Assignment #3 Group 4 Lars Wrede, Dennis Blaufuss, Nicolas Kepper, Sophie Merl, Philipp Voit **Unlucky Optimization Competition** Modify the Expectation-Maximization (EM) Python program for the two coins, as discussed in class. (a) Generate unrepresentative series of exactly n = 125 total coin flips (5 times 25 flips with a randomly selected coin), (b) given two coins are chosen with equal probability (1/2). (c) The coins must have the following heads biases, θ_A = 0.9 (coin A), and θ_B = 0.1 (coin B), and the generation must follow exactly this random process. In a nutshell, the task is to generate a series of (H)eads and (T)ails that are highly unlikely, given the ground truth, by brute forcing an unlucky realizations you generate and scan, the better will be the score, so it is about optimization (and computational power). Monitor the MLE estimates for $\hat{\theta_A}$ and $\hat{\theta_B}$. The solution with the largest value of score = $min[abs(log(\hat{\theta_A}/\theta_A)), abs(log(\hat{\theta_A}/\theta_A)), abs(log(\hat{\theta_B}/\theta_B))]$ (that you need to compute and print) wins a price, handed over by the lecturer but only if this value is unique among the submissions. If it is not, the 2nd largest score wins, if unique, and so on. If there is no winner, the present may, sadly, be thrown out of one randomly selected window. Good unluck! import numpy as np from matplotlib import pyplot as plt import matplotlib as mpl from math import log import random import time %matplotlib inline #EM algorithm def coin_em(rolls, theta_A=None, theta_B=None, max_iter=50): #add =50 # Initial Guess theta_A = theta_A or random.random() #take value or start wild between 0 and 1 theta B = theta B or random.random() # theta vector thetas = [(theta_A, theta_B)] score = [0]# Iterate for i in range(max iter): #print("#%d:\t Thetas: %0.4f %0.4f | Score: %0.4f" % (i, theta_A, theta_B, score[i])) #significant digits #print(round(variable, 3)) heads A, tails A, heads B, tails B = e step(rolls, theta A, theta B) theta A, theta B = m step(heads A, tails A, heads B, tails B) thetas.append((theta_A,theta_B)) score.append(min(abs(log(theta_A/0.9)), abs(log(theta_B/0.1)))) # Our biases .9 and .1 pass # doing nothing on exception return thetas, (theta_A,theta_B), score #thetas are conveniently needed for a unnecessary plot at the end # Compute expected value for heads_A, tails_A, heads_B, tails_B over rolls given coin biases def e_step(rolls, theta_A, theta_B): heads_A, tails_A = 0,0heads_B, tails_B = 0.0for trial in rolls: likelihood_A = coin_likelihood(trial, theta_A) likelihood_B = coin_likelihood(trial, theta_B) p_A = likelihood_A / (likelihood_A + likelihood_B) p_B = likelihood_B / (likelihood_A + likelihood_B) heads_A += p_A * trial.count("H") tails_A += p_A * trial.count("T") heads_B += p_B * trial.count("H") tails_B += p_B * trial.count("T") return heads_A, tails_A, heads_B, tails_B # M step: Compute values for theta that maximize the likelihood of expected number of heads/tails def m_step(heads_A, tails_A, heads_B, tails_B): theta_A = np.divide(heads_A, heads_A + tails_A) #np.divide avoids divby0s theta_B = np.divide(heads_B, heads_B + tails_B) return theta_A, theta_B $\# p(X \mid Z, theta)$ def coin_likelihood(roll, bias): numHeads = roll.count("H") flips = len(roll) return pow(bias, numHeads) * pow(1-bias, flips-numHeads) # plot EM convergence def plot_coin_likelihood(rolls, thetas=None): xvals = np.linspace(0.01, 0.99, 100)yvals = np.linspace(0.01, 0.99, 100)X,Y = np.meshgrid(xvals, yvals) # compute likelihood Z = []for i,r in enumerate(X): z = []for j,c in enumerate(r): z.append(coin_marginal_likelihood(rolls,c,Y[i][j])) Z.append(z) # plot plt.figure(figsize=(10,8)) C = plt.contour(X,Y,Z,150)cbar = plt.colorbar(C) plt.title(r"Likelihood \$\log p(\mathcal{X}|\theta_A,\theta_B)\$", fontsize=20) plt.xlabel(r"\$\theta_A\$", fontsize=20) plt.ylabel(r"\$\theta_B\$", fontsize=20) # plot thetas if thetas is not None: thetas = np.array(thetas) plt.plot(thetas[:,0], thetas[:,1], '-k', lw=2.0) plt.plot(thetas[:,0], thetas[:,1], 'ok', ms=5.0) # $\log P(X \mid \text{theta})$, only used for plot def coin_marginal_likelihood(rolls, biasA, biasB): trials = [] for roll in rolls: h = roll.count("H") t = roll.count("T") likelihoodA = coin_likelihood(roll, biasA) likelihoodB = coin likelihood(roll, biasB) trials.append(np.log(0.5 * (likelihoodA + likelihoodB))) return sum(trials) # Generate surrogate data # Number of experiments experiments = 5 #the smaller this number to worst the performance/estimate # Number of coin tosses for each trial coin_tosses = 25 #the smaller this number to worst the performance/estimate # Experiment ground truth properties: Prob to choose coin A for the trial pA = 0.5pB = 1-pA# Coin ground truth properties: Prob for heads and tails p heads A = 0.9 $p_heads_B = 0.1$ max score = 0 all_scores = [] max_rolls = [] max_thetas = [] begin = time.time() for zzz in range(100000000): # empty array where all tosses are stored rolls= [] A heads = 0 B heads = 0 $A_{tails} = 0$ $B_{tails} = 0$ for i in range(0,experiments): trial = "" A=0 # Choose coin: p fixed for single trial if (random.uniform(0, 1) \leq pA): $p = p_heads_A$ A=1 else: $p = p_heads_B$ A=0 for j in range(0,coin_tosses): # generate outcome outcome = random.uniform(0, 1) if (outcome < p):</pre> trial += "H" **if** (A==1): $A_heads += 1$ else: B heads += 1 else: trial += "T" **if** (A==1): $A_{tails} += 1$ else: $B_{tails} += 1$ rolls.append(trial) #print entire outcomes of experiment #print(rolls) # Call EM thetas , , scores = coin em(rolls, 0.9, 0.1, max iter=15) if max(scores) > max_score: max_score = max(scores) all_scores = scores max_rolls = rolls max thetas = thetas max_A_heads, max_A_tails, max_B_heads, max_B_tails = A_heads, A_tails, B_heads, B_tails max_p_heads_A, max_p_heads_B = p_heads_A, p_heads_B print(f"Round: {zzz}") print(f"{max_score}, {max_rolls}") #significant digits print() #print("Chosen ground truth (which is sample-independent!): ") #print("%0.6f %0.6f" % (max_p_heads_A, max_p_heads_B)) # In fact, here, we do not need EM since we can compute MLE directly. So MLE serves as validation. #print("MLE estimates from data (finite sample size estimates are the theoretical optimum!):") #MLE_pA, MLE_pB = m_step(max_A_heads, max_A_tails, max_B_heads, max_B_tails) #print("%0.6f %0.6f" % (MLE_pA, MLE_pB)) #print(round(MLE_pA,3), round(MLE_pB,3)) Round: 0 Round: 5 Round: 38 Round: 39 Round: 96 Round: 468 Round: 1716 Round: 2369 Round: 15918 Round: 63888 Round: 87903 Round: 89556 Round: 545017 end = time.time() hours, rem = divmod(end-begin, 3600) minutes, seconds = divmod(rem, 60) print("It took {:0>2}:{:0>2}:{:05.2f} hours to run the script.".format(int(hours),int(minutes),seconds)) It took 10:45:42.36 hours to run the script. Round: 545.017 / 100.000.000 Max Score: 3.214068526732354 all scores Out[5]: [0, 2.5257286443082556, 3.214068526732354, 3.164755498401984, 3.0328463205118807, 2.9245604286377977,

(0.008936750553157765, 0.00706305471132083),(0.008757095297172059, 0.007242821678342752),(0.008611426235769317, 0.0073885384654641005),(0.008493539092708315, 0.007506445926709576),(0.0083982528890787, 0.007601740760706793),(0.008321296078564333, 0.00767870123165411)]

2.8399940301083, 2.774060041868091, 2.7225257853279823, 2.6821080921257,

2.6502925494040177, 2.625159320939532, 2.605240242513801, 2.5894080776728123, 2.5767929174617508, 2.5667197635910015] max_rolls ['TTTTTTTTTTTTTTTTTTTTTTTTTTT',

'THTTTTTTTTTTTTTTTTTTTTTTT, ' TTTTTTTTTTTTTTTTTTTTTTTTTTT max_thetas Out[7]: [(0.9, 0.1), (0.03811764705882353, 0.008),(0.014175441379642283, 0.004019275486928029),(0.011841431351472875, 0.00422244645011442),(0.011160662819649735, 0.004817831186421574),(0.010619189933825574, 0.005368828655984204),(0.01015192206742085, 0.005842601476044025),(0.00975676570885466, 0.006240811013948512),(0.009428086922320581, 0.006570857888840055),(0.009157668302224593, 0.006841876895101844),