import torch import numpy as np import os, json import pandas as pd import matplotlib.pyplot as plt import seaborn as sns from evaluation based sampling import evaluate, evaluate program from daphne import daphne from graph based sampling import sample from joint Problem 3 In [2]: from load helper import ast helper, graph helper Importance sampling • 10k samples in 1.59s implies 384k samples in 10 min 1k samples in 5.29s implies 113k samples in 10 min In [3]: import parse import importance sampling In [4]: fname = '3.daphne' ast = ast_helper(fname) ast [['let', Out[4]: ['data', ['vector', 1.1, 2.1, 2.0, 1.9, 0.0, -0.1, -0.05]], ['let', ['likes', ['vector', ['let', ['mu', ['sample', ['normal', 0.0, 10.0]]], ['let', ['sigma', ['sample', ['gamma', 1.0, 1.0]]], ['normal', 'mu', 'sigma']]], ['let', ['mu', ['sample', ['normal', 0.0, 10.0]]], ['let', ['sigma', ['sample', ['gamma', 1.0, 1.0]]], ['normal', 'mu', 'sigma']]], ['let', ['mu', ['sample', ['normal', 0.0, 10.0]]], ['let', ['sigma', ['sample', ['gamma', 1.0, 1.0]]], ['normal', 'mu', 'sigma']]]], ['let', ['pi', ['sample', ['dirichlet', ['vector', 1.0, 1.0, 1.0]]]], ['let', ['z-prior', ['discrete', 'pi']], ['let', ['z', ['vector', ['let', ['y', ['get', 'data', 0]], ['let', ['z', ['sample', 'z-prior']], ['let', ['_', ['observe', ['get', 'likes', 'z'], 'y']], 'z']]], ['let', ['y', ['get', 'data', 1]], ['let', ['z', ['sample', 'z-prior']], ['let', ['_', ['observe', ['get', 'likes', 'z'], 'y']], 'z']]], ['let', ['y', ['get', 'data', 2]], ['let', ['z', ['sample', 'z-prior']], ['let', [' ', ['observe', ['get', 'likes', 'z'], 'y']], 'z']]], ['y', ['get', 'data', 3]], ['let', ['z', ['sample', 'z-prior']], ['let', ['_', ['observe', ['get', 'likes', 'z'], 'y']], 'z']]], ['y', ['get', 'data', 4]], ['let', ['z', ['sample', 'z-prior']], ['let', [' ', ['observe', ['get', 'likes', 'z'], 'y']], 'z']]], ['let', ['y', ['get', 'data', 5]], ['let', ['z', ['sample', 'z-prior']], ['let', ['_', ['observe', ['get', 'likes', 'z'], 'y']], 'z']]], ['y', ['get', 'data', 6]], ['let', ['z', ['sample', 'z-prior']], ['let', [' ', ['observe', ['get', 'likes', 'z'], 'y']], 'z']]]]], ['=', ['first', 'z'], ['second', 'z']]]]]]] In [36]: %%time num samples=113000 samples, sigmas = parse.take samples(num samples,ast=ast) CPU times: user 10min 7s, sys: 1.91 s, total: 10min 9s Wall time: 10min 11s In [37]: samples = np.array([sample.item() for sample in samples]) In [38]: posterior_mean, probs = importance_sampling.weighted_average(samples, sigmas) In [39]: = plt.hist(samples.astype(int), weights=probs, bins=2) plt.xlabel('(= (first z) (second z))') plt.title('Problem {} \n Importance sampling \n importance sampling weighted counts from proposal'.format(fname plt.xticks([0,1],["False","True"]) plt.ylabel('Counts') Text(0, 0.5, 'Counts') Out[39]: Problem 3.daphne Importance sampling importance sampling weighted counts from proposal 0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0.0 False True (= (first z) (second z)) In [40]: method = "Importance sampling" """ {}: The posterior probability that the first and second datapoint are in the same cluster,\ i.e. the posterior probability that z[1] == z[2]: {:0.3f}\ """.format (method, posterior mean) ' Importance sampling: The posterior probability that the first and second datapoint are in the same cluster, i. Out[40]: e. the posterior probability that z[1] == z[2]: 0.806' MH Gibbs 0.27 s / sample implies ~2.2k samples in 10 min 0.1k in 30.3s implies 1.98k in 10 min My code is slow, perhaps because of some internal logging and so the burn in needs to be quite large compared with the total run. But the relatively long burn in is justified by the joint increasing. In [10]: import graph_based_sampling import mh gibbs from hmc import compute log joint prob In [11]: fname = '3.daphne' graph = graph helper(fname) graph [{}, Out[11]: {'V': ['sample5', 'sample0', 'observe18' 'observe12', 'sample17', 'sample7', 'sample9', 'sample15', 'sample19', 'sample6', 'observe14', 'observe10', 'sample13', 'sample4', 'sample2', 'sample1', 'observe8', 'sample3', 'sample11' 'observe16', 'observe20'], 'A': {'sample5': ['observe18', 'observe12', 'observe14', 'observe10', 'observe8', 'observe16', 'observe20'], 'sample0': ['observe18', 'observe12', 'observe14', 'observe10', 'observe8', 'observe16', 'observe20'], 'sample17': ['observe18'], 'sample7': ['observe8'], 'sample9': ['observe10'], 'sample15': ['observe16'], 'sample19': ['observe20'], 'sample6': ['sample17', 'sample7', 'sample9', 'sample15', 'sample19', 'sample13', 'sample11'], 'sample13': ['observe14'], 'sample4': ['observe18', 'observe12', 'observe14', 'observe10' 'observe8', 'observe16', 'observe20'], 'sample2': ['observe18', 'observe12', 'observe14', 'observe10', 'observe8', 'observe16', 'observe20'], 'sample1': ['observe18', 'observe12', 'observe14', 'observe10', 'observe8', 'observe16', 'observe20'], 'sample3': ['observe18', 'observe12', 'observe14', 'observe10', 'observe8', 'observe16', 'observe20'], 'sample11': ['observe12']}, 'P': {'sample5': ['sample*', ['gamma', 1.0, 1.0]], 'sample0': ['sample*', ['normal', 0.0, 10.0]], 'observe18': ['observe*', ['get', ['vector', ['normal', 'sample0', 'sample1'], ['normal', 'sample2', 'sample3'],
['normal', 'sample4', 'sample5']], 'sample17'], -0.1], 'observe12': ['observe*', ['get', ['vector', ['normal', 'sample0', 'sample1'], ['normal', 'sample2', 'sample3'],
['normal', 'sample4', 'sample5']], 'sample11'], 2.0], 'sample17': ['sample*', ['discrete', 'sample6']], 'sample7': ['sample*', ['discrete', 'sample6']],
'sample9': ['sample*', ['discrete', 'sample6']], 'sample15': ['sample*', ['discrete', 'sample6']],
'sample19': ['sample*', ['discrete', 'sample6']], 'sample6': ['sample*', ['dirichlet', ['vector', 1.0, 1.0, 1.0]]], 'observe14': ['observe*', ['get', ['vector', ['normal', 'sample0', 'sample1'], ['normal', 'sample2', 'sample3'],
['normal', 'sample4', 'sample5']], 'sample13'], 1.9], 'observe10': ['observe*', ['get', ['vector', ['normal', 'sample0', 'sample1'], ['normal', 'sample2', 'sample3'],
['normal', 'sample4', 'sample5']], 'sample9'], 2.1], 'sample13': ['sample*', ['discrete', 'sample6']], 'sample4': ['sample*', ['normal', 0.0, 10.0]], 'sample2': ['sample*', ['normal', 0.0, 10.0]], 'sample1': ['sample*', ['gamma', 1.0, 1.0]], 'observe8': ['observe*', ['get', ['normal', 'sample0', 'sample1'], ['normal', 'sample2', 'sample3'], ['normal', 'sample4', 'sample5']], 'sample7'], 1.1], 'sample3': ['sample*', ['gamma', 1.0, 1.0]], 'sample11': ['sample*', ['discrete', 'sample6']], 'observe16': ['observe*', ['get', ['vector', ['normal', 'sample0', 'sample1'], ['normal', 'sample2', 'sample3'],
['normal', 'sample4', 'sample5']], 'sample15'], 0.0], 'observe20': ['observe*', ['get', ['vector', ['normal', 'sample0', 'sample1'], ['normal', 'sample2', 'sample3'],
['normal', 'sample4', 'sample5']], 'sample19'], -0.05]}, 'Y': {'observe8': 1.1, 'observe10': 2.1, 'observe12': 2.0, 'observe14': 1.9, 'observe16': 0.0, 'observe18': -0.1, 'observe20': -0.05}}, ['=', 'sample7', 'sample9']] In []: num steps=1980 return_list, samples_whole_graph = mh_gibbs.mh_gibbs_wrapper(graph,num_steps) In [44]: samples = np.array([sample.item() for sample in return list]) In [54]: burn in = 1500 # int(0.01 * num steps)pd.Series(samples[burn_in:]).astype(float).plot.hist() plt.xlabel('(= (first z) (second z))') plt.title('MH Gibbs | {}'.format(fname)) Text(0.5, 1.0, 'MH Gibbs | 3.daphne') Out [54]: MH Gibbs | 3.daphne 350 300 250 Frequency 200 150 100 50 0.2 0.0 0.4 0.6 0.8 1.0 (= (first z) (second z)) In [55]: posterior_mean = samples[burn_in:].mean(0) In [56]: method = "MH Gibbs" """ {}: The posterior probability that the first and second datapoint are in the same cluster,\ i.e. the posterior probability that z[1] == z[2]: {:0.3f}\ """.format(method, posterior mean) ' MH Gibbs: The posterior probability that the first and second datapoint are in the same cluster, i.e. the post Out[56]: erior probability that z[1] == z[2]: 0.778' In [17]: pd.Series(samples).astype(int).plot() plt.xlabel('Iteration') plt.ylabel('z[1] == z[2]')plt.title('{} | MH Gibbs \n Sample trace'.format(fname)) Text(0.5, 1.0, '3.daphne | MH Gibbs \n Sample trace') Out[17]: 3.daphne | MH Gibbs Sample trace 1.0 0.8 z[1] == z[2]0.6 0.4 0.2 0.0 500 1000 1250 1500 1750 0 250 750 Iteration In [18]: G = graph[1]Y = G['Y']Y = {key:evaluate([value])[0] for key, value in Y.items()} P = G['P'] In [19]: size = len(samples_whole_graph) jll = np.zeros(size) for idx in range(size): jll[idx] = compute_log_joint_prob(samples_whole_graph[idx],Y,P) In [20]: pd.Series(jll).plot() plt.xlabel('Iteration (t)') plt.ylabel(r'\$-\log p(X=x t,Y=y t)\$') plt.title('{} | MH Gibbs \n Joint density'.format(fname)) Text(0.5, 1.0, '3.daphne | MH Gibbs \n Joint density') Out[20]: 3.daphne | MH Gibbs Joint density -50 -100 $-\log p(X = x_t, Y = y_t)$ -150-200 -250-300-350 1000 1250 750 1500 1750 Iteration (t)

In [1]: