# **CP3 Official Solution by Course Staff**

## **Collaboration Statement:**

Mike Hughes prepared this solution, working alone.

Total hours spent: 4 hours

Links: [CP3 instructions] [Course collaboration policy]

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### 1a: Figure

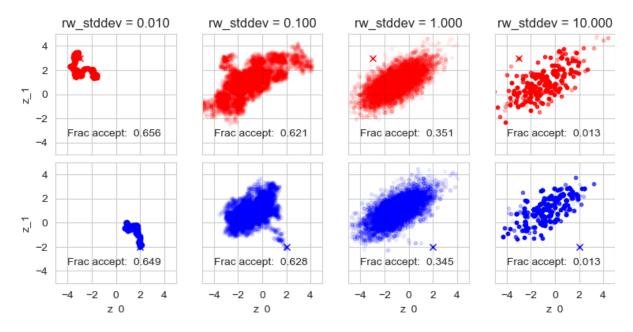


Fig. 1a: Behavior of RW Sampler from different proposal standard deviation values (columns) and initializations (rows, initial value marked with 'X'). Takeaway 1: Only  $\sigma=1.0$  seems to converge well. Smaller  $\sigma$  show that the Markov chain still depends on initial state. Larger  $\sigma$  values have too few accepted samples to yet be useful.

#### 1b: Solution

No, I should always be skeptical that an MCMC chain has converged just from accept rate alone (or even just one chain alone). See figure 1a: high accept rate at low proposal width (small  $\sigma$ ) means poor sampling from target.

#### 2a: Solution

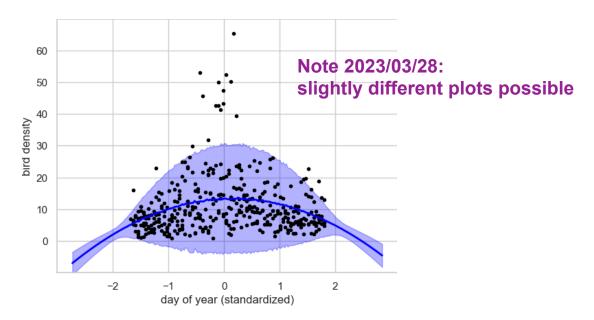


Fig. 2a: Predictive posterior for  $t_*$ : Both mean and variance can change as quadratic (order 2) functions of  $x_*$ .

### **2b: Solution**

order	test score
0	-4.52 +/- 0.002
2	-4.04 + /- 0.005

# Note 2023/03/28: others may get slightly different results we'll release more authoritative answers later after further investigation, based on

student-submitted answers

#### 2c: Solution

```
def calc_score(list_of_z_D, phi_RM, t_R):
''' Calculate per-example score averaged over provided test set of size R
'''
S = len(list_of_z_D)
list_of_logpdf_R = []
for ss in range(S):
    z_ss_D = list_of_z_D[ss]
    mean_R, stddev_R = unpack_mean_N_and_stddev_N(z_ss_D, phi_RM)
    logpdf_ss_R = scipy.stats.norm.logpdf(t_R, mean_R, stddev_R)
    list_of_logpdf_R.append(logpdf_ss_R)
logpdf_SR = np.vstack(list_of_logpdf_R)
logpdf_R = scipy.special.logsumexp(logpdf_SR, axis=0) - np.log(S)
return np.mean(logpdf_R)
```