In [1]: import load helper import pandas as pd import matplotlib.pyplot as plt import numpy as np import importlib from torch import tensor In [14]: fname = '2.daphne' graph = load helper.graph helper(fname) %cat 2.daphne (defn observe-data [_ data slope bias] (let [xn (first data) yn (second data) zn (+ (* slope xn) bias)] (observe (normal zn 1.0) yn) (rest (rest data)))) (let [slope (sample (normal 0.0 10.0)) bias (sample (normal 0.0 10.0)) data (vector 1.0 2.1 2.0 3.9 3.0 5.3 4.0 7.7 5.0 10.2 6.0 12.9)] (loop 6 data observe-data slope bias) (vector slope bias)) In [3]: import bbvi importlib.reload(bbvi) from bbvi import graph bbvi algo12 In [4]: %%time T=10000 L=10 lr=0.05 r, logW, sigma = bbvi.graph_bbvi_algo12(graph,T=T,L=L,lr=lr, do log=False) t=0, Q after step={'sample1': Normal(loc: 0.04999999701976776, scale: 9.999954223632812), 'sample2': Normal(lo c: 0.04999999701976776, scale: 9.999954223632812)} t=1000, Q after step={'sample1': Normal(loc: 1.966282606124878, scale: 0.35881099104881287), 'sample2': Normal (loc: -0.07611042261123657, scale: 2.1672756671905518)} t=2000, Q after step={'sample1': Normal(loc: 2.102851629257202, scale: 0.18338362872600555), 'sample2': Normal (loc: -0.42446640133857727, scale: 0.6566195487976074)} t=3000, Q after step={'sample1': Normal(loc: 2.1381676197052, scale: 0.12904785573482513), 'sample2': Normal(loc c: -0.4206306040287018, scale: 0.45331424474716187)} t=4000, Q after step={'sample1': Normal(loc: 2.13557505607605, scale: 0.11017777770757675), 'sample2': Normal(l oc: -0.5013607144355774, scale: 0.4187203347682953)} t=5000, Q after step={'sample1': Normal(loc: 2.1337504386901855, scale: 0.10388973355293274), 'sample2': Normal (loc: -0.506049394607544, scale: 0.4013504683971405)} t=6000, Q after step={'sample1': Normal(loc: 2.173062324523926, scale: 0.10475638508796692), 'sample2': Normal (loc: -0.5092238187789917, scale: 0.4144499897956848)} t=7000, Q after step={'sample1': Normal(loc: 2.187255620956421, scale: 0.10510562360286713), 'sample2': Normal (loc: -0.696744441986084, scale: 0.39388900995254517)} t=8000, Q after step={'sample1': Normal(loc: 2.1886229515075684, scale: 0.10825375467538834), 'sample2': Normal (loc: -0.5877746939659119, scale: 0.41785284876823425)} t=9000, Q after step={'sample1': Normal(loc: 2.0912787914276123, scale: 0.09985072910785675), 'sample2': Normal (loc: -0.5837337374687195, scale: 0.4200637638568878)} CPU times: user 4min 27s, sys: 888 ms, total: 4min 28s Wall time: 4min 29s In [5]: elbo = logW.mean(1)pd.Series(elbo).plot() plt.xlabel('t') plt.ylabel('ELBO') plt.title(' $\{\}$ \n Best ELBO $\{:1.2f\}$ \n T= $\{\}$ | L= $\{\}$ | Adam, lr= $\{\}$ '.format(fname,elbo.max(),T,L,lr)) Text(0.5, 1.0, '2.daphne \n Best ELBO -12.32 \n T=10000 | L=10 | Adam, 1r=0.05 ') Out[5]: 2.daphne Best ELBO -12.32 T=10000 | L=10 | Adam, Ir=0.05 0 -2000-4000-6000-8000 0 2000 4000 6000 8000 10000 In [6]: sr = pd.Series(elbo[-200:]) sr.index = np.arange(elbo.size-200,elbo.size) sr.plot() plt.xlabel('t') plt.ylabel('ELBO') plt.title(' $\{\}$ \n Best ELBO $\{:1.2f\}$ \n T= $\{\}$ | L= $\{\}$ | Adam, lr= $\{\}$ '.format(fname,elbo.max(),T,L,lr)) Text(0.5, 1.0, '2.daphne \n Best ELBO -12.32 \n T=10000 | L=10 | Adam, 1r=0.05 ') Out[6]: 2.daphne Best ELBO -12.32 T=10000 | L=10 | Adam, Ir=0.05 -13.00-13.25-13.50-13.75-14.00-14.25-14.50-14.75-15.009825 9850 9800 9875 9900 9925 9950 9975 10000 In [7]: $r_{array} = np.zeros((T,L,2))$ for t in range(T): for l in range(L): $r_array[t,l,:] = r[t][l].detach().numpy()$ In [8]: probs = np.exp(logW)probs /= probs.sum() probs = probs.reshape(T,L,1) posterior_r = (probs * r_array).sum(axis=(0,1)) posterior_r2 = (probs * r_array**2).sum(axis=(0,1)) std_r = np.sqrt(posterior_r2 - posterior_r**2) In [9]: print('{} expected posterior slope {:1.3f} | std posterior slope {:1.3f}'.format(fname,posterior r[idx],std r[j print('{} expected posterior bias {:1.3f} | std posterior bias {:1.3f}'.format(fname,posterior r[idx],std r[idx 2.daphne expected posterior slope 2.154 | std posterior slope 0.206 2.daphne expected posterior bias -0.530 | std posterior bias 0.800In [10]: trace = r array[:,:,0].flatten() pd.Series(trace).plot() plt.xlabel('time t, sample l') plt.ylabel('slope') plt.title('{} \n Trace \n T={} | L={} | Adam, lr={} '.format(fname,T,L,lr)) Text(0.5, 1.0, '2.daphne \n Trace \n T=10000 | L=10 | Adam, 1r=0.05 ') Out[10]: 2.daphne Trace T=10000 | L=10 | Adam, lr=0.05 30 20 10 slope -10-20-3020000 40000 60000 80000 100000 time t, sample I In [11]: trace = r array[:,:,1].flatten() pd.Series(trace).plot() plt.xlabel('time t, sample l') plt.ylabel('bias') plt.title('{} \n Trace \n T={} | L={} | Adam, lr={} '.format(fname,T,L,lr)) Text(0.5, 1.0, '2.daphne \n Trace \n T=10000 | L=10 | Adam, 1r=0.05 ') Out[11]: 2.daphne Trace T=10000 | L=10 | Adam, lr=0.05 30 20 10 bias -10-20-3020000 40000 60000 80000 100000 time t, sample I In [12]: Q = sigma['Q best t'] q = Q['sample1'] loc = q.loc.detach().numpy() scale = q.scale.detach().numpy() support = np.linspace(loc-3*scale,loc+3*scale,100) log pdf = np.zeros like(support) for idx,c in enumerate(support): log pdf[idx] = q.log prob(tensor(c)) pdf = np.exp(log pdf)sr = pd.Series(pdf) sr.index = support sr.plot() plt.xlabel('\$X\$') plt.ylabel('\$p(X|Y)\$') plt.title(\ '{} \n posterior of slope (learned proposal) \n'.format(fname) +\ 'slope \$\sim \mathcal{N}\$' +\ '\$[loc={:1.3f}, scale={:1.3f}]\$'.format(loc, scale) Text(0.5, 1.0, '2.daphne \n posterior of slope (learned proposal) \nslope \$\\sim \\mathcal{N}\$\$[loc=2.127, scal Out[12]: e=0.102]\$') 2.daphne posterior of slope (learned proposal) slope $\sim N[loc = 2.127, scale = 0.102]$ 4.0 3.5 3.0 2.5 2.0 1.5 1.0 0.5 0.0 1.8 1.9 2.0 2.1 2.2 2.3 Х In [13]: Q = sigma['Q best t'] q = Q['sample2'] loc = q.loc.detach().numpy() scale = q.scale.detach().numpy() support = np.linspace(loc-3*scale,loc+3*scale,100) log pdf = np.zeros like(support) for idx,c in enumerate(support): log pdf[idx] = q.log prob(tensor(c)) pdf = np.exp(log pdf)sr = pd.Series(pdf) sr.index = supportsr.plot() plt.xlabel('\$X\$') plt.ylabel('\$p(X|Y)\$') plt.title(\ '{} \n posterior of bias (learned proposal) \n'.format(fname) +\ 'bias \$\sim \mathcal{N}\$' +\ '\$[loc={:1.3f}, scale={:1.3f}]\$'.format(loc, scale) Text(0.5, 1.0, '2.daphne \n posterior of bias (learned proposal) \nbias \$\\sim \\mathcal{N}\\$\$[loc=-0.504, scale Out[13]: =0.463]\$') 2.daphne posterior of bias (learned proposal) bias $\sim N[loc = -0.504, scale = 0.463]$ 0.8 0.6 0.4 0.2 0.0 -1.5-0.5-2.0-1.00.0 0.5 1.0

Problem 2