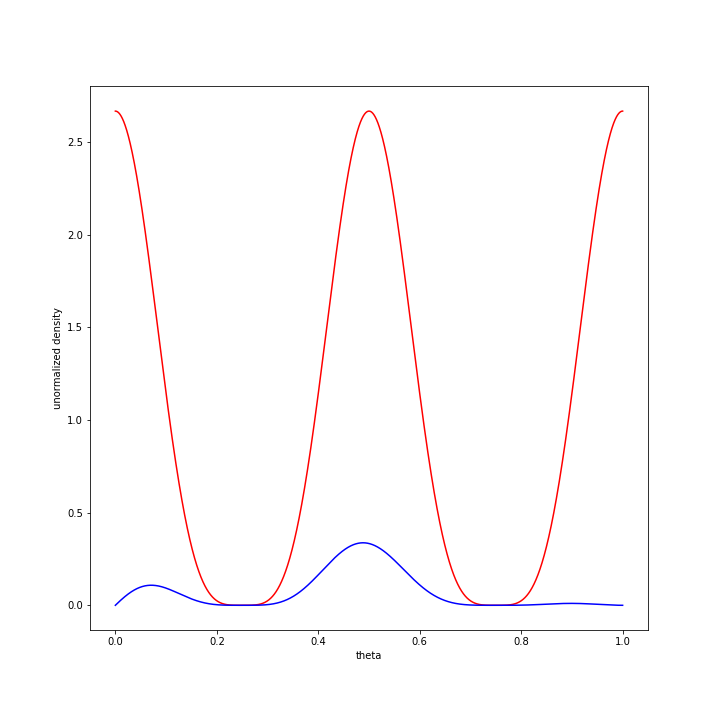
**Bayesian statistics HW2**

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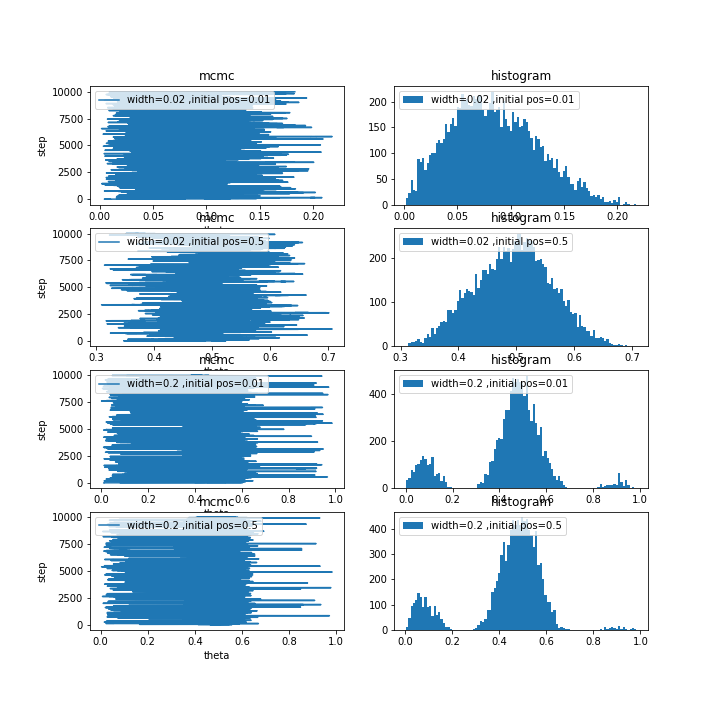
1. The function is attached.
2. Using the grid method I got the following results:



*Figure 1- The shape of the prior(red) and the posterior (blue)*

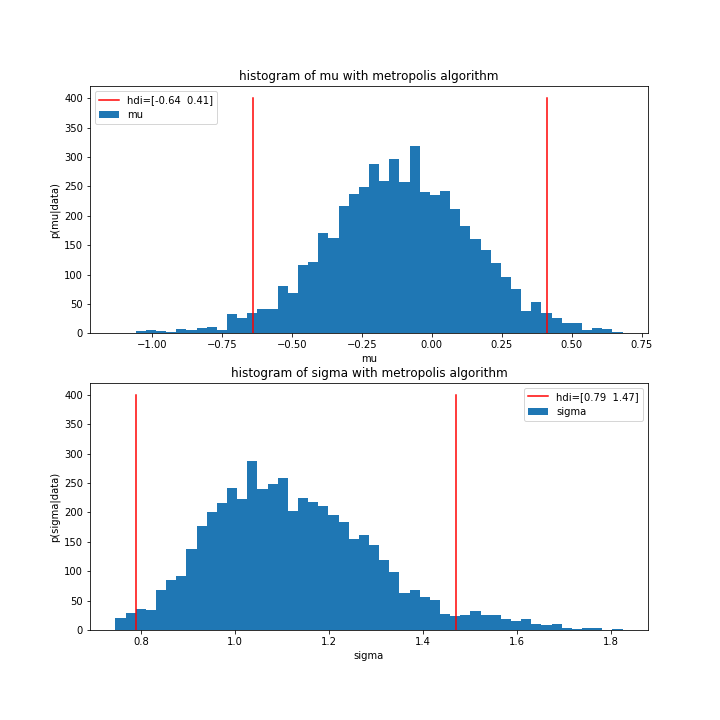
As figure 1 suggests, the prior is periodic with respect to theta, and bounded between 0 to 1 due to possible value of coin bias. Given the data, we can that the posterior is dense around a fair coin, but since there are more heads than tails, there is also credibility that the coin is bias towards a "head" coin (more chance for head).

1. Using the functions I wrote, I got the following results:



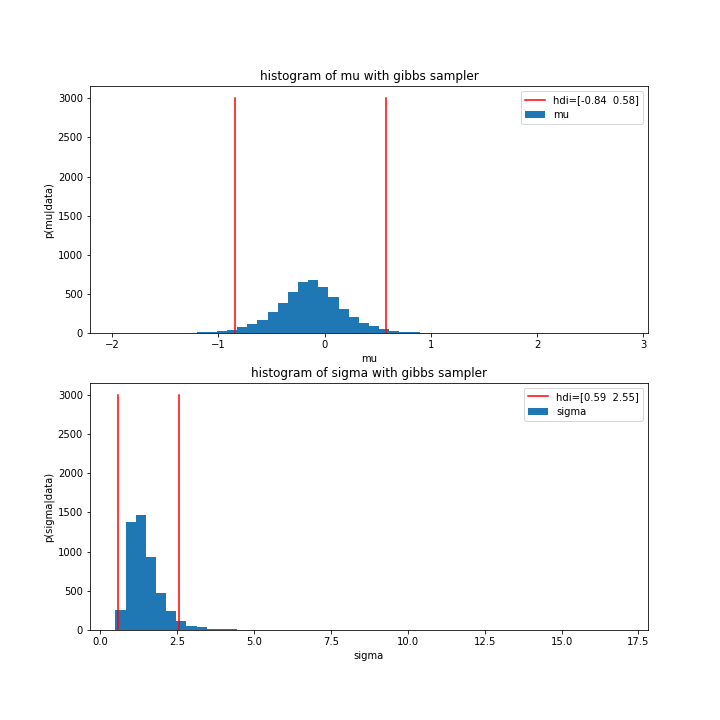
*Figure 2- Metropolis results(left) and corresponding histograms (right)*

The results of figure 2 are very interesting. In the first row, we can see an initialization and width of . If we look in figure 1 we can see that the metropolis algorithm is "stuck" at the local maxima. The reason for it is that the initial point is near the maxima, in adittion to a relative small gaussian width, which doesn’t "allow" a big "jump" towards the global maximum. In contrast, we can see in row 3, that for the same initial point, we get a good estimation of the posterior, because the width of the gaussian is relative big (0.2). The same discussion can be done on rows 2 and 4, where the width of the gaussian has a big effect on the estimation of the prior. To conclude, that isn’t a surprise that for a multimodal prior, a width of 0.01 doesn’t estimate the posterior well, since it is almost impossible in probability for the Metropolis algorithm to jump the another pick.

1. The function is attached.
2. ****After generating 20 samples from unit normal distribution, and applying the Metropolis algorithm, we got the following results:

*Figure 3-Posterior of and and 95 % hdi with Metropolis algorithm*

It is worth mentioning that the initial guess was the 0 for and1 for and for priors I used the values that are given in the exercise. As figure 3 suggests, the estimation of the parameters are good (around the true value) and included in the hdi.

1. The function is attached.
2. ****Using the gibbs sampler, we got the following results:

*Figure 4-Posterior of and and 95 % hdi with Gibbs sampler*

In figure 4 we can see (on a different scale) that we get approximately the same result using the Gibbs sampler. Gibbs sampler is much more reliable in estimating the posterior of 2 parameters, although we cant see it in this example. In my opinion. The reason for it due to the impudence between the priors of , and due to reason that the initial guess for the Metropolis algorithm was quite accurate.