('https://raw.githubusercontent.com/marypazrf/bdd/main/kc_house_data.
df.sample(10)
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqf
735	2591820310	20141006T000000	365000.0	4	2.25	2070	
2830	7974200820	20140821T000000	865000.0	5	3.00	2900	
4106	7701450110	20140815T000000	1038000.0	4	2.50	3770	
16218	9522300010	20150331T000000	1490000.0	3	3.50	4560	
19964	9510861140	20140714T000000	711000.0	3	2.50	2550	
1227	1761300310	20140827T000000	211000.0	4	2.00	1710	
18849	7732410120	20140819T000000	790000.0	4	2.50	2690	
19369	7010701383	20141017T000000	680000.0	3	2.50	1800	
20164	291310170	20140804T000000	384500.0	3	2.50	1600	
7139	4232901990	20140516T000000	605000.0	2	1.00	910	

10 rows × 21 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21613 non-null  int64  
 1   date           21613 non-null  object 
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64  
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64  
 6   sqft_lot       21613 non-null  int64  
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64  
 9   view           21613 non-null  int64  
 10  condition      21613 non-null  int64  
 11  grade          21613 non-null  int64  
 12  sqft_above     21613 non-null  int64  
 13  sqft_basement  21613 non-null  int64  
 14  yr_built       21613 non-null  int64  
 15  yr_renovated   21613 non-null  int64  
 16  zipcode        21613 non-null  int64  
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64  
 20  sqft_lot15     21613 non-null  int64  
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

```
df.describe()
```

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.161300e+04	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04
mean	4.580302e+09	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04
std	2.876566e+09	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04
min	1.000102e+06	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02
25%	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06

```
df.drop('id', axis = 1, inplace = True)
df.drop('date', axis = 1, inplace = True)
df.drop('zipcode', axis = 1, inplace = True)
df.drop('lat', axis = 1, inplace = True)
df.drop('long', axis = 1, inplace = True)
```

```
plt.figure(figsize=(12,8))
sns.heatmap(df.corr(), annot=True, cmap='Dark2_r', linewidths = 2)
plt.show()
```


```
columns = df.columns.drop('price')

features = columns
label = ['price']

X = df[features]
y = df[label]
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.1, random_sta

print(f'Numero total de registros en la bdd: {len(X)}')
print("*****"*10)
print(f'Numero total de registros en el training set: {len(X_train)}')
print(f'Tamaño de X_train: {X_train.shape}')
print("*****"*10)
print(f'Mumero total de registros en el test dataset: {len(X_test)}')
print(f'Tamaño del X_test: {X_test.shape}')
```

```
Numero total de registros en la bdd: 21613
**************************************************
Numero total de registros en el training set: 19451
Tamaño de X_train: (19451, 15)
**************************************************
Mumero total de registros en el test dataset: 2162
Tamaño del X_test: (2162, 15)
```

```
#tu codigo aquí


plt.plot(X_train,y_train,'b.')
plt.show()
```


```
linear_reg = LinearRegression(fit_intercept=True)
linear_reg.fit(X_train, y_train)
```

```
LinearRegression()
```

```
linear_reg.coef_,
```

```
(array([[-3.82008048e+04,  4.14661380e+04,  1.07992584e+02,
          1.71356997e-02,  3.16916913e+04,  5.52691023e+05,
          4.12493228e+04,  2.12221443e+04,  1.19493216e+05,
          4.77750271e+01,  6.02175565e+01, -3.55090216e+03,
          1.32602215e+01,  2.90059284e+01, -5.48132603e-01]]),)
```

```
linear_reg.intercept_
```

```
array([6151359.2627409])
```

```
y_pred = linear_reg.predict(X_train)
from sklearn import metrics
from sklearn.metrics import r2_score
linear_Mae_train=metrics.mean_absolute_error(y_train,y_pred)
linear_r2_train=r2_score(y_train,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_train, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_pred)
print('r2_score', r2_score(y_train, y_pred))
```

```
Error medio Absoluto (MAE): 139269.32939115583
Root Mean Squared Error: 214234.8822754647
r2_score 0.6529196653133833
```

```
y_pred = linear_reg.predict(X_test)
from sklearn import metrics
from sklearn.metrics import r2_score
linear_Mae=metrics.mean_absolute_error(y_test,y_pred)
linear_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('r2_score', r2_score(y_test, y_pred))
```

```
Error medio Absoluto (MAE): 137480.1388273178
Root Mean Squared Error: 232133.3676240749
r2_score 0.6579723205007814
```

```
from sklearn.preprocessing import PolynomialFeatures

poly_transform = PolynomialFeatures(degree=3, include_bias = False)
polyX = poly_transform.fit_transform(X_train)
polyX
```

```
array([[5.00000000e+00, 2.75000000e+00, 3.75000000e+03, ...,
        7.06230720e+10, 1.64221278e+11, 3.81867106e+11],
       [4.00000000e+00, 4.50000000e+00, 5.25000000e+03, ...,
        3.02200000e+11, 5.84478976e+12, 1.13042910e+14],
       [3.00000000e+00, 2.50000000e+00, 2.88000000e+03, ...,
        9.21194624e+10, 3.27210820e+11, 1.16226168e+12],
       ...,
       [3.00000000e+00, 2.25000000e+00, 1.78000000e+03, ...,
        1.73857625e+10, 8.77923438e+10, 4.43322266e+11],
       [2.00000000e+00, 1.00000000e+00, 1.15000000e+03, ...,
        9.24639408e+09, 2.73030912e+10, 8.06215680e+10],
       [3.00000000e+00, 1.00000000e+00, 1.45000000e+03, ...,
        8.37158400e+09, 6.23039040e+10, 4.63684824e+11]])
```

```
poly_regression = LinearRegression(fit_intercept=True)
poly_regression.fit(polyX, y_train)
poly_regression.intercept_
```

```
array([19759145.24258333])
```

```
poly_regression.coef_
```

```
array([[ 3.17395792e+02, -2.70130239e+02,  1.30610945e+01,
        -1.40757708e+01,  2.62496809e+00,  3.24633595e+00,
        -8.08938960e-01,  3.60826046e-01, -6.17577143e-01,
         1.54124566e-01,  9.07922470e-01, -2.42302232e-01,
         1.57944629e-01, -4.12303248e-01, -1.89494993e+01,
         2.57497810e-01,  3.31180922e-01,  2.56156276e+01,
        -9.51793255e-02, -6.36531339e-01,  6.24165339e-01,
        -6.14143248e-02,  9.57006257e-01,  1.21507890e+00,
         1.85183285e+01,  7.24785462e+00,  3.94289500e+02,
         4.24069045e+00,  5.07845227e+00, -1.89095034e+01,
        -4.03258004e-01, -2.08156624e+02, -6.15751437e+01,
        -4.82898236e-01, -6.40532068e-02, -8.73845428e-02,
        -1.73829295e-01, -5.97615346e-01, -1.69018199e+02,
        -3.91260224e+01, -1.76779529e+02, -4.47565136e+00,
        -1.70541213e+02,  1.09037853e+02, -3.48181375e-01,
         5.54961266e-03, -3.10542727e+02, -2.04577118e+01,
        -5.10909707e+01,  1.44081886e+02,  1.11581166e+02,
         2.16670060e-01, -5.64909219e-01, -1.27410167e-01,
        -1.12568260e-01,  1.58018890e+00, -3.54328039e-02,
         4.38742488e-05,  6.16058584e+01, -2.69898947e+01,
         1.91781121e+01,  1.20426825e+01,  1.31650265e+01,
         9.34375304e-03, -3.73525411e-03, -1.04398912e-01,
         1.38884709e-02,  3.01381870e-02,  6.78520767e-05,
        -5.34102837e-01, -5.78470986e-02, -1.13822284e-01,
```

```
       -4.03570695e-01, -1.05966620e+00, -2.67524020e+02,
       -4.30187377e+01, -2.93222557e+02, -3.35793147e+00,
       -2.91958127e+02, -9.76415380e+01, -1.57122761e-02,
       -1.68119414e-01, -1.13491517e-01, -1.64619588e-01,
       -1.74203932e+01, -3.03731175e+00, -1.52993218e+01,
        2.89521925e-01, -1.93075606e+01, -1.08573905e+02,
       -1.08424368e-01, -7.86651310e-02, -1.31888702e-01,
       -4.03527763e+01, -1.07382336e+01, -4.51049163e+01,
       -3.19195216e+00, -5.69571664e+01, -2.42072671e+01,
        5.39400863e-01,  6.90456940e-01,  1.18106862e+02,
        2.59750399e+01,  1.42884610e+02, -1.84020119e+00,
        1.37140757e+02,  4.79912276e+00,  7.61197307e-01,
        8.82755148e+01,  2.33056421e+01,  9.42517326e+01,
        7.84046146e-01,  9.95172836e+01, -1.51103170e+01,
       -2.02758252e+00,  2.24427261e+00,  9.40121740e-01,
       -1.85322322e+00,  1.45017708e+00, -1.97077053e-03,
       -2.80914700e+00, -1.06751495e+00,  1.74066651e+00,
        1.30002356e-01, -3.34363391e-02, -1.65748055e+01,
        4.33882740e+01,  1.57874743e+00,  2.34932788e-02,
       -4.25386312e+01, -4.37936627e-01,  8.20919268e-02,
       -1.48254749e+00,  6.97841641e-03,  3.89241075e-04,
        1.29106646e+02, -7.16509286e-01,  4.15395793e+00,
        2.29637081e-01,  4.75102521e-01, -7.01819595e-01,
       -1.06920772e+00,  7.56507260e+00,  2.69567648e+00,
       -4.22023433e+00,  8.37419219e+00, -6.85156850e+00,
        3.79756814e+00,  3.61539631e-01,  1.60344901e-02,
       -1.34799509e+00,  2.13243059e+00, -6.39846626e-01,
       -1.28598317e+00, -1.03087982e-01,  1.41973419e-01,
        4.08102711e-01, -1.10957527e-01, -8.95127159e+00,
        1.10837021e+01, -2.37618609e+01, -1.72495794e+01,
        3.64892153e+01,  5.39841200e-01, -5.29031580e-03,
        5.17471543e-06, -1.82434474e+01,  2.48592345e+01,
        9.70652876e+00, -2.58285326e+00, -1.18894778e+00,
        1.25486887e-02, -1.78456991e-02,  1.38371287e-02,
```

```
polyX = poly_transform.fit_transform(X_train)

y_pred = poly_regression.predict(polyX)
from sklearn import metrics
from sklearn.metrics import r2_score
Poly_Mae_train=metrics.mean_absolute_error(y_train,y_pred)
Poly_r2_train=r2_score(y_train,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_train, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_pred)
print('r2_score',r2_score(y_train, y_pred ))
```

```
Error medio Absoluto (MAE): 120111.24464567527
Root Mean Squared Error: 174164.006294397
r2_score 0.7706142422681812
```

```
polyX = poly_transform.fit_transform(X_test)

y_pred = poly_regression.predict(polyX)
```

```
from sklearn import metrics
from sklearn.metrics import r2_score
Poly_Mae=metrics.mean_absolute_error(y_test,y_pred)
Poly_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('r2_score',r2_score(y_test, y_pred ))
```

```
Error medio Absoluto (MAE): 127640.87573988685
Root Mean Squared Error: 212376.50824233124
r2_score 0.7137146909613681
```

ridge

```
X_train2=X_train.to_numpy().reshape(-1,1)
```

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
model = Pipeline([("poly_features", PolynomialFeatures(degree=2, include_bias=False))
                  ("scaler", StandardScaler()),
                  ("linear_reg", LinearRegression())])
model.fit(X_train, y_train)
```

```
Pipeline(steps=[('poly_features', PolynomialFeatures(include_bias=False)),
                ('scaler', StandardScaler()),
                ('linear_reg', LinearRegression())])
```

```
from sklearn import metrics
from sklearn.metrics import r2_score
Ridge_Mae=metrics.mean_absolute_error(y_test,y_pred)
Ridge_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('r2_score',r2_score(y_test, y_pred ))
```

```
Error medio Absoluto (MAE): 127640.87573988685
Root Mean Squared Error: 212376.50824233124
r2_score 0.7137146909613681
```

lasso

```
from sklearn.linear_model import Lasso
```

```
model_lasso = Pipeline([("poly_features", PolynomialFeatures(degree=5, include_bias=F
                        ("scaler", StandardScaler()),
                        ("lasso", Lasso(alpha = 1, random_state = 42,tol=0.1,max_iter
```

```
model_lasso.fit(X_train, y_train)
```

```
Pipeline(steps=[('poly_features',
                 PolynomialFeatures(degree=5, include_bias=False)),
                ('scaler', StandardScaler()),
                ('lasso', Lasso(alpha=1, random_state=42, tol=0.1))])
```

```
y_pred = model_lasso.predict(X_train)
from sklearn import metrics
from sklearn.metrics import r2_score

Lasso_MAE_train = metrics.mean_absolute_error(y_train, y_pred)
Lasso_r2_train= r2_score(y_train, y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_train, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_pred)
print('r2_score', r2_score(y_train, y_pred))
```

```
Error medio Absoluto (MAE): 113884.60002386104
Root Mean Squared Error: 162623.202988018
r2_score 0.8000070629856829
```

```
y_pred = model_lasso.predict(X_test)
```

```
from sklearn import metrics
from sklearn.metrics import r2_score
Lasso_MAE=metrics.mean_absolute_error(y_test,y_pred)
Lasso_r2=r2_score(y_test,y_pred)
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('r2_score',r2_score(y_test, y_pred ))
```

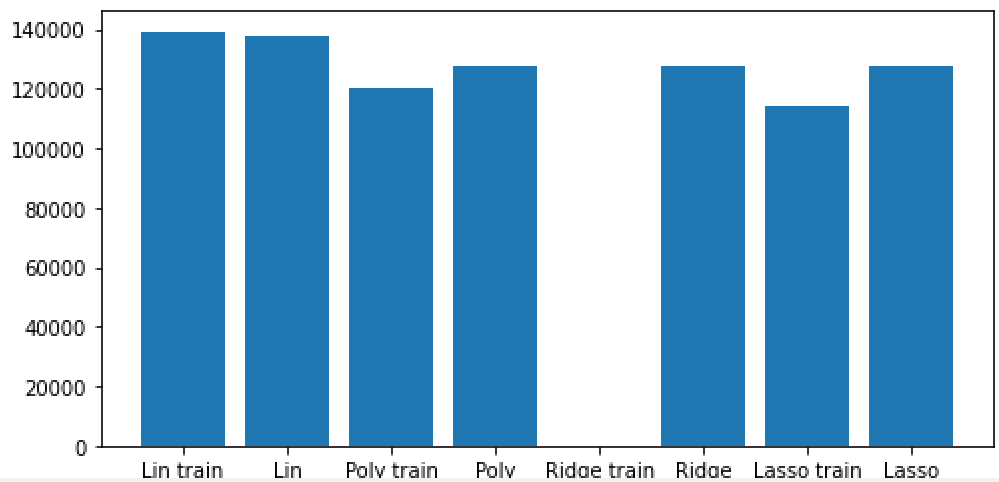
```
Error medio Absoluto (MAE): 127385.85985379248
Root Mean Squared Error: 254950.23977556612
r2_score 0.5874306511507208
```

```
Metricas = list()
Metricas.append('Lin train')
Metricas.append('Lin')
Metricas.append('Poly train')
Metricas.append('Poly')
Metricas.append('Ridge train')
Metricas.append('Ridge')
```

```
Metricas.append('Lasso train')
Metricas.append('Lasso')
```

```
MAE_list = list()
MAE_list.append(linear_Mae_train)
MAE_list.append(linear_Mae)
MAE_list.append(Poly_Mae_train)
MAE_list.append(Poly_Mae)
MAE_list.append(Ridge_Mae_train)
MAE_list.append(Ridge_Mae)
MAE_list.append(Lasso_MAE_train)
MAE_list.append(Lasso_MAE)


fig, ax = plt.subplots(figsize =(8, 4))
print("MAE")
print(MAE_list)
Metricas=list(Metricas)
MAE=list(MAE_list)
plt.bar(Metricas,MAE_list)


plt.show()
```

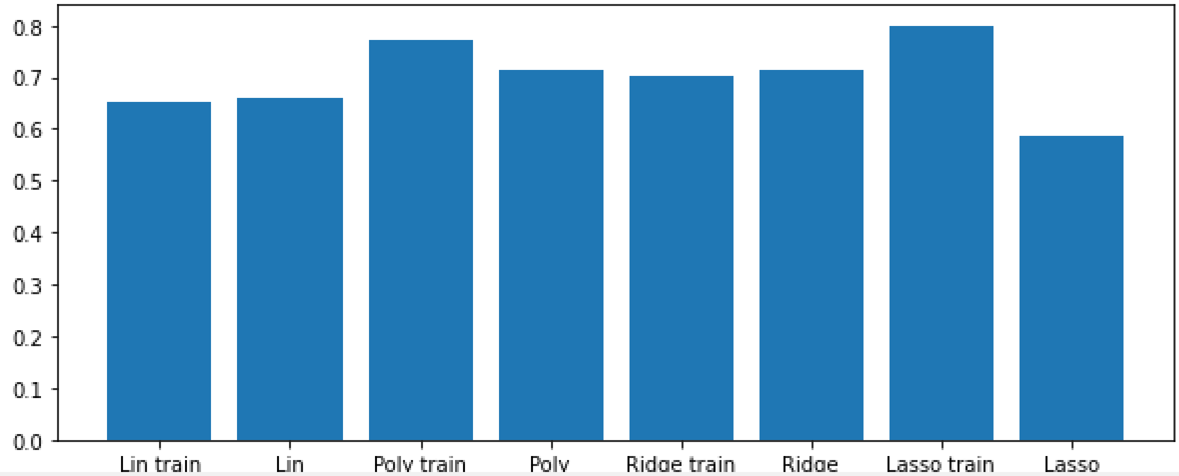
```
MAE
[139269.32939115583, 137480.1388273178, 120111.24464567527, 127640.87573988685,
```




```
R2_list = list()
R2_list.append(linear_r2_train)
R2_list.append(linear_r2)
R2_list.append(Poly_r2_train)
R2_list.append(Poly_r2)
R2_list.append(Ridge_r2_train)
R2_list.append(Ridge_r2)
R2_list.append(Lasso_r2_train)
R2_list.append(Lasso_r2)
fig, ax = plt.subplots(figsize=(10, 4))
print("r2")
print(R2_list)
```

```
plt.bar(Metricas, R2_list)
plt.show()
```

```
r2
[0.6529196653133833, 0.6579723205007814, 0.7706142422681812, 0.7137146909613681,
```



Conclusiones

El comportamiento de Ridge es mas estable en cuanto a sus resultados. Pudiera ser una buena opcion. Dentro de todos los modelos, se vio que tuve mejor desempeno y fue el mas estable.