In [2]: theta0 = Var('theta0', 1) thetas = [theta0]xs = [1] ys = [2] predict = lambda _: f(xs, thetas) print("f =", predict(xs)) cost = J(predict, xs, ys)print("J =", cost) theta0_deriv = cost.derivative('theta0') print("dJ/dw =", theta0_deriv)
print("dJ/dw =", theta0_deriv.evaluate()) print("w' =", theta0.evaluate() - theta0_deriv.evaluate()) theta0 = theta0.evaluate() - theta0_deriv.evaluate() thetas = [theta0] print("f' =", f(xs, thetas).evaluate()) f = theta0 * 1 $J = 1 / (2 * 1) * ((y - (theta0 * 1))^2)$ $dJ/dw = (2 * 1)^{(-1 - 1)} * 2 * 0 * ((y - (theta0 * 1))^2) + 1 / (2 * 1) * (2 * (y - (theta0 * 1))^2 - 1) * (0 + 1) * (1 + 1) * (2 * (1 + 1)) * (1 + 1) * (2 * (1 + 1)) * (1 + 1) * (1$ 1 + theta0 * 0)) dJ/dw = -1.0w' = 2.0f' = 2.0In [3]: theta0 = Var('theta0', 1) theta1 = Var('theta1', 1) thetas = [theta0, theta1]xs = [1.25]ys = [2.5]predict = lambda x: f([Const(1), Var('x', x)], thetas)print("f =", predict(xs)) cost = J(predict, xs, ys)print("J =", cost) theta0 deriv = cost.derivative('theta0') print("dJ/dw =", theta0_deriv)
print("dJ/dw =", theta0_deriv.evaluate()) print("w' =", theta0.evaluate() - theta0_deriv.evaluate()) theta1_deriv = cost.derivative('theta1') print("dJ/db =", thetal_deriv)
print("dJ/db =", thetal_deriv.evaluate()) print("b' =", thetal.evaluate() - thetal deriv.evaluate()) theta0 = $Sub(theta0, theta0_deriv)$ theta1 = Sub(theta1, theta1_deriv) thetas = [theta0, theta1]
print("f' =", f([Const(1), Var('x', xs[0])], thetas).evaluate()) f = theta0 * 1 + theta1 * x $J = 1 / (2 * 1) * ((y - (theta0 * 1 + theta1 * x))^2)$ $dJ/dw = (2 * 1)^{-1} - 1) * 2 * 0 * ((y - (theta0 * 1 + theta1 * x))^2) + 1 / (2 * 1) * (2 * (y - (theta0 * 1 + theta1 * x))^2)$ heta1 * x))^(2 - 1) * (0 + 1 + theta0 * 0 + 0 * x + theta1 * 0))dJ/dw = -0.25w' = 1.25heta1 * x))^(2 - 1) * (0 + 0 * 1 + theta0 * 0 + x + theta1 * 0))dJ/db = -0.3125b' = 1.3125f' = 2.890625Generate data that looks similar to a straight line, which we will fit our model to. In [4]: # Generate data and display data = generate(240)# Print with matplotlib xs = [x[0] for x in data]ys = [x[1] for x in data]plt.scatter(xs, ys) Out[4]: <matplotlib.collections.PathCollection at 0x7a7f168e7b30> 1400 1200 1000 800 600 400 200 25 50 75 100 125 150 175 200 Normalize the data for easier fitting: In [5]: trf_x = lambda x: (x - min(xs)) / (max(xs) - min(xs)) $trf_y = lambda y: (y - min(ys)) / (max(ys) - min(ys))$ xs trf = [trf x(x) for x in xs] $ys_{trf} = [trf_y(y) for y in ys]$ $xs = xs_trf$ ys = ys_trf plt.scatter(xs, ys) Out[5]: <matplotlib.collections.PathCollection at 0x7a7f1675ef90> 1.0 0.8 0.6 0.4 0.2 0.0 0.0 0.4 1.0 0.2 0.6 0.8 Use cross-validation to train several models and determine the best one: In [6]: crossval = 0.75 $n_{models} = 4$ models = []m_val = int((1 - crossval) * len(data)) data_idx = [i for i in range(n_models)] $data_idx = [(i * m_val, (i + 1) * m_val) for i in data_idx]$ $data_{cv} = [((xs[:l] + xs[r:], ys[:l] + ys[r:]), (xs[l:r], ys[l:r]))$ for l, r in data_idx] print(data idx) print([[len(p) for t in d for p in t] for d in data_cv]) [(0, 60), (60, 120), (120, 180), (180, 240)][[180, 180, 60, 60], [180, 180, 60, 60], [180, 180, 60, 60], [180, 180, 60, 60]] Run gradient descent for the given number of epochs. Train the models and plot the cost, gradient descent, and final function: In [7]: epochs = 800 $batch_size = 30$ alpha = 1e-1best_theta0 = None best_theta1 = None best_val = float('inf') for i in range(n models): # Initialize data xs_train, ys_train = data_cv[i][0] # Initialize params theta0 = Var('theta0', 0) theta1 = Var('theta1', 0) thetas = [theta0, theta1] predict = lambda x: f([Const(1), Var('x', x)], thetas)# Run training theta0_history = [] $J_history = []$ for _ in range(epochs):
 # Get current batch idx = random.randint(0, len(xs_train) - batch_size) xs_batch, ys_batch = xs_train[idx:idx + batch_size], ys_train[idx:idx + batch_size] assert len(xs_batch) == batch_size assert len(ys_batch) == batch_size # Get cost predict = lambda x: f([Const(1), Var('x', x)], [theta0, theta1]) cost = J(predict, xs_batch, ys_batch) cost_train = cost.evaluate() # Get derivatives theta0_deriv = cost.derivative('theta0').evaluate() theta1_deriv = cost.derivative('theta1').evaluate() # if J_history and cost_train > J_history[-1]: alpha *= .95 theta0.value = theta0.evaluate() - alpha * theta0_deriv theta1.value = theta1.evaluate() - alpha * theta1_deriv theta0_history.append(theta0.evaluate()) J_history.append(cost_train) # Validate xs_val, ys_val = data_cv[i][1] cost = J(predict, xs_val, ys_val) cost val = cost.evaluate() if cost_val < best_val:</pre> $best_theta0 = theta0$ best_theta1 = theta1 best val = cost val# Plot J history and final line along with data, on two subplots plt.figure() plt.subplot(221) $plt.scatter([i \ \textit{for} \ i \ \textit{in} \ range(len(J_history))], \ J_history, \ c='g', \ marker='+', \ s=1)$ plt.subplot(222) plt.subplot(223) plt.scatter(xs, ys) # Plot the line $x \min, x_{\max} = \min(xs), \max(xs)$ y_{min} , $y_{max} = f([Const(1), Var('x', x_{min})], thetas).evaluate(), <math>f([Const(1), Var('x', x_{max})], thetas).evaluate()$ plt.plot([x_min, x_max], [y_min, y_max], 'r') plt.show() print(f"Model {i} function:") print(f"Val cost: {cost_val}") $print("f_{theta}(x) = ", f([Const(1), Var('x')], [theta0.evaluate(), theta1.evaluate()]))$ 0.05 0.20 0.04 0.15 0.03 0.10 0.02 0.05 0.01 0.00 0.00 0 200 600 800 0.1 0.2 0.3 0.4 1.0 0.8 0.6 0.4 0.2 0.0 0.00 0.25 0.50 0.75 1.00 Model 0 function: Val cost: 0.003093862759782482 $f_{total} = 0.1713793028626016 * 1 + 0.7600478541179951 * x$ 0.25 -0.04 0.20 0.03 0.15 0.10 0.02 0.05 0.01 0.00 0.00 600 800 0.2 200 400 0.1 0.3 1.0 0.8 0.6 0.4 0.2 0.25 0.50 0.75 1.00 0.00 Model 1 function: Val cost: 0.001471281359360993 $f_{\text{theta}}(x) = 0.13952383564451182 * 1 + 0.8067606428304525 * x$ 0.03 0.2 0.02 0.1 0.01 0.0 0.3 0.4 0.2 200 400 600 800 0.1 1.0 0.8 0.6 0.4 0.2 0.0 0.00 0.25 0.50 0.75 1.00 Model 2 function: Val cost: 0.0024557977505230573 $f_{total} = 0.13814506737150847 * 1 + 0.8056613430970873 * x$ 0.03 0.15 0.02 0.10 0.05 0.01 0.00 200 800 0.1 0.2 0.3 0.4 400 600 1.0 0.8 0.6 0.4 0.0 0.00 0.25 0.50 0.75 1.00 Model 3 function: Val cost: 0.0019979515819370628 $f_{total} = 0.1455441363580537 * 1 + 0.7775337535123441 * x$ Calculate statistics for the best model. In [8]: print(f"Best model function:") $print("f_theta(x) = ", f([Const(1), Var('x')], [best_theta0.evaluate(), best_theta1.evaluate()]))$ $f_{total} = 0.13952383564451182 * 1 + 0.8067606428304525 * x$ Visualize the data mean: In [9]: data_mean = sum(ys) / len(ys) plt.plot([0, 1], [data_mean, data_mean], 'r') plt.scatter(xs, ys) plt.plot([0, 1], [best_theta0.evaluate(), best_theta0.evaluate() + best_theta1.evaluate()], c='y') Out[9]: [<matplotlib.lines.Line2D at 0x7a7f160aeb40>] 1.0 0.8 0.6 0.4 0.2 1.0 Calculate correlation (\$R^2\$) and \$F\$-value: In [10]: $var_mean = sum([x ** 2 for x in [y - data_mean for y in ys]]) / len(ys)$ $var_{fit} = sum([x ** 2 for x in [y - (best_theta0.evaluate() + best_theta1.evaluate() * x) for x, y in zip(xs, y) for x, y in zip(xs,$ rsquared = 1 - var_fit / var_mean print(f"Data mean: {data_mean}") print(f"Data variance: {var_mean}") print(f"Fit variance: {var_fit}") print(f"R^2: {rsquared}") Data mean: 0.526481845527067 Data variance: 0.0625788260341672 Fit variance: 0.004168417530939422 R^2: 0.9333893299841783 Calculate \$F\$-value: In [11]: p_fit = 2 $p_mean = 1$ m = len(ys)p = (1 - var_fit) / var_mean * (p_fit - p_mean) / (m - p_fit)

print(f"Adjusted R^2: {p}")
Adjusted R^2: 0.06686233312543628

Simple Linear Regression

Let's check if our mathematical expressions are correct:

In [1]: import matplotlib.pyplot as plt
from src import *