It has happened. Aliens have arrived. They hail from a planet called Valhalla-23, where the temperature is measured in Valks. These visitors tell you that they have come to solve Earth's global warming crisis*. They offer you a machine that will solve the problem, but they warn you:

1. The machine must be set up in Valks.
2. If you input a wrong temperature value, you may end up freezing or scorching the Earth.
3. No one knows how to transform between Celsius and Valks.

You are tasked with finding a model for solving this problem, so you ask Humans and Valkians to collect temperature readings from several objects. The data are given in the Valhalla23.csv file.

Will you become Earth's savior? Or will you obliterate life?

The choice is yours...

Cargamos y vemos los datos

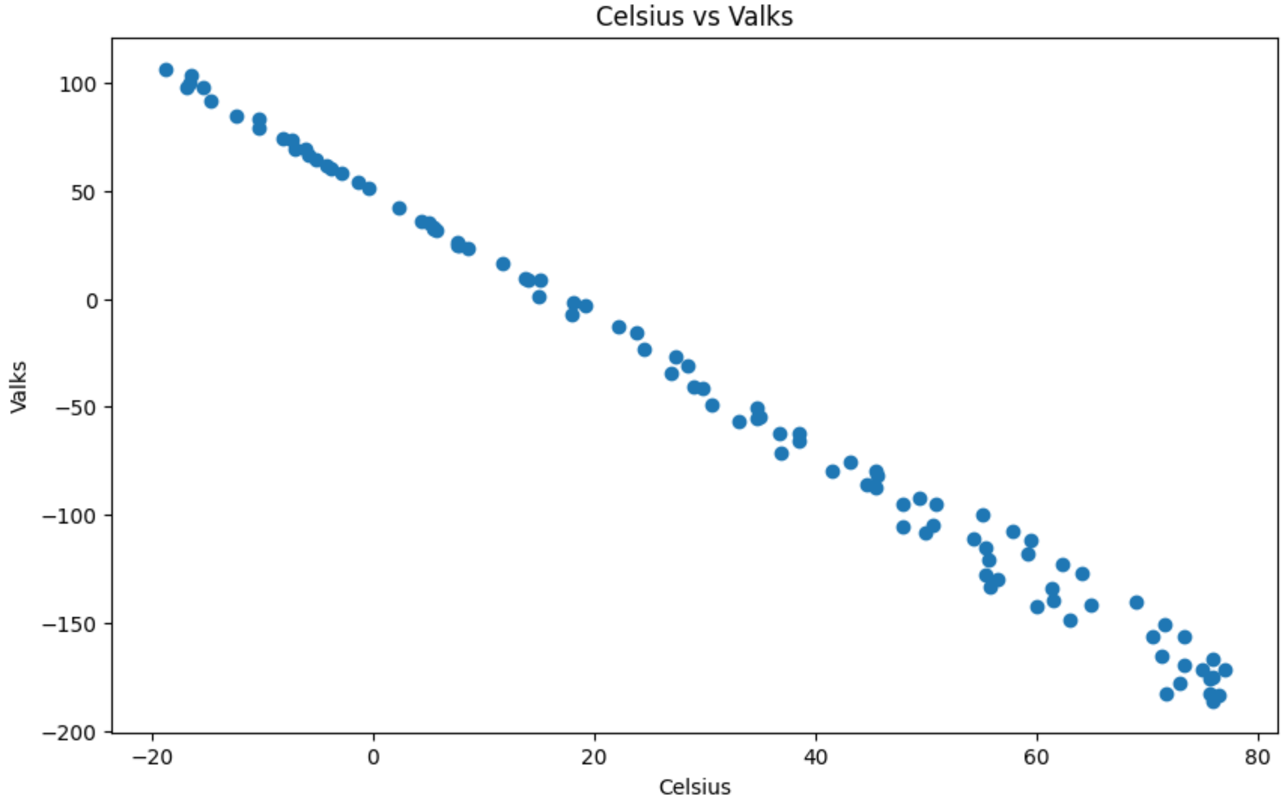
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

data = pd.read_csv('Valhalla23.csv')

print(data.head())
print("")
print(data.isnull().sum())
```

```
   Celsius    Valks
0  61.4720 -139.740
1  70.5790 -156.600
2  -7.3013   73.269
3  71.3380 -165.420
4  43.2360  -75.835

Celsius    0
Valks      0
dtype: int64
```

En el siguiente recuadro, se creó un gráfico de dispersión de Celsius vs Valks

```
plt.figure(figsize=(10, 6))
```

```
plt.scatter(data['Celsius'], data['Valks'])
plt.xlabel('Celsius')
plt.ylabel('Valks')
plt.title('Celsius vs Valks')
plt.show()
```



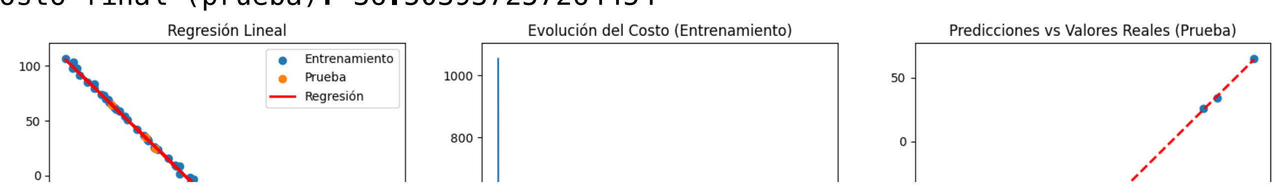
Inicio de Modelo

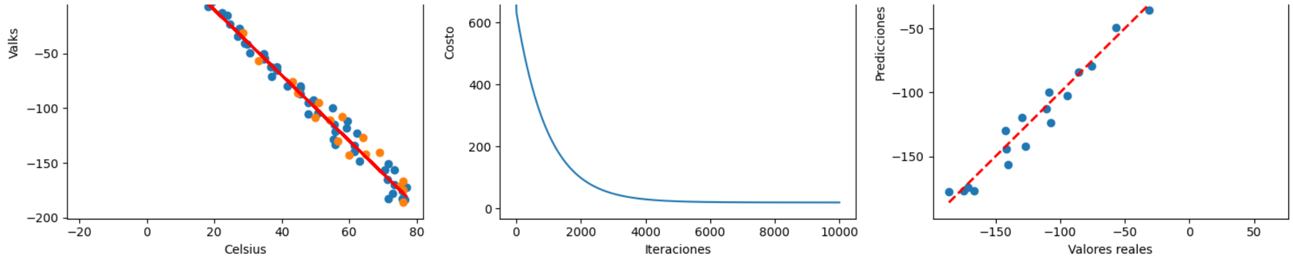
```
import numpy as np
import matplotlib.pyplot as plt

# Dividir el conjunto de datos en entrenamiento (80%) y prueba (20%)
def train_test_split(X, y, test_size=0.2):
    n = len(X)
    n_test = int(n * test_size)
    indices = np.random.permutation(n)
    test_indices = indices[:n_test]
```

```
    train_indices = indices[n_test:]
    return X[train_indices], X[test_indices], y[train_indices], y[test_indices]

X_train, X_test, y_train, y_test = train_test_split(X, y)

# Añadir una columna de unos para el término de sesgo
def add_bias(X):
    return np.c_[np.ones((X.shape[0], 1)), X]

X_train_b = add_bias(X_train)
X_test_b = add_bias(X_test)

# Inicializar parámetros
theta = np.random.randn(2, 1)
n_iterations = 10000

# Función para calcular el costo
def compute_cost(X, y, theta):
    m = len(y)
    predictions = X.dot(theta)
    cost = (1/(2*m)) * np.sum((predictions - y)**2)
    return cost

# Función para realizar el descenso del gradiente
def gradient_descent(X, y, theta, n_iterations, alpha):
    m = len(y)
    cost_history = np.zeros(n_iterations)
    theta_history = np.zeros((n_iterations, 2))

    for it in range(n_iterations):
        prediction = np.dot(X, theta)
        theta = theta - (1/m) * alpha * (X.T.dot((prediction - y)))
        theta_history[it, :] = theta.T
        cost_history[it] = compute_cost(X, y, theta)

    return theta, cost_history, theta_history

# Búsqueda de la tasa de aprendizaje óptima
alphas = [0.001, 0.0001, 0.00001, 0.000001, 0.0000001]
costs = []

for alpha in alphas:
    theta_temp, cost_history, _ = gradient_descent(X_train_b, y_train, theta, n_it
    costs.append(cost_history[-1])

optimal_alpha = alphas[np.argmin(costs)]

# Ejecutar el descenso del gradiente con la tasa de aprendizaje óptima
theta, cost_history, theta_history = gradient_descent(X_train_b, y_train, theta, n
```

```
# Predecir usando el conjunto de prueba
y_pred = X_test_b.dot(theta)

# Calcular el costo para el conjunto de prueba
test_cost = compute_cost(X_test_b, y_test, theta)

# Imprimir resultados
print(f"Tasa de aprendizaje óptima: {optimal_alpha}")
print(f"Theta final: {theta.ravel()}")
print(f"Costo final (entrenamiento): {cost_history[-1]}")
print(f"Costo final (prueba): {test_cost}")

# Graficar los resultados
plt.figure(figsize=(15, 5))

# Graficar los datos y la línea de regresión
plt.subplot(131)
plt.scatter(X_train, y_train, label='Entrenamiento')
plt.scatter(X_test, y_test, label='Prueba')
plt.plot(X, add_bias(X).dot(theta), color='red', linewidth=2, label='Regresión')
plt.xlabel('Celsius')
plt.ylabel('Valks')
plt.title('Regresión Lineal')
plt.legend()

# Graficar la evolución del costo
plt.subplot(132)
plt.plot(range(n_iterations), cost_history)
plt.xlabel('Iteraciones')
plt.ylabel('Costo')
plt.title('Evolución del Costo (Entrenamiento)')

# Graficar predicciones vs valores reales
plt.subplot(133)
plt.scatter(y_test, y_pred)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.xlabel('Valores reales')
plt.ylabel('Predicciones')
plt.title('Predicciones vs Valores Reales (Prueba)')

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

```
Tasa de aprendizaje óptima: 0.001
Theta final: [49.49356635 -2.98614431]
Costo final (entrenamiento): 18.767722180163936
Costo final (prueba): 36.503937257264454
```




Valks
Celsius
Costo
Iteraciones
Predicciones
Valores reales