

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
```

```
In [2]: from sklearn.datasets import make_regression

# Générer un dataset de régression avec 1000 échantillons, 10 variables indépe
X, y = make_regression(n_samples=300, n_features=2, noise=0.1)

# Afficher la forme (shape) du jeu de données
print(X.shape, y.shape)

(300, 2) (300,)
```

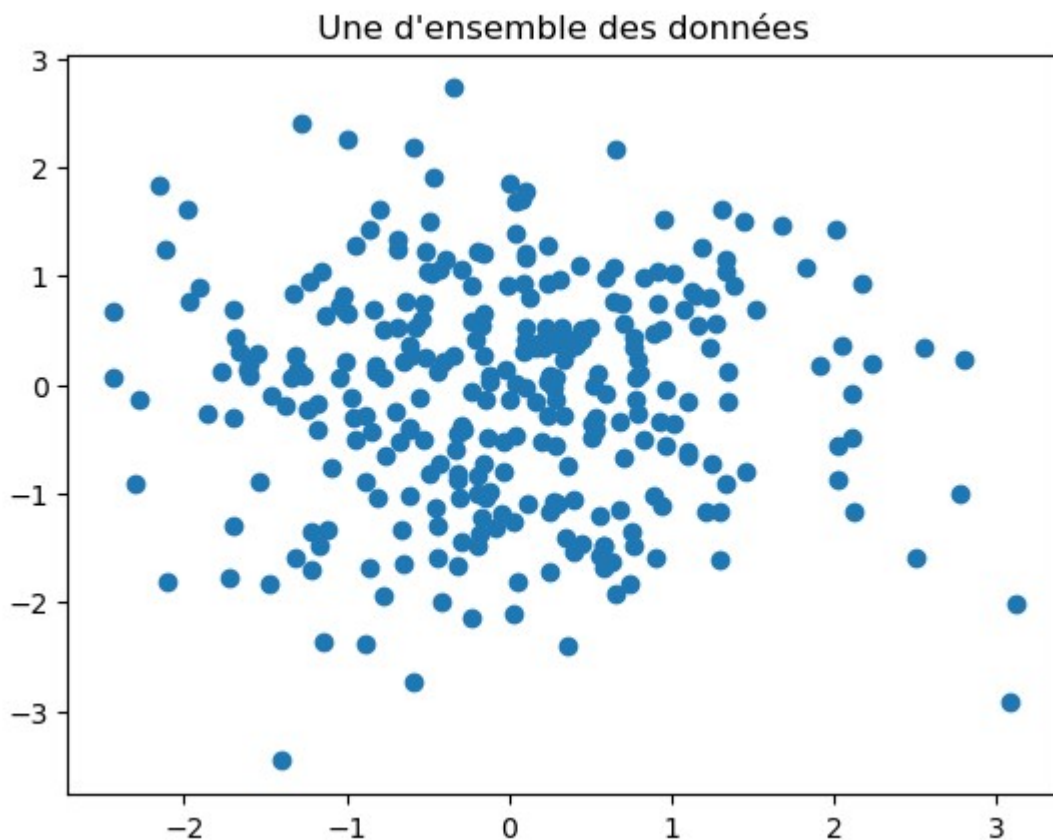
```
In [3]: X[:10]
```

```
Out[3]: array([[ 1.44355747,  1.49602438],
 [ 0.09991212,  0.53388109],
 [ 2.16953126,  0.93622951],
 [-0.59467912, -2.73936821],
 [ 1.5135368 ,  0.6948388 ],
 [ 1.30090994, -1.1644402 ],
 [ 0.64673424,  0.76546513],
 [ 1.67824473,  1.46634802],
 [-1.3053947 ,  0.1370236 ],
 [-0.88706305, -2.39193614]])
```

```
In [4]: y[:10]
```

```
Out[4]: array([ 120.82487052,  22.15043648, 139.33078596, -117.78287807,
 98.53745021,  28.15041055,  57.09571466, 131.51488316,
-61.46491274, -121.31720354])
```

```
In [5]: plt.scatter(X[:,0], X[:,1])  
plt.title("Une d'ensemble des données")  
plt.show()
```



```
In [6]: def initialization(X):  
        w = np.random.randn(X.shape[1])  
        b = np.random.randn()  
        return (w, b)
```

```
In [7]: w, b = initialization(X)  
print(f"w = {w}\nb = {b}")
```

```
w = [ 0.21173674 -0.90809524]  
b = -0.5642824996045938
```

```
In [8]: def linear_fonction(X, w, b):  
        return np.matmul(X, w) + b
```

```
In [9]: y_hat = linear_fonction(X,w,b)  
y_hat[:10]
```

```
Out[9]: array([-1.61716095, -1.02794231, -0.95509858,  1.7974093 , -0.87479095,  
               0.76859053, -1.12246034, -1.54052008, -0.965113 ,  1.41999947])
```

```
In [10]: def cost(y, y_hat):  
         return np.sum((y_hat-y)**2)/(2*y.shape[0])
```

```
In [11]: cost(y, y_hat)
```

```
Out[11]: 1908.1689385589716
```

```
In [12]: def gradients(X, y, w, b):  
    m = X.shape[0]  
    j_w = np.dot(X.T, X.dot(w) + b - y) / m  
    j_b = np.sum(X.dot(w) + b - y) / m  
    return (j_w, j_b)
```

```
In [13]: j_w, j_b = gradients(X, y, w, b)  
print(f"j_w = {j_w}, j_b = {j_b}")  
  
j_w = [-53.00196049 -35.14234747], j_b = 2.764745791602798
```

```
In [14]: def update(X, y, w, b, alpha):  
    j_w, j_b = gradients(X, y, w, b)  
    w = w - alpha*j_w  
    b = b - alpha*j_b  
    return (w, b)
```

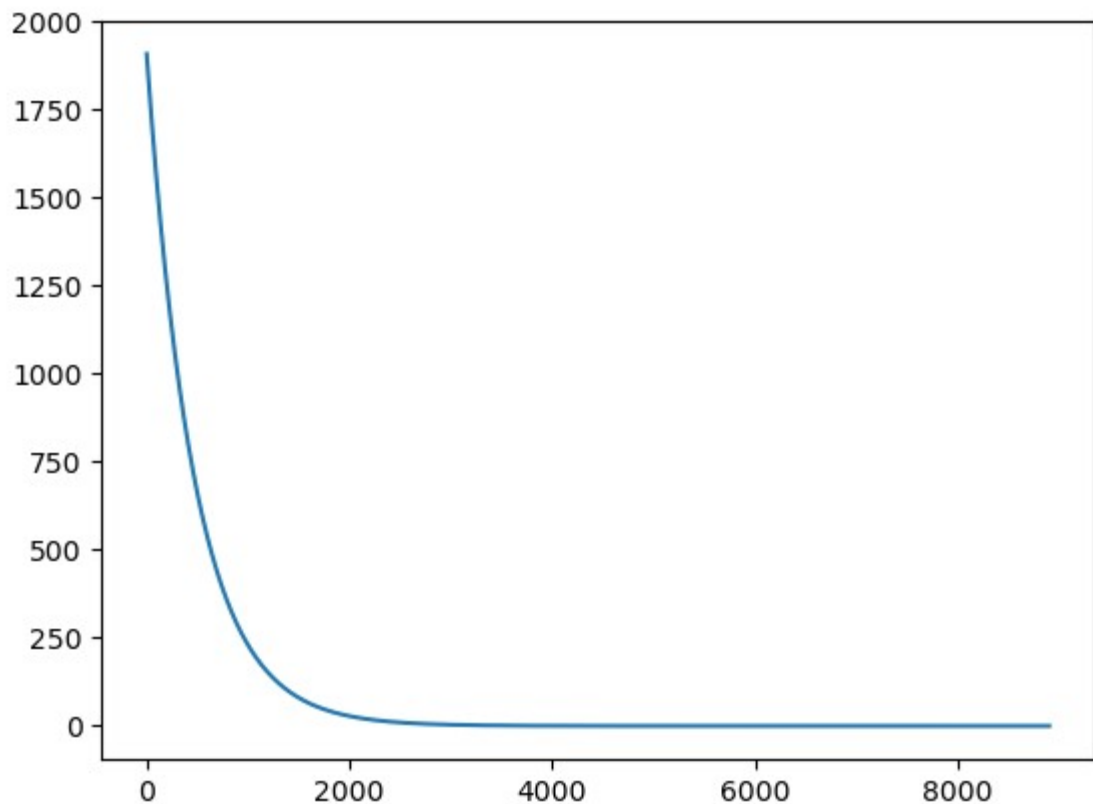
```
In [15]: update(X, y, w, b, 0.001)
```

```
Out[15]: (array([ 0.2647387 , -0.87295289]), -0.5670472453961966)
```

```
In [16]: def gradient_descent(X, y, w, b, alpha=0.001, n_iter = 1000):  
    cost_ = []  
    for i in range(n_iter):  
        y_hat = linear_fonction(X, w, b)  
        cost_.append(cost(y, y_hat))  
        w, b = update(X, y, w, b, alpha)  
    print(f"First_cost = {cost_[0]}\nLast_cost = {cost_[-1]}")  
    print(f"W = {w}\nb = {b}")  
    plt.plot(cost_)  
    plt.show()
```

```
In [17]: gradient_descent(X, y, w, b, n_iter = 8900)
```

```
First_cost = 1908.1689385589716  
Last_cost = 0.005365711351339526  
W = [50.37363646 32.06808891]  
b = -0.0017528732341618096
```



```
In [18]: def predict(X):  
         return np.matmul(X, w) + b
```

```
In [19]: y_hat = predict(X)
```

```
In [20]: y_hat[:10]
```

```
Out[20]: array([-1.61716095, -1.02794231, -0.95509858,  1.7974093 , -0.87479095,  
                0.76859053, -1.12246034, -1.54052008, -0.965113 ,  1.41999947])
```

Version 2

```
In [22]: def initialization(X):  
         w = np.random.randn(X.shape[1])  
         b = np.random.randn()  
         return (w, b)
```

```
In [23]: def predict(X, w, b):  
         return np.dot(X, w) + b
```

```
In [24]: def cost(X, y, w, b):  
        m = len(y)  
        y_hat = predict(X, w, b)  
        return np.sum((y_hat - y)**2) / (2 * m)
```

```
In [25]: def gradient(X, y, w, b):  
        m = len(y)  
        y_hat = predict(X, w, b)  
        dw = np.dot(X.T, (y_hat - y)) / m  
        db = np.mean(y_hat - y)  
        return dw, db
```

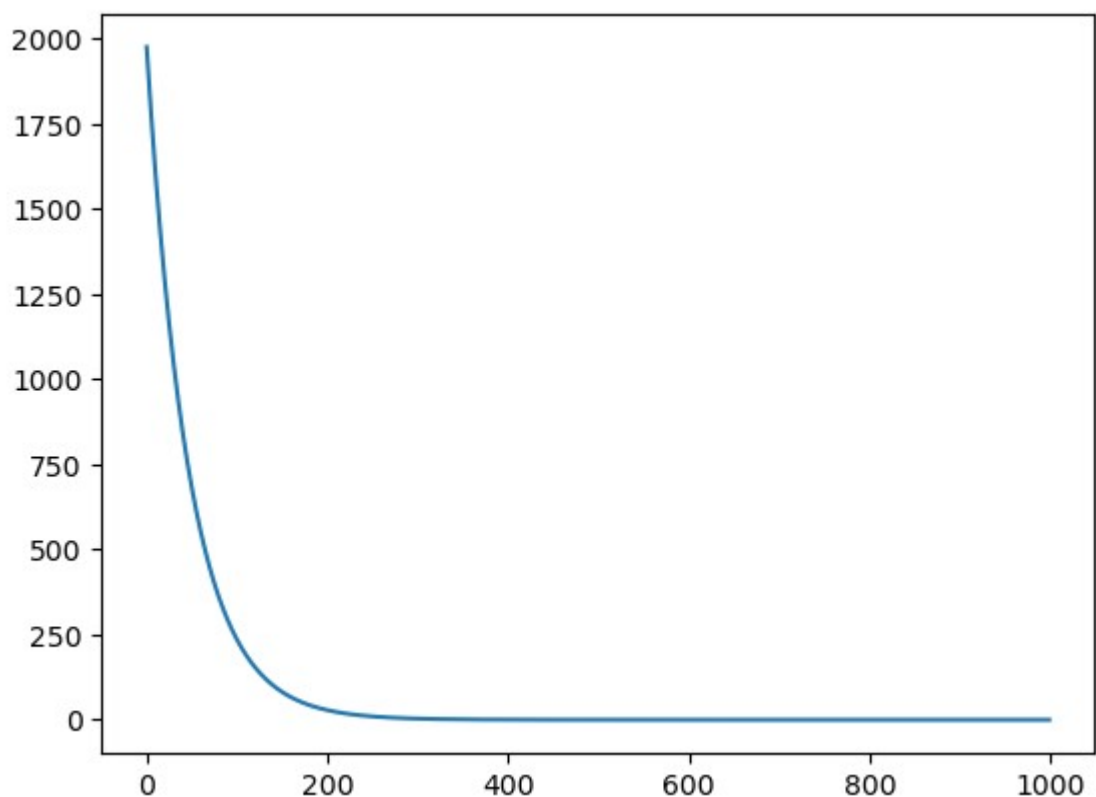
```
In [26]: def train(X, y, w, b, learning_rate, n_iterations):  
        costs = []  
        for i in range(n_iterations):  
  
            y_hat = predict(X, w, b)  
            cost_i = cost(X, y, w, b)  
            costs.append(cost_i)  
  
            dw, db = gradient(X, y, w, b)  
            w -= learning_rate * dw  
            b -= learning_rate * db  
  
            if i % 100 == 0:  
                print(f"Iteration {i} : cost = {cost_i}")  
  
        return w, b, costs
```

```
In [27]: w, b = initialization(X)
```

```
In [28]: w_, b_, costs = train(X, y, w, b, 0.01, 1000)
```

```
Iteration 0 : cost = 1974.7730915463476  
Iteration 100 : cost = 235.20342002259665  
Iteration 200 : cost = 28.382742556288722  
Iteration 300 : cost = 3.478278832767265  
Iteration 400 : cost = 0.43700973175284646  
Iteration 500 : cost = 0.05989263344466968  
Iteration 600 : cost = 0.01235743117952742  
Iteration 700 : cost = 0.006261947904959221  
Iteration 800 : cost = 0.00546652145282869  
Iteration 900 : cost = 0.005360908866497035
```

```
In [29]: plt.plot(costs)
plt.show()
```



```
In [ ]:
```

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In [ ]:
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```
In [30]: from sklearn.metrics import mean_squared_error, r2_score

# Calculer la racine carrée de l'erreur quadratique moyenne (RMSE)
rmse = mean_squared_error(y, y_hat, squared=False)

# Calculer le coefficient de détermination (R²)
r2 = r2_score(y, y_hat)

# Afficher les résultats
print('RMSE:', rmse)
print('R²:', r2)
```

```
RMSE: 61.776515579287434
R²: -0.012633216260934388
```

```
In [149]: import numpy as np

class LinearRegression:
    """
    Régression linéaire avec la descente de gradient
    """

    def __init__(self, learning_rate=0.01, n_iterations=1000):
        self.learning_rate = learning_rate
        self.n_iterations = n_iterations
        self.w = None
        self.b = None
        self.costs = []

    def fit(self, X, y):
        # Normalization of the features
        mean = np.mean(X, axis=0)
        std = np.std(X, axis=0)
        X = (X - mean) / std

        self.w = np.random.randn(X.shape[1])
        self.b = 0

        for i in range(self.n_iterations):
            y_hat = self.predict(X)
            cost_i = self.cost(X, y)
            self.costs.append(cost_i)

            # Gradients descent
            dw, db = self.gradient(X, y)
            self.w -= self.learning_rate * dw
            self.b -= self.learning_rate * db

            if i % 100 == 0:
                print(f"Iteration {i} : cost = {cost_i}")

    def predict(self, X):
        y_hat = np.matmul(X, self.w) + self.b
        return y_hat

    def cost(self, X, y):
        mean = np.mean(X, axis=0)
        std = np.std(X, axis=0)
        X = (X - mean) / std

        m = len(y)
        y_hat = self.predict(X)
        return np.sum((y_hat - y)**2) / (2 * m)

    def gradient(self, X, y):
        m = X.shape[0]
        j_w = (1/m) * np.matmul(X.T, np.matmul(X, self.w) + self.b - y)
        j_b = (1/m) * np.sum(np.matmul(X, self.w) + self.b - y)
        return (j_w, j_b)
```

```
def score(self, X, y):
    y_hat = self.predict(X)
    ss_res = np.sum((y - y_hat)**2)
    ss_tot = np.sum((y - np.mean(y))**2)
    r2 = 1 - (ss_res / ss_tot)

    return r2

def plot_cost(self):
    import matplotlib.pyplot as plt
    plt.plot(self.costs)
    plt.xlabel("Nombre d'itérations")
    plt.ylabel("Fonction de coût")
    plt.title("Apprentissage de la régression linéaire avec la descente de
    plt.show()
```

```
In [191]: from sklearn.datasets import fetch_california_housing
```

```
california = fetch_california_housing()
X, y = california.data, california.target
```

```
In [192]: X.shape
```

```
Out[192]: (20640, 8)
```

```
In [193]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
print(f"X_train : {X_train.shape}\nX_test : {X_test.shape}")
```

```
X_train : (14448, 8)
X_test : (6192, 8)
```

```
In [194]: w = np.random.randn(X_train.shape[1])
b = 0
```

```
In [195]: w
```

```
Out[195]: array([-0.34599958, -0.59214479,  2.26072964,  0.91255674, -0.01854483,
                -0.01894474, -0.16903714, -0.01982737])
```

```
In [196]: (np.matmul(X_train, w) + b).shape
```

```
Out[196]: (14448,)
```



```
In [197]: m = X_train.shape[0]
j_w = (1/m) * np.matmul(X_train.T, np.matmul(X_train, w) + b - y_train)
j_b = (1/m) * np.sum(np.matmul(X_train, w) + b - y_train)

# Vérifier Les dimensions des gradients
print(j_w) # devrait être (2, 1)
print(j_b) # devrait être un scalaire
```

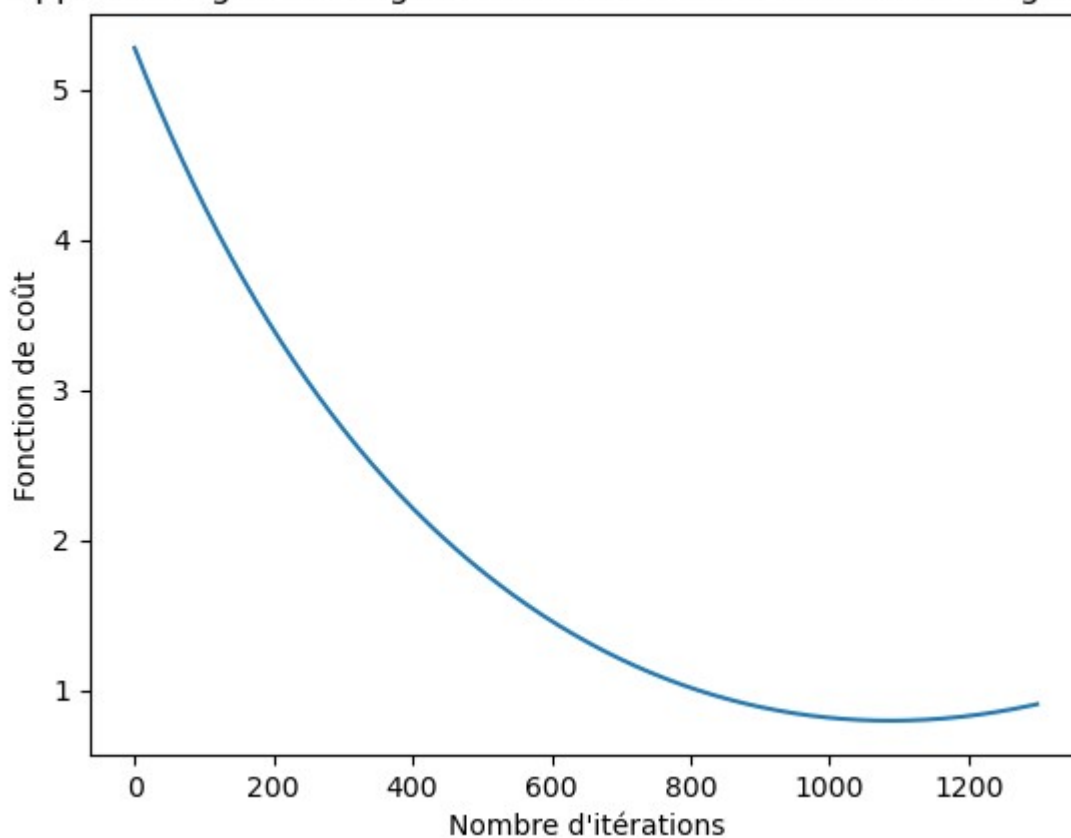
```
[-1.41746747e+02 -1.09054015e+03 -1.84231523e+02 -3.77585991e+01
 -7.53718918e+04 -1.25322924e+02 -1.32052269e+03  4.44925442e+03]
-37.23164909728779
```

```
In [221]: L = LinearRegression(0.001, 1300)
L.fit(X_train, y_train)
```

```
Iteration 0 : cost = 5.276841839117968
Iteration 100 : cost = 4.227026910036307
Iteration 200 : cost = 3.398915124807732
Iteration 300 : cost = 2.7396830612995826
Iteration 400 : cost = 2.212633718429792
Iteration 500 : cost = 1.7921682863788355
Iteration 600 : cost = 1.4603465411721577
Iteration 700 : cost = 1.20452980658227
Iteration 800 : cost = 1.015762471628613
Iteration 900 : cost = 0.8876580321511504
Iteration 1000 : cost = 0.8156303073877478
Iteration 1100 : cost = 0.796361225584863
Iteration 1200 : cost = 0.827431072991162
```

```
In [222]: L.plot_cost()
```

Apprentissage de la régression linéaire avec la descente de gradient



```
In [219]: L.score(X_test, y_test)
```

```
Out[219]: -402066.7492498711
```

```
In [ ]:
```

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