Simulation laboratory 5: Markov Chain Monte Carlo methods

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Goals

MCMC:

- Understand how to draw from a complex distribution
- Use Markov Chain Monte Carlo methods

Implementation:

1. Markov Chain
2. Metropolis-Hastings algorithm
3. Gibbs sampling

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2. Metropolis-Hastings algorithm
3. Gibbs sampling
4. My results

Markov Chain

Exercise:

- Implement a Markov chain model representing the "machine" example introduced in the lecture.

Codes:

1. **MarkovChain.m**: to code a function
2. **MarkovChainTest.m**: to test the function

TODO:

- Play with different state space, initial state and transition matrix.

1 Markov Chain

2 Metropolis-Hastings algorithm

3 Gibbs sampling

4 My results

Metropolis-Hastings algorithm

Context:

- Professor B. sees that the students in his course are extremely emotional.
- He records their emotional states, which change every hour.
- In the total duration of the course, he records the following statistics:
  - Sad: 15 hours,
  - So-so: 20 hours,
  - Happy: 31 hours.

Metropolis-Hastings algorithm

Exercise:

- Implement a Metropolis Hastings to represent the emotional state of students.

Codes:

1. **MetropolisHastings.m**: to code a function
2. **MetropolisHastingsTest.m**: to test the function

1 Markov Chain

2 Metropolis-Hastings algorithm

3 Gibbs sampling

4 My results

Gibbs sampling

Exercise:

- Use the Gibbs sampling algorithm to draw from the bivariate normal distribution introduced in the lecture.

Codes:

1. **GibbsSamplingBN.m**: to code a function
2. **GibbsSamplingBNTest.m**: to test the function

Note:

1. You can use a library `randn()` to draw a normal distributed random number.

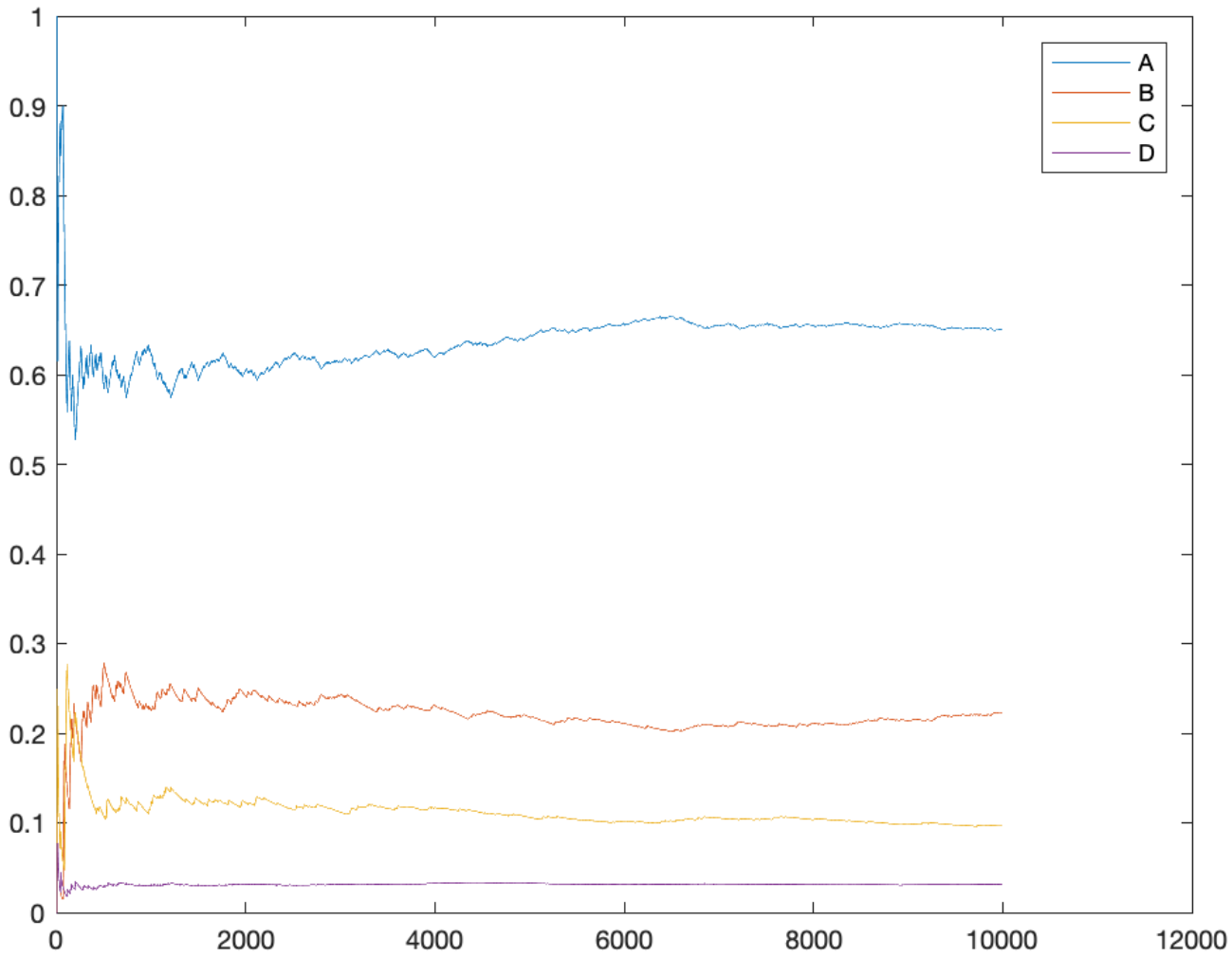
1 Markov Chain

2 Metropolis-Hastings algorithm

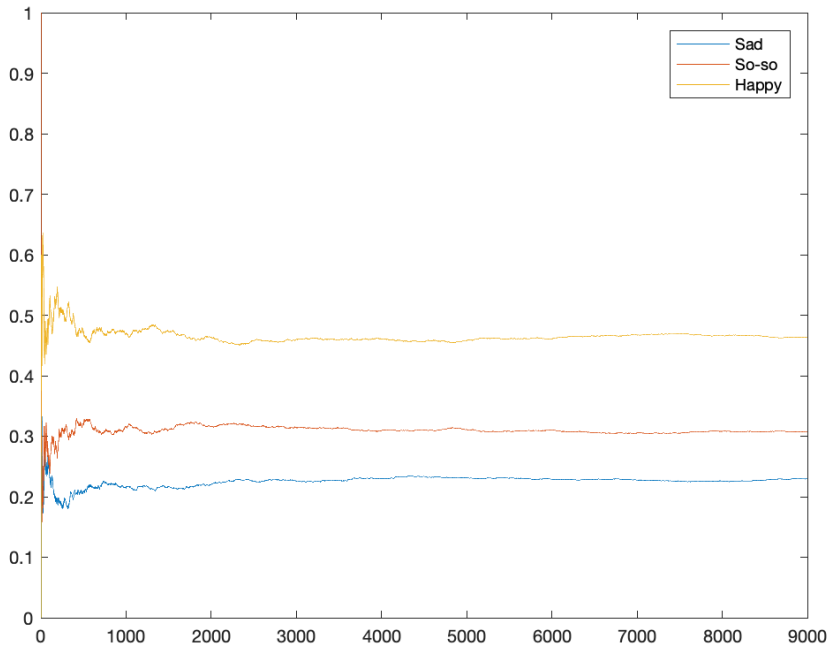
3 Gibbs sampling

4 My results

Markov Chain Monte Carlo sampling



Metropolis-Hastings



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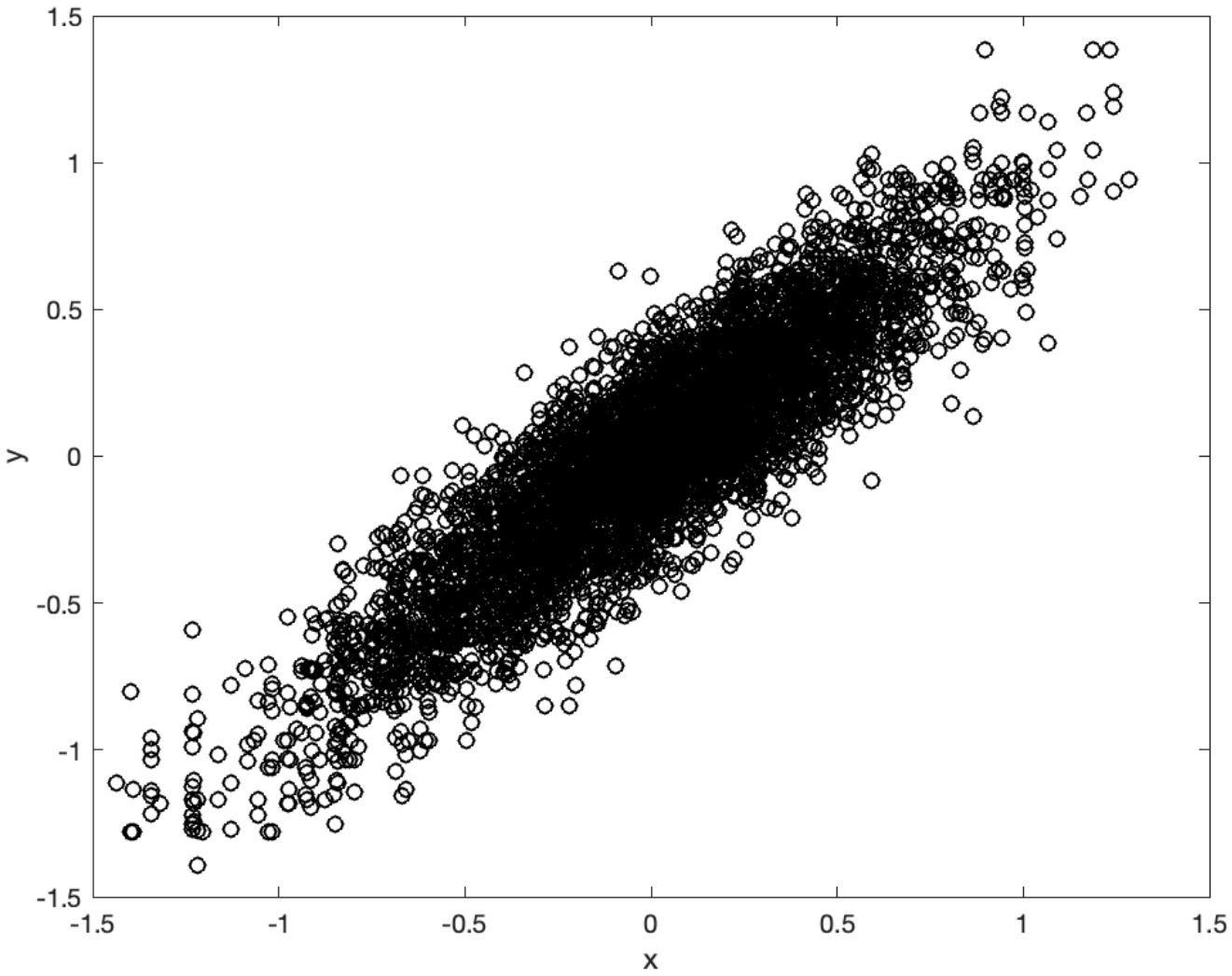
- Reject: [942 524 0]
- Simulated: [0.2293 0.3076 0.4631]
- Target: [0.2273 0.3030 0.4697]

Gibbs sampling