Aprendizado Supervisionado

Classificação & Regressão

1 - Carregando bibliotecas

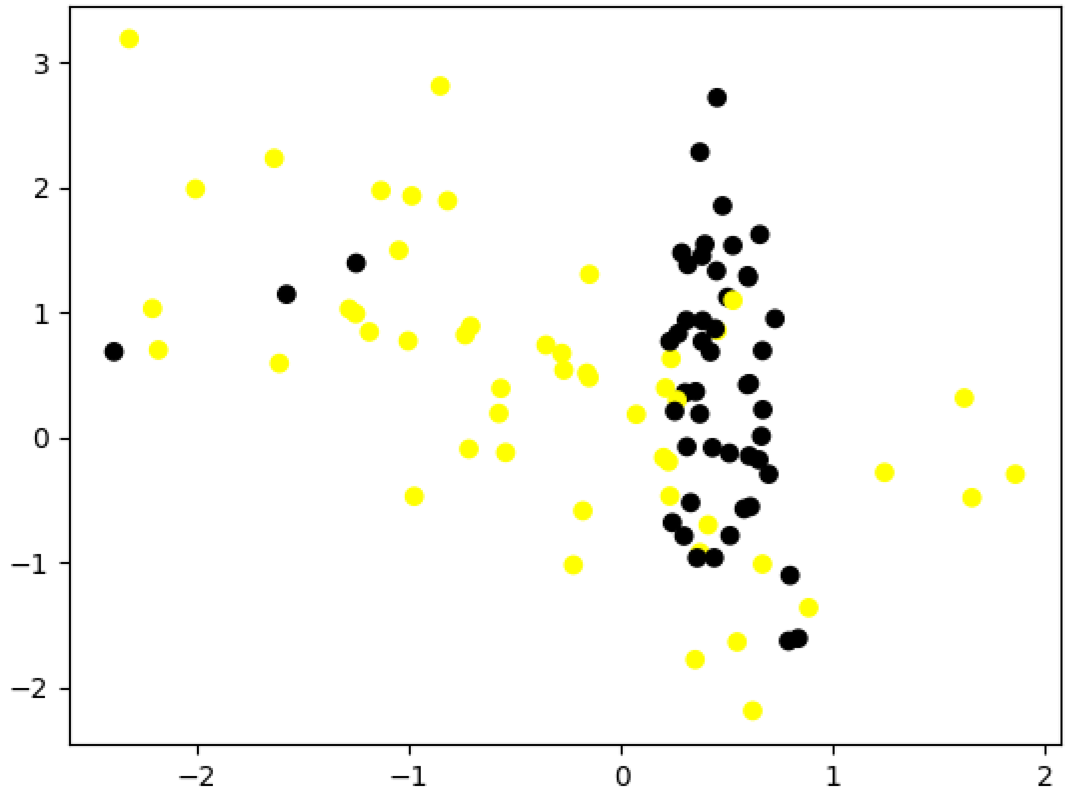
In [1]:

```
%matplotlib notebook
import numpy as np
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt


from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import neighbors

from matplotlib.colors import ListedColormap

cmap_light = ListedColormap(['#FFFFAA', '#AAFFAA', '#AAAAFF','#EFEFEF'])
cmap_bold  = ListedColormap(['#FFFF00', '#00FF00', '#0000FF','#000000'])
```

2 - Conjunto de dados sintético para classificação binária

In [2]:

```
from sklearn.datasets import make_classification

plt.figure()

X_C2, y_C2 = make_classification(n_samples = 100, n_features=2,
                                n_redundant=0, n_informative=2,
                                n_clusters_per_class=1, flip_y = 0.2,
                                class_sep = 0.5, random_state=0)

plt.scatter(X_C2[:, 0], X_C2[:, 1], c=y_C2, marker='o', cmap=cmap_bold)

plt.show()
```

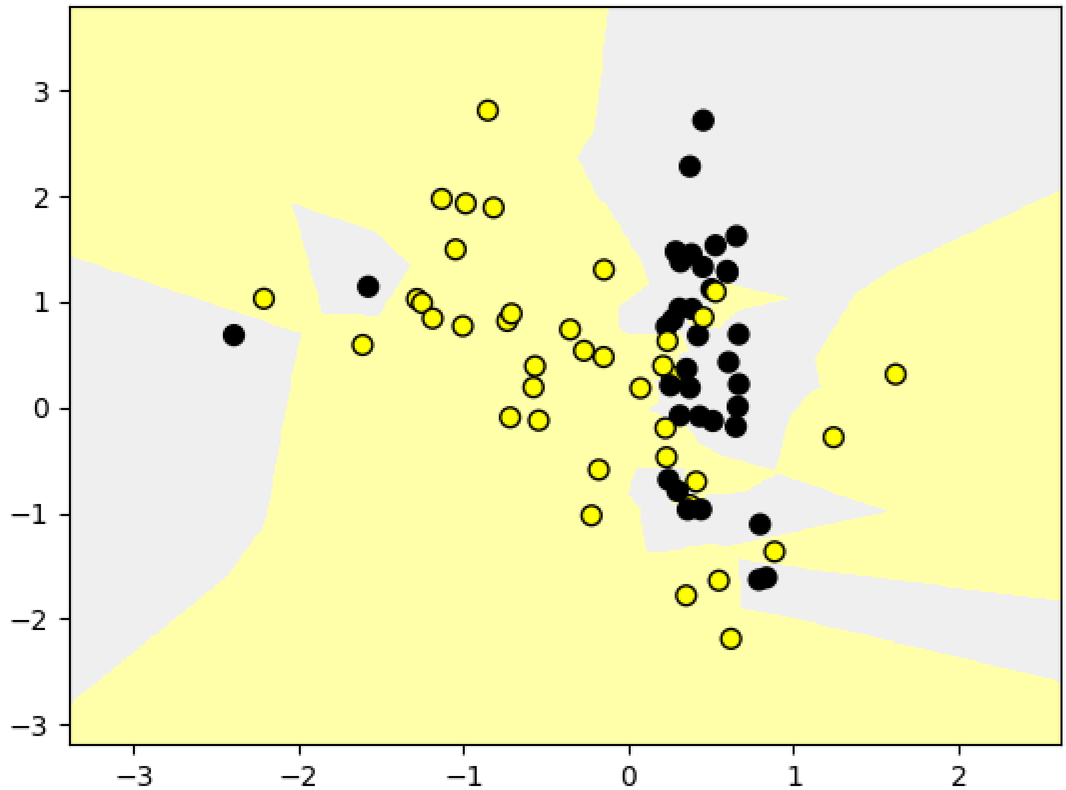


3 - KNN binário

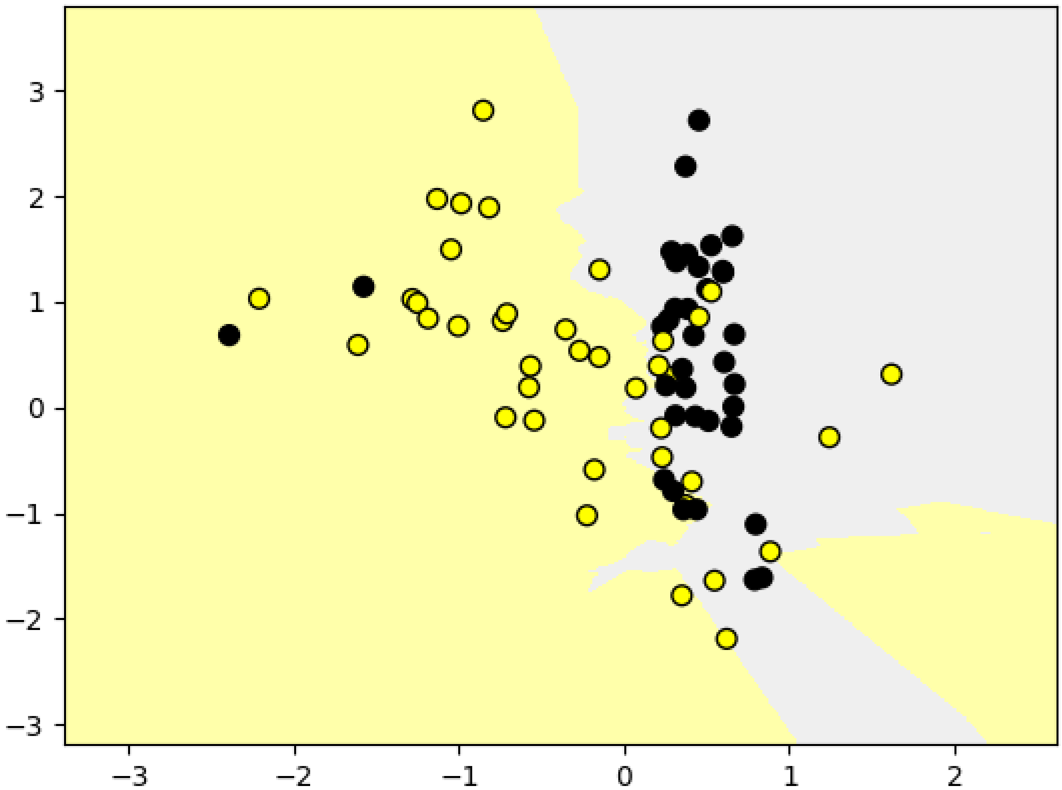
In [3]:

```
def plot_two_class_knn(X, y, n_neighbors, X_test, y_test):
    X_mat = X
    y_mat = y

    clf = neighbors.KNeighborsClassifier(n_neighbors)
    clf.fit(X_mat, y_mat)

    mesh_step_size = .01

    x_min, x_max = X_mat[:, 0].min() - 1, X_mat[:, 0].max() + 1
    y_min, y_max = X_mat[:, 1].min() - 1, X_mat[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, mesh_step_size),
                         np.arange(y_min, y_max, mesh_step_size))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

    Z = Z.reshape(xx.shape)
    plt.figure()
    plt.pcolormesh(xx, yy, Z, cmap=cmap_light)

    plt.scatter(X_mat[:, 0], X_mat[:, 1], s=50, c=y, cmap=cmap_bold, edgecolor = 'black')
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())

    print('Escore treinamento:', clf.score(X_mat, y_mat))
    print('Escore teste:',clf.score(X_test, y_test))


    plt.show()

X_train, X_test, y_train, y_test = train_test_split(X_C2, y_C2,
                                                    random_state=0)
```

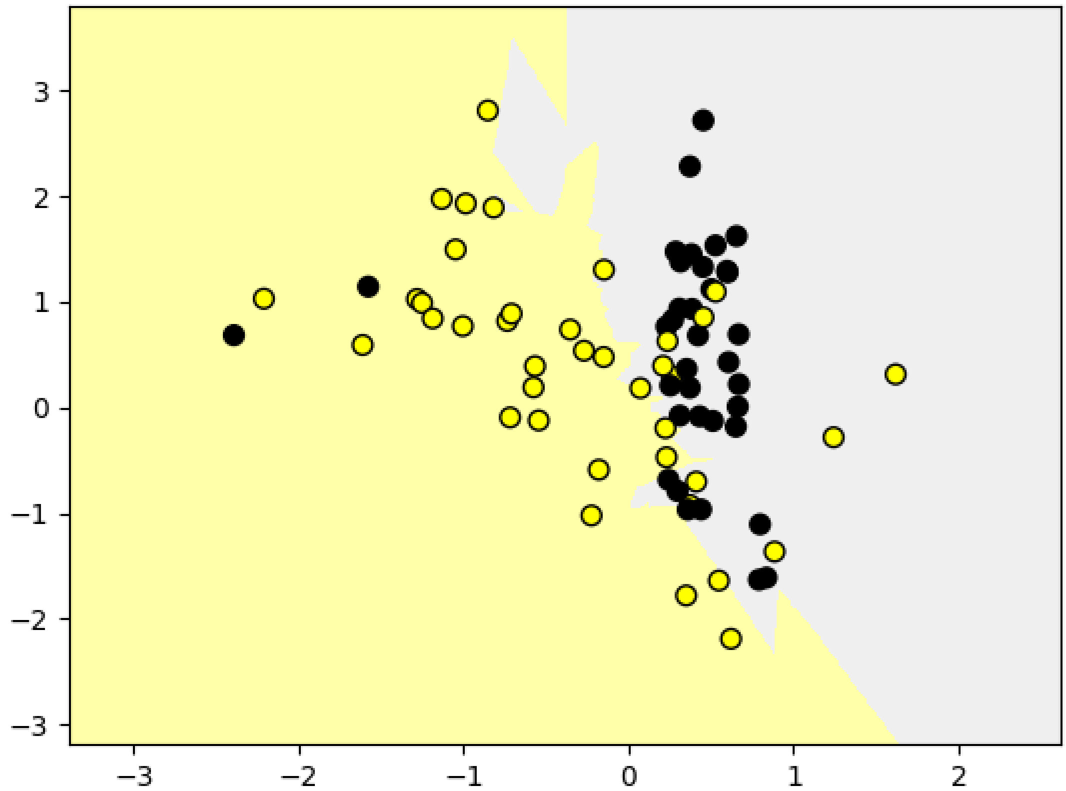
```
plot_two_class_knn(X_train, y_train, 1, X_test, y_test)
plot_two_class_knn(X_train, y_train, 11, X_test, y_test)
plot_two_class_knn(X_train, y_train, 30, X_test, y_test)
```




```
/var/folders/01/_r7b02r11p15j0s54gb9x0040000gn/T/ipykernel_22746/2284455823.py:18: Matplot
libDeprecationWarning: shading='flat' when X and Y have the same dimensions as C is deprec
ated since 3.3.  Either specify the corners of the quadrilaterals with X and Y, or pass sh
ading='auto', 'nearest' or 'gouraud', or set rcParams['pcolor.shading'].  This will become
an error two minor releases later.
  plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
Escore treinamento: 1.0
Escore teste: 0.64
```




```
/var/folders/01/_r7b02r11p15j0s54gb9x0040000gn/T/ipykernel_22746/2284455823.py:18: Matplot
libDeprecationWarning: shading='flat' when X and Y have the same dimensions as C is deprec
ated since 3.3.  Either specify the corners of the quadrilaterals with X and Y, or pass sh
ading='auto', 'nearest' or 'gouraud', or set rcParams['pcolor.shading'].  This will become
an error two minor releases later.
  plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
Escore treinamento: 0.7333333333333333
Escore teste: 0.8
```



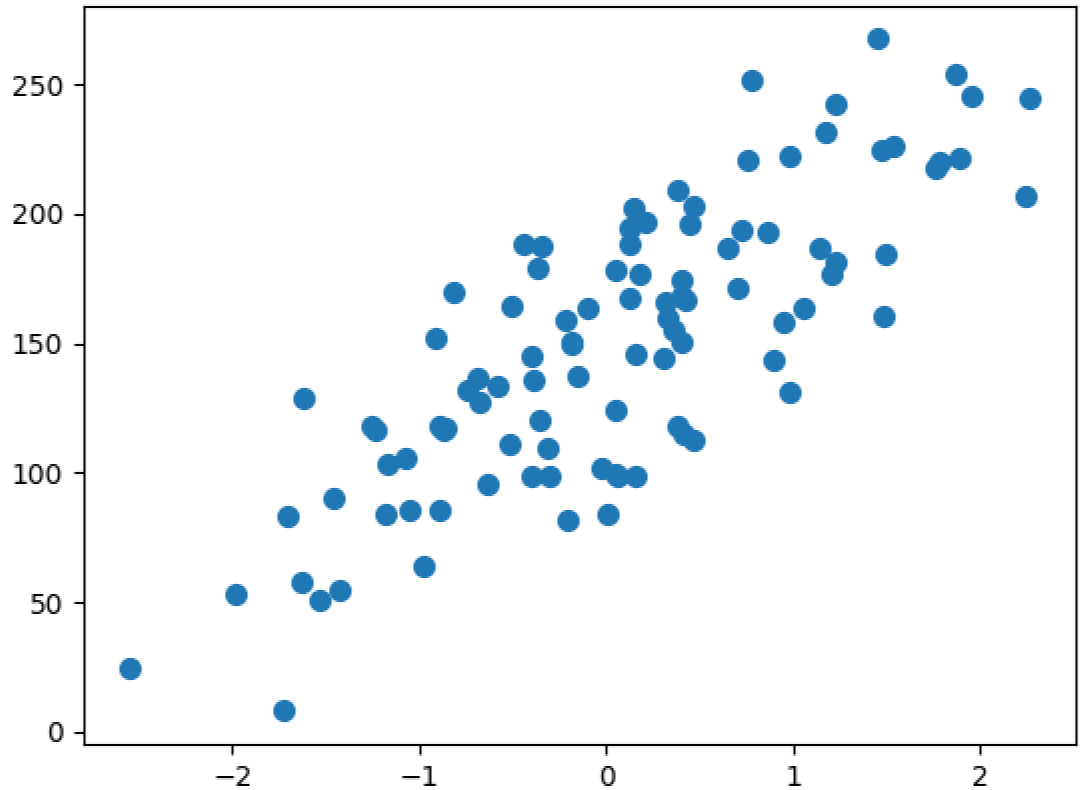

```
Escore treinamento: 0.8266666666666667
Escore teste: 0.76
```

```
/var/folders/01/_r7b02r11p15j0s54gb9x0040000gn/T/ipykernel_22746/2284455823.py:18: MatplotlibDeprecationWarning: shading='flat' when X and Y have the same dimensions as C is deprecated since 3.3.  Either specify the corners of the quadrilaterals with X and Y, or pass shading='auto', 'nearest' or 'gouraud', or set rcParams['pcolor.shading'].  This will become an error two minor releases later.
  plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
```

4 - Conjunto de dados sintético para regressão simples

In [4]:

```python
from sklearn.datasets import make_regression

plt.figure()

make_regression?

X_R1, y_R1 = make_regression(n_samples = 100, n_features=1,
                            n_informative=1, bias = 150.0,
                            noise = 30, random_state=0)
plt.scatter(X_R1, y_R1, marker= 'o', s=50)

plt.show()
```



5 - Regressão com KNN

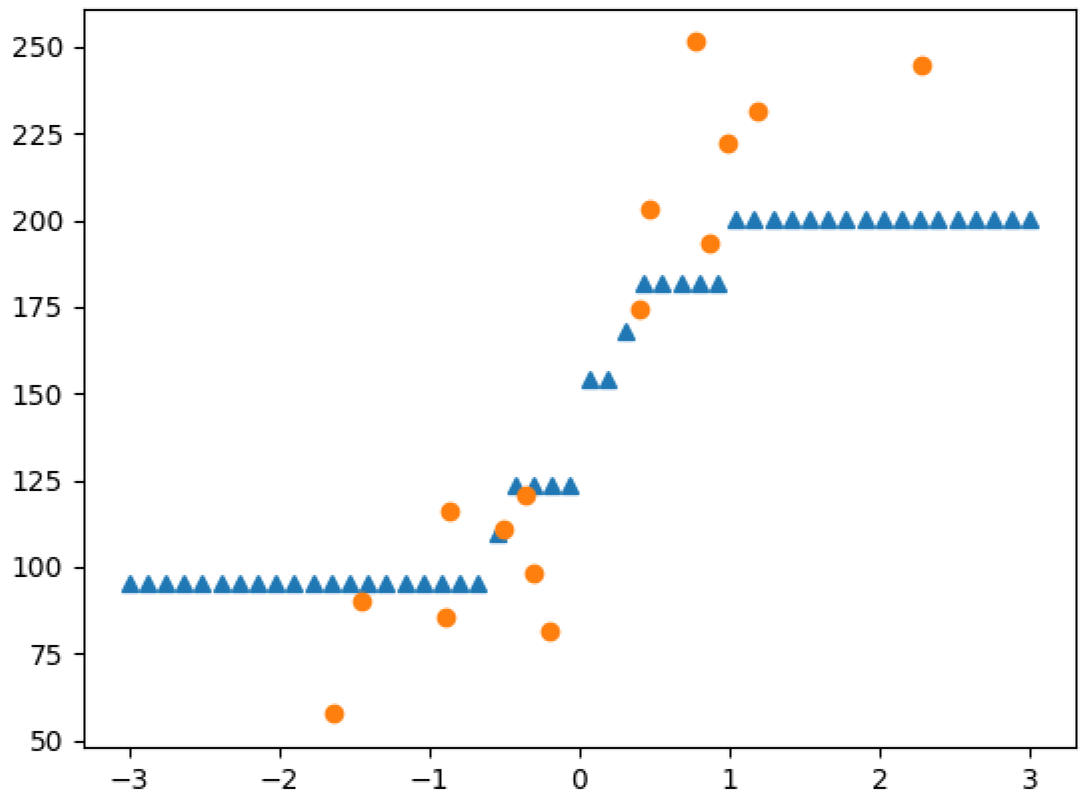
In [5]:
```
from sklearn.neighbors import KNeighborsRegressor

X_train, X_test, y_train, y_test = train_test_split(X_R1, y_R1, random_state=0)

knnreg = KNeighborsRegressor(n_neighbors = 5).fit(X_train, y_train)

print(knnreg.predict(X_test))

print(knnreg.score(X_test, y_test))
```

```
[231.70974697 148.35572605 150.58852659 150.58852659  72.14859259
 166.50590948 141.90634426 235.57098756 208.25897836 102.10462746
 191.31852674 134.50044902 228.32181403 148.35572605 159.16911306
 113.46875166 144.03646012 199.23189853 143.19242433 166.50590948
 231.70974697 208.25897836 128.01545355 123.14247619 141.90634426]
0.4246800858234563
```

6 - Variando o parâmetro K na Regressão

In [6]:
```
plt.figure()
X_predict_input = np.linspace(-3, 3, 50).reshape(-1,1)
X_train, X_test, y_train, y_test = train_test_split(X_R1[0::5], y_R1[0::5], random_state =

knnreg = KNeighborsRegressor(n_neighbors = 8).fit(X_train, y_train)
y_predict_output = knnreg.predict(X_predict_input)
plt.plot(X_predict_input, y_predict_output, '^')
plt.plot(X_train, y_train, 'o')


print(knnreg.score(X_train, y_train))
```

```
print(knnreg.score(X_test, y_test))


plt.show()
```

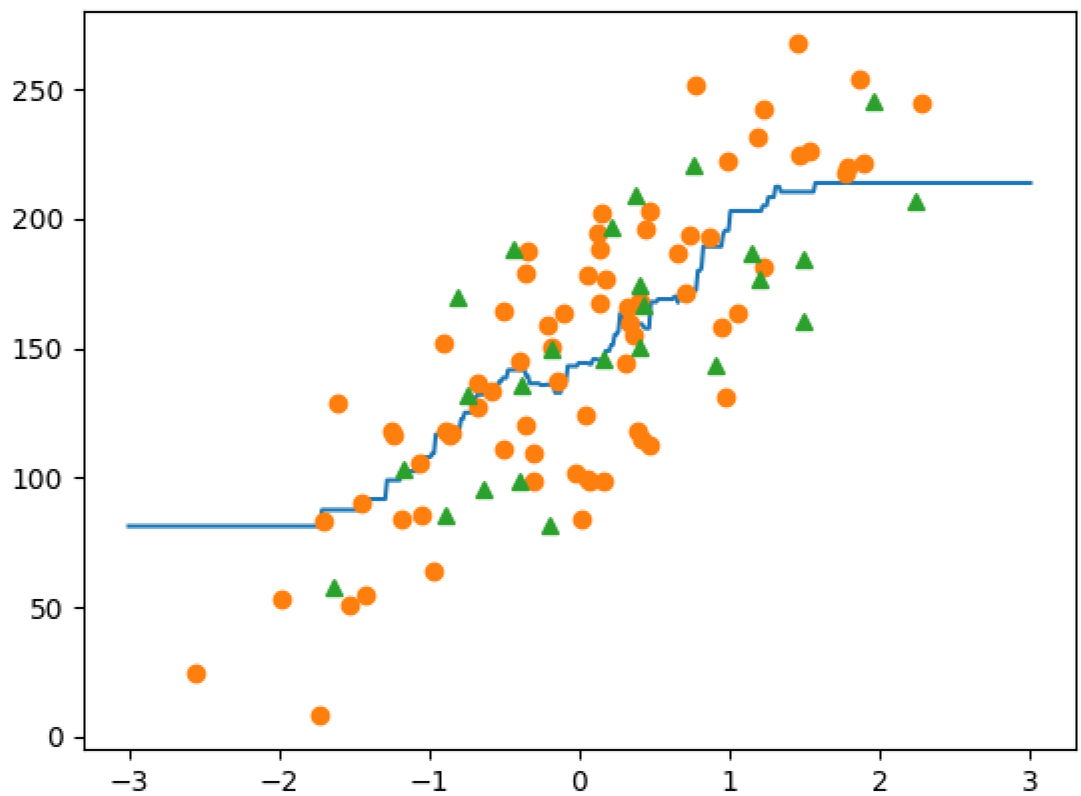



```
0.7726463757325022
0.05003882842284102
```

7 - R^2 escore

In [7]:

```
plt.figure()
X_predict_input = np.linspace(-3, 3, 500).reshape(-1,1)
X_train, X_test, y_train, y_test = train_test_split(X_R1, y_R1,
                                                    random_state = 0)

# k = 1, 3, 7, 15, 55

knnreg = KNeighborsRegressor(n_neighbors = 15).fit(X_train, y_train)
y_predict_output = knnreg.predict(X_predict_input)

plt.plot(X_predict_input, y_predict_output)
plt.plot(X_train, y_train, 'o')
plt.plot(X_test, y_test, '^')

print('Escore do treinamento:', knnreg.score(X_train, y_train))
print('Escore do teste:', knnreg.score(X_test, y_test))

plt.show()
```




```
Escore do treinamento: 0.6474391325499353
Escore do teste: 0.48493932421593966
```

Regressão com modelos lineares

Vetor de características: $x = (x_0, x_1, \ldots, x_n)$

Saída prevista: $\hat{y} = \widehat{w_0} x_0 + \widehat{w_1} x_1 + \cdots \widehat{w_n} x_n + \hat{b}$

Parâmentros a se estimar:

1. $\widehat{\boldsymbol{w}} = (\widehat{w_0}, \cdots, \widehat{w_n})$: coeficientes do modelo (pesos das características)
2. $\hat{\boldsymbol{b}}$: viés (bias) constante

8 - Regressão linear em dados sintéticos

In [8]:

```
from sklearn.linear_model import LinearRegression

X_train, X_test, y_train, y_test = train_test_split(X_R1, y_R1,
                                                   random_state = 0)

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

print('Coeff (w):',linreg.coef_)

print('Intercept (b):', linreg.intercept_)

print('R-2 score (treinamento):', linreg.score(X_train, y_train))
print('R-2 score (teste):', linreg.score(X_test, y_test))
```

```
Coeff (w): [45.70870465]
Intercept (b): 148.44575345658873
R-2 score (treinamento): 0.6785950771141656
R-2 score (teste): 0.4915961593493031
```

9 - Mínimos Quadrados

Minimizar $RSS(\boldsymbol{w}, b) = \sum_{\{i=1\}}^{N} (\boldsymbol{y}_i - (\boldsymbol{w} \cdot \boldsymbol{x}_i + b))^2$

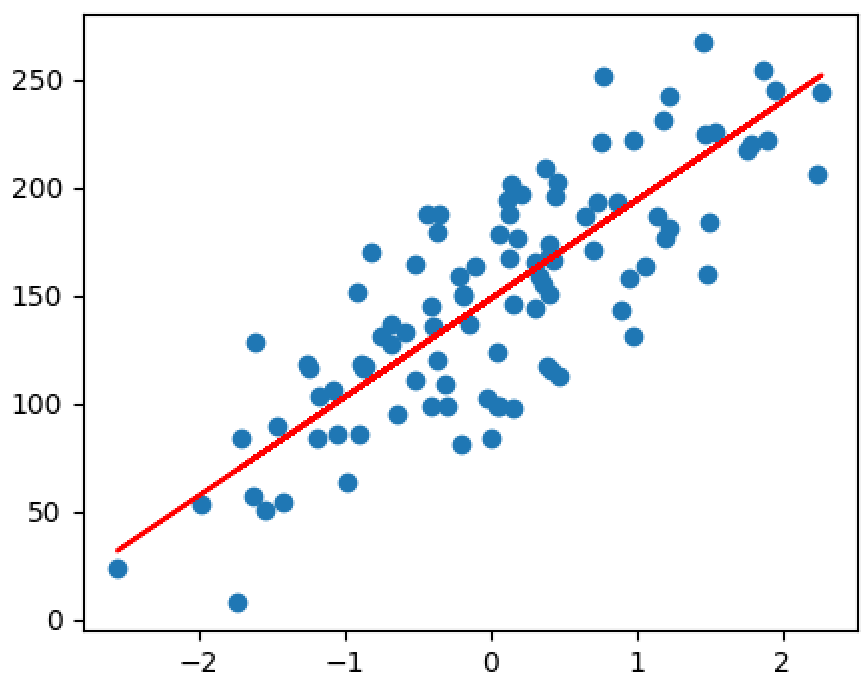
$\hat{y} = w_0 x_0 + b$

w_0 = linreg.coef_

b = linreg.intercept_

In [9]:

```
plt.figure(figsize=(5,4))
plt.scatter(X_R1, y_R1, marker= 'o')
plt.plot(X_R1, linreg.coef_ * X_R1 + linreg.intercept_, 'r-')
plt.show()
```



10 - Carregando a base de dados sobre crimes no EUA

In [11]:

```
crime = pd.read_table('./Data/CommViolPredUnnormalizedData.txt', sep=',', na_values='?')

# remove características com baixa relevância e com inconsistências
columns_to_keep = [5, 6] + list(range(11,26)) + list(range(32, 103)) + [145]
crime = crime.iloc[:,columns_to_keep].dropna()

# A coluna ViolentCrimesPerPop é o valor-alvo (y)

X_crime = crime.iloc[:,range(0,88)]
y_crime = crime['ViolentCrimesPerPop']

crime.head()
```

Out[11]:

	population	householdsize	agePct12t21	agePct12t29	agePct16t24	agePct65up	numbUrban	pctUrban
0	11980	3.10	12.47	21.44	10.93	11.33	11980	100.0
1	23123	2.82	11.01	21.30	10.48	17.18	23123	100.0
2	29344	2.43	11.36	25.88	11.01	10.28	29344	100.0
3	16656	2.40	12.55	25.20	12.19	17.57	0	0.0
5	140494	2.45	18.09	32.89	20.04	13.26	140494	100.0

5 rows × 89 columns

11 - Regressão linear na base de crimes

In [12]:

```
X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                    random_state = 0)
linreg = LinearRegression().fit(X_train, y_train)

print('Coeff (w):',linreg.coef_)

print('Intercept (b):', linreg.intercept_)

print('R-2 score (treinamento):', linreg.score(X_train, y_train))
print('R-2 score (teste):', linreg.score(X_test, y_test))
```

```
Coeff (w): [ 1.61892346e-03 -9.43009110e+01  1.36067510e+01 -3.13380670e+01
 -8.15482726e-02 -1.69455128e+01 -2.42730375e-03  1.53013232e+00
 -1.39193248e-02 -7.72112833e+00  2.28112354e+01 -5.65708295e+00
  9.34751364e+00  2.06969566e-01 -7.43413626e+00  9.65856476e-03
  4.38030290e-03  4.79754625e-03 -4.46469212e+00 -1.60907140e+01
  8.82778012e+00 -5.06734503e-01 -1.42198055e+00  8.17551991e+00
 -3.87048268e+00 -3.54209213e+00  4.48758304e+00  9.30645715e+00
  1.73644996e+02  1.18220766e+01  1.51120836e+02 -3.29613007e+02
 -1.35343395e+02  6.95380108e-01 -2.38369008e+01  2.77038981e+00
  3.82248925e-01  4.38813358e+00 -1.06410851e+01 -4.92294176e-03
  4.14031827e+01 -1.16206866e-03  1.18568968e+00  1.75418465e+00
 -3.68283678e+00  1.59679443e+00 -8.42180230e+00 -3.79703897e+01
  4.74076990e+01 -2.50768374e+01 -2.88246410e-01 -3.65633234e+01
  1.89516080e+01 -4.53336736e+01  6.82698598e+02  1.04478671e+02
 -3.28575414e+02 -3.14364068e+01  2.74053494e+01  5.12336432e+00
  6.91580764e+01  1.98267157e-02 -6.12133638e-01  2.65335065e+01
  1.00704633e+01 -1.58621594e+00  2.24025322e+00  7.38288450e+00
 -3.13915504e+01 -9.77773885e-05  5.01970945e-05 -3.48067770e-04
 -2.50217578e-04 -5.26610456e-01 -5.16564774e-01 -4.10464090e-01
  1.16146366e-01  1.46167357e+00 -3.04019816e-01  2.43792841e+00
 -3.65615457e+01  1.41488917e-01  2.88800603e-01  1.77464865e+01
  5.96587698e-01  1.98257510e+00 -1.36380442e-01 -1.85303461e+00]
Intercept (b): -1728.1306725979102
R-2 score (treinamento): 0.6731208442568581
R-2 score (teste): 0.49554452278844185
```

12 - Regressão de Cume

$$RSS_{RIDGE}(\boldsymbol{w}, b) = \sum_{[i=1]}^{N} (\boldsymbol{y}_i - (\boldsymbol{w} \cdot \boldsymbol{x}_i + b))^2 + \alpha \sum_{j=1}^{p} w_j^2$$

In [13]:

```
from sklearn.linear_model import Ridge
X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                    random_state = 0)

linridge = Ridge(alpha=1e-3).fit(X_train, y_train)
```

```python
print('Coeff (w):',linridge.coef_)

print('Intercept (b):', linridge.intercept_)

print('R-2 score (treinamento):', linridge.score(X_train, y_train))
print('R-2 score (teste):', linridge.score(X_test, y_test))
```

```
Coeff (w): [ 1.61911459e-03 -9.41406956e+01  1.35989717e+01 -3.13448327e+01
 -7.00739195e-02 -1.69460702e+01 -2.42750930e-03  1.53020056e+00
 -1.39159394e-02 -7.71999482e+00  2.28074980e+01 -5.65705906e+00
  9.34654289e+00  2.07063787e-01 -7.43253925e+00  9.65626037e-03
  4.38118872e-03  4.79776889e-03 -4.46417097e+00 -1.60918145e+01
  8.82814441e+00 -5.07298974e-01 -1.41939074e+00  8.17828454e+00
 -3.87038112e+00 -3.54223303e+00  4.48836339e+00  9.30578174e+00
  1.73590654e+02  1.18194311e+01  1.51063462e+02 -3.29507727e+02
 -1.34693455e+02  6.94685224e-01 -2.38376383e+01  2.77068015e+00
  3.82582627e-01  4.38782791e+00 -1.06411972e+01 -4.92300167e-03
  4.14010579e+01 -1.16212658e-03  1.18575752e+00  1.75396867e+00
 -3.68270616e+00  1.59652556e+00 -8.43284200e+00 -3.79543999e+01
  4.73984357e+01 -2.50709074e+01 -2.88017117e-01 -3.65600728e+01
  1.89102062e+01 -4.52871999e+01  6.81281583e+02  1.05064534e+02
 -3.28506177e+02 -3.14634503e+01  2.74096196e+01  5.12213682e+00
  6.91544670e+01  1.98263931e-02 -6.11702323e-01  2.65622324e+01
  1.00712780e+01 -1.58638421e+00  2.24072144e+00  7.38220316e+00
 -3.13914307e+01  4.71962805e-04  5.00125606e-05 -9.17505918e-04
  3.19347569e-04 -5.26579921e-01 -5.16506597e-01 -4.10463022e-01
  1.16157679e-01  1.46153851e+00 -3.00706906e-01  2.43764483e+00
 -3.65629533e+01  1.41476856e-01  2.88818089e-01  1.77430764e+01
  5.96135391e-01  1.98270094e+00 -1.36007341e-01 -1.85332048e+00]
Intercept (b): -1729.5016769316958
R-2 score (treinamento): 0.6731208422793948
R-2 score (teste): 0.4955530805905023
```

13 - Regressão de Cume com normalização de característica

In [14]:
```python
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                    random_state = 0)

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

linridge = Ridge(alpha=20.0).fit(X_train_scaled, y_train)

print('Coeff (w):',linridge.coef_)

print('Intercept (b):', linridge.intercept_)

print('R-2 score (treinamento):', linridge.score(X_train_scaled, y_train))
print('R-2 score (teste):', linridge.score(X_test_scaled, y_test))
```

```
Coeff (w): [  88.68827454   16.48947987  -50.30285445  -82.90507574  -65.89507244
   -2.27674244   87.74108514  150.94862182   18.8802613   -31.05554992
  -43.13536109 -189.44266328   -4.52658099  107.97866804  -76.53358414
    2.86032762   34.95230077   90.13523036   52.46428263  -62.10898424
  115.01780357    2.66942023    6.94331369   -5.66646499 -101.55269144
  -36.9087526    -8.7053343    29.11999068  171.25963057   99.36919476
   75.06611841  123.63522539   95.24316483 -330.61044265 -442.30179004
 -284.49744001 -258.37150609   17.66431072 -101.70717151  110.64762887
  523.13611718   24.8208959     4.86533322  -30.46775619   -3.51753937
   50.57947231   10.84840601   18.27680946   44.11189865   58.33588176
   67.08698975  -57.93524659  116.1446052    53.81163718   49.01607711
   -7.62262031   55.14288543  -52.08878272  123.39291017   77.12562171
```

```
   45.49795317  184.91229771  -91.35721203    1.07975971  234.09267451
   10.3887921    94.7171829   167.91856631  -25.14025088   -1.18242839
   14.60362467   36.77122659   53.19878339  -78.86365997   -5.89858411
   26.04790298  115.1534917    68.74143311   68.28588166   16.5260514
  -97.90513652  205.20448474   75.97304123   61.3791085   -79.83157049
   67.26700741   95.67094538  -11.88380569]
Intercept (b): 933.3906385044153
R-2 score (treinamento): 0.6146175955616784
R-2 score (teste): 0.5986066019999294
```

14 - Regressão de Cume, normalização e o parâmetro alpha

In [15]:

```python
for this_alpha in [0, 1, 10, 20, 50, 100, 1000]:
    linridge = Ridge(alpha = this_alpha).fit(X_train_scaled, y_train)
    r2_train = linridge.score(X_train_scaled, y_train)
    r2_test = linridge.score(X_test_scaled, y_test)
    num_coeff_bigger = np.sum(abs(linridge.coef_) > 1.0)
    print('Alpha = {:.2f}\ncoeff > 1.0: {}, \
R-2 treinamento: {:.2f}, R-2 teste: {:.2f}\n'
         .format(this_alpha, num_coeff_bigger, r2_train, r2_test))
```

```
Alpha = 0.00
coeff > 1.0: 88, R-2 treinamento: 0.67, R-2 teste: 0.50

Alpha = 1.00
coeff > 1.0: 87, R-2 treinamento: 0.66, R-2 teste: 0.56

Alpha = 10.00
coeff > 1.0: 87, R-2 treinamento: 0.63, R-2 teste: 0.59

Alpha = 20.00
coeff > 1.0: 88, R-2 treinamento: 0.61, R-2 teste: 0.60

Alpha = 50.00
coeff > 1.0: 86, R-2 treinamento: 0.58, R-2 teste: 0.58

Alpha = 100.00
coeff > 1.0: 87, R-2 treinamento: 0.55, R-2 teste: 0.55

Alpha = 1000.00
coeff > 1.0: 84, R-2 treinamento: 0.31, R-2 teste: 0.30
```

15 - Regressão Lasso com normalização

$$RSS_{LASSO}(\boldsymbol{w}, b) = \sum_{\{i=1\}}^{N} (y_i - (\boldsymbol{w} \cdot \boldsymbol{x}_i + b))^2 + \alpha \sum_{\{j=1\}}^{p} |w_j|$$

In [16]:

```python
from sklearn.linear_model import Lasso
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

X_train, X_test, y_train, y_test = train_test_split(X_crime, y_crime,
                                                    random_state = 0)

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

linlasso = Lasso(alpha=2.0, max_iter = 10000).fit(X_train_scaled, y_train)



print('Lasso intercept: {}'
     .format(linlasso.intercept_))
```

```
print('Lasso coeff:\n{}'
     .format(linlasso.coef_))
print('Características não zeradas: {}'
     .format(np.sum(linlasso.coef_ != 0)))
print('R-2 score (treinamento): {:.3f}'
     .format(linlasso.score(X_train_scaled, y_train)))
print('R-2 score (teste): {:.3f}\n'
     .format(linlasso.score(X_test_scaled, y_test)))
print('Características com peso diferente de zero:')

for e in sorted (list(zip(list(X_crime), linlasso.coef_)),
                key = lambda e: -abs(e[1])):
    if e[1] != 0:
        print('\t{}, {:.3f}'.format(e[0], e[1]))
```

```
Lasso intercept: 1186.612061998579
Lasso coeff:
[    0.           0.          -0.        -168.18346054
    -0.          -0.           0.         119.6938194
     0.          -0.           0.        -169.67564456
    -0.           0.          -0.           0.
     0.           0.          -0.          -0.
     0.          -0.           0.           0.
   -57.52991966  -0.          -0.           0.
   259.32889226  -0.           0.           0.
     0.          -0.       -1188.7396867  -0.
    -0.          -0.        -231.42347299  0.
  1488.36512229   0.          -0.          -0.
    -0.           0.           0.           0.
     0.           0.          -0.           0.
    20.14419415   0.           0.           0.
     0.           0.         339.04468804   0.
     0.         459.53799903  -0.           0.
   122.69221826  -0.          91.41202242   0.
    -0.           0.           0.          73.14365856
     0.          -0.           0.           0.
    86.35600042   0.           0.           0.
  -104.57143405 264.93206555   0.          23.4488645
   -49.39355188   0.           5.19775369   0.        ]
Características não zeradas: 20
R-2 score (treinamento): 0.631
R-2 score (teste): 0.624

Características com peso diferente de zero:
	PctKidsBornNeverMar, 1488.365
	PctKids2Par, -1188.740
	HousVacant, 459.538
	PctPersDenseHous, 339.045
	NumInShelters, 264.932
	MalePctDivorce, 259.329
	PctWorkMom, -231.423
	pctWInvInc, -169.676
	agePct12t29, -168.183
	PctVacantBoarded, 122.692
	pctUrban, 119.694
	MedOwnCostPctIncNoMtg, -104.571
	MedYrHousBuilt, 91.412
	RentQrange, 86.356
	OwnOccHiQuart, 73.144
	PctEmplManu, -57.530
	PctBornSameState, -49.394
	PctForeignBorn, 23.449
	PctLargHouseFam, 20.144
	PctSameCity85, 5.198
```

16 - Regressão Lasso com normalização e o parâmetro alpha

In [17]:

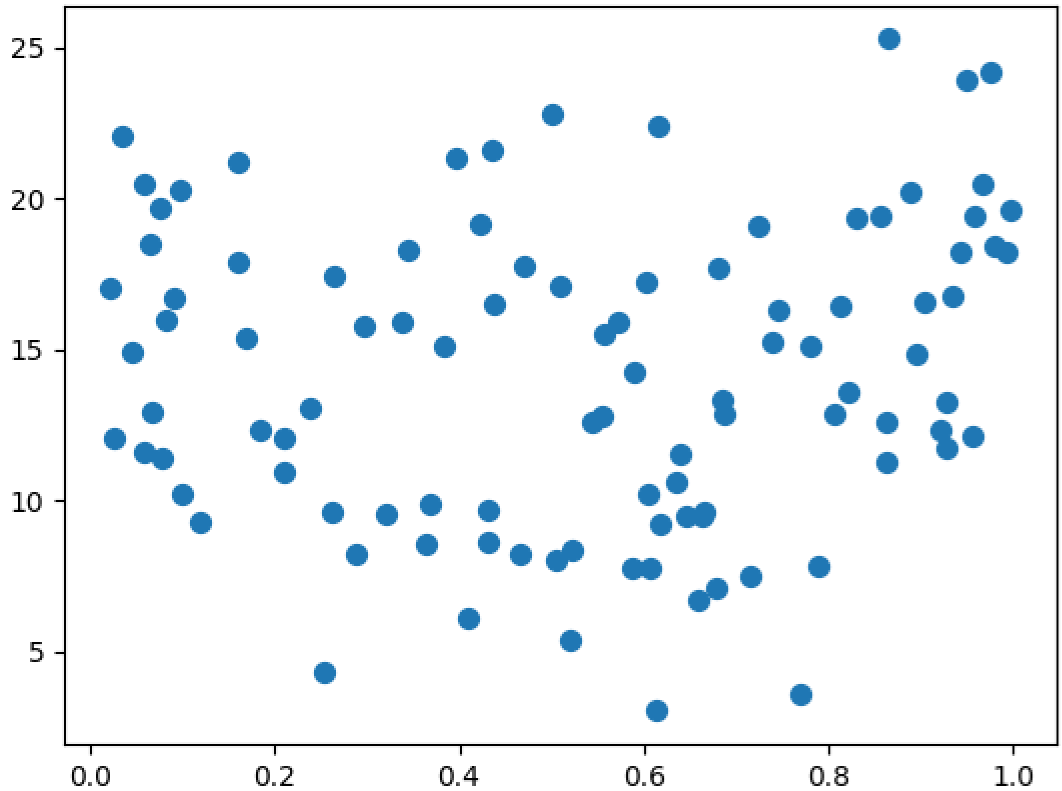
```
for alpha in [0.5, 1, 2, 3, 5, 10, 20, 50]:
    linlasso = Lasso(alpha, max_iter = 10000).fit(X_train_scaled, y_train)
    r2_train = linlasso.score(X_train_scaled, y_train)
    r2_test = linlasso.score(X_test_scaled, y_test)

    print('Alpha = {:.2f}\nCaracterísticas: {}, R-2 treinamento: {:.2f}, \
R-2 teste: {:.2f}\n'
         .format(alpha, np.sum(linlasso.coef_ != 0), r2_train, r2_test))
```

```
Alpha = 0.50
Características: 35, R-2 treinamento: 0.65, R-2 teste: 0.58

Alpha = 1.00
Características: 25, R-2 treinamento: 0.64, R-2 teste: 0.60

Alpha = 2.00
Características: 20, R-2 treinamento: 0.63, R-2 teste: 0.62

Alpha = 3.00
Características: 17, R-2 treinamento: 0.62, R-2 teste: 0.63

Alpha = 5.00
Características: 12, R-2 treinamento: 0.60, R-2 teste: 0.61

Alpha = 10.00
Características: 6, R-2 treinamento: 0.57, R-2 teste: 0.58

Alpha = 20.00
Características: 2, R-2 treinamento: 0.51, R-2 teste: 0.50

Alpha = 50.00
Características: 1, R-2 treinamento: 0.31, R-2 teste: 0.30
```

17 - Base de dados para regressões mais complexas

In [18]:

```
from sklearn.datasets import make_friedman1
plt.figure()

X_F1, y_F1 = make_friedman1(n_samples = 100,
                           n_features = 7, random_state=0)

plt.scatter(X_F1[:, 2], y_F1, marker= 'o', s=50)
plt.show()
```



18 - Regressão polinomial

$x = (x_0, x_1) \longrightarrow x' = \left(x_0, x_1, x_0^2, x_0 x_1, x_1^2\right)$

$\hat{y} = \widehat{w}_0 x_0 + \widehat{w}_1 x_1 + \widehat{w}_{00} x_0^2 + \widehat{w}_{01} x_0 x_1 + \widehat{w}_{11} x_1^2 + b$

In [19]:

```
from sklearn.preprocessing import PolynomialFeatures


X_train, X_test, y_train, y_test = train_test_split(X_F1, y_F1,
                                                    random_state = 0)
linreg = LinearRegression().fit(X_train, y_train)

print('Modelo linear coeff (w): {}'
     .format(linreg.coef_))
print('Modelo linear intercept (b): {:.3f}'
     .format(linreg.intercept_))
print('R-squared score (treinamento): {:.3f}'
     .format(linreg.score(X_train, y_train)))
print('R-squared score (teste): {:.3f}'
     .format(linreg.score(X_test, y_test)))

print('\nTransformação polinomial quadrática\n')
poly = PolynomialFeatures(degree=2)
X_F1_poly = poly.fit_transform(X_F1)

X_train, X_test, y_train, y_test = train_test_split(X_F1_poly, y_F1,
                                                    random_state = 0)
linreg = LinearRegression().fit(X_train, y_train)

print('Polinomial coeff (w):\n{}'
     .format(linreg.coef_))
print('Polinomial intercept (b): {:.3f}'
```

```python
      .format(linreg.intercept_))
print('Polinomial R-2 score (treinamento): {:.3f}'
      .format(linreg.score(X_train, y_train)))
print('Polinomial R-2 score (teste): {:.3f}\n'
      .format(linreg.score(X_test, y_test)))


X_train, X_test, y_train, y_test = train_test_split(X_F1_poly, y_F1,
                                                    random_state = 0)
linreg = Ridge().fit(X_train, y_train)

print('Polinomial + Cume coeff (w):\n{}'
      .format(linreg.coef_))
print('Polinomial + Cume intercept (b): {:.3f}'
      .format(linreg.intercept_))
print('Polinomial + Cume R-2 score (treinamento): {:.3f}'
      .format(linreg.score(X_train, y_train)))
print('Polinomial + Cume R-2 score (teste): {:.3f}'
      .format(linreg.score(X_test, y_test)))
```

```
Modelo linear coeff (w): [ 4.42036739  5.99661447  0.52894712 10.23751345  6.5507973  -2.0
2082636
 -0.32378811]
Modelo linear intercept (b): 1.543
R-squared score (treinamento): 0.722
R-squared score (teste): 0.722

Transformação polinomial quadrática

Polinomial coeff (w):
[ 3.40951018e-12  1.66452443e+01  2.67285381e+01 -2.21348316e+01
  1.24359227e+01  6.93086826e+00  1.04772675e+00  3.71352773e+00
 -1.33785505e+01 -5.73177185e+00  1.61813184e+00  3.66399592e+00
  5.04513181e+00 -1.45835979e+00  1.95156872e+00 -1.51297378e+01
  4.86762224e+00 -2.97084269e+00 -7.78370522e+00  5.14696078e+00
 -4.65479361e+00  1.84147395e+01 -2.22040650e+00  2.16572630e+00
 -1.27989481e+00  1.87946559e+00  1.52962716e-01  5.62073813e-01
 -8.91697516e-01 -2.18481128e+00  1.37595426e+00 -4.90336041e+00
 -2.23535458e+00  1.38268439e+00 -5.51908208e-01 -1.08795007e+00]
Polinomial intercept (b): -3.206
Polinomial R-2 score (treinamento): 0.969
Polinomial R-2 score (teste): 0.805

Polinomial + Cume coeff (w):
[ 0.          2.229281    4.73349734 -3.15432089  3.8585194   1.60970912
 -0.76967054 -0.14956002 -1.75215371  1.5970487   1.37080607  2.51598244
  2.71746523  0.48531538 -1.9356048  -1.62914955  1.51474518  0.88674141
  0.26141199  2.04931775 -1.93025705  3.61850966 -0.71788143  0.63173956
 -3.16429847  1.29161448  3.545085    1.73422041  0.94347654 -0.51207219
  1.70114448 -1.97949067  1.80687548 -0.2173863   2.87585898 -0.89423157]
Polinomial + Cume intercept (b): 5.418
Polinomial + Cume R-2 score (treinamento): 0.826
Polinomial + Cume R-2 score (teste): 0.825
```

In [ ]: