November 1, 2021

Question 1. Consider the coin tossing example, discussed in the first lecture. Simulate 1000 tosses of the coins, setting H = 0.3. Consider a uniform prior and update the posterior at each toss. Plot the resulting posterior after 1, 50, 100, 300, 700, 1000 tosses. Repeat the simulated experiment by setting a Gaussian prior centered in H = 0.5, with standard deviation $\sigma = 0.1$. Do both posteriors converge a similar distribution in the end? What does that mean? Which posterior converges faster and why?

My Answer 1. Here we are simulating 1000 coin tosses for a biased coin, which will give heads only 30% of the time. My final results are plotted just below.

These graphs clearly show that in both cases we converge to a similar posterior: this means that no matter our initial choice regarding the prior, large numbers are going to force our guess towards the actual distribution. The fact is, a wrong guess at the beginning will take longer to converge. Also, the more peaked a chosen distribution is, the harder it's going to be for it to evolve towards the correct centroid (unless our guess was actually correct, then there's no need for converging).

For instance, in our case the wrongfully assumed Gaussian centered in H=0.5 takes a little longer to converge with respect to the case of the uniform prior, which is an uninformative but prudent choice. The former only converges at $N\approx 1000$, while the latter is stabilizing already at $N\approx 300$.



