

## GIBBS SAMPLING

In [statistics](#), **Gibbs sampling** or a **Gibbs sampler** is a [Markov chain Monte Carlo](#) (MCMC) [algorithm](#) for obtaining a sequence of observations which are approximated from a specified [multivariate probability distribution](#), when direct sampling is difficult. This sequence can be used to approximate the joint distribution (e.g., to generate a histogram of the distribution); to approximate the [marginal distribution](#) of one of the variables, or some subset of the variables (for example, the unknown [parameters](#) or [latent variables](#)); or to compute an [integral](#) (such as the [expected value](#) of one of the variables). Typically, some of the variables correspond to observations whose values are known, and hence do not need to be sampled.

Gibbs sampling is commonly used as a means of [statistical inference](#), especially [Bayesian inference](#). It is a [randomized algorithm](#) (i.e. an algorithm that makes use of [random numbers](#)), and is an alternative to [deterministic algorithms](#) for statistical inference such as the [expectation-maximization algorithm](#) (EM).

As with other MCMC algorithms, Gibbs sampling generates a [Markov chain](#) of samples, each of which is [correlated](#) with nearby samples. As a result, care must be taken if independent samples are desired. Generally, samples from the beginning of the chain (the *burn-in period*) may not accurately represent the desired distribution and are usually discarded. It has been shown, however, that using a longer chain instead (e.g. a chain that is  $n$  times as long as the initially considered chain using a thinning factor of  $n$ ) leads to better estimates of the true posterior. Thus, *thinning* should only be applied when time or computer memory are restricted.

## GIBBS ALGORITHM

Although the Bayes optimal classifier obtains the best performance that can be achieved from the given training data, it can be quite costly to apply. The expense is due to the fact that it computes the posterior probability for every hypothesis in  $H$  and then combines the predictions of each hypothesis to classify each new instance. An alternative, less optimal method is the Gibbs algorithm (see Oppor and Haussler 1991), defined as follows:

1. Choose a hypothesis  $h$  from  $H$  at random, according to the posterior probability distribution over  $H$ .
2. Use  $h$  to predict the classification of the next instance  $x$ .

Given a new instance to classify, the Gibbs algorithm simply applies a hypothesis drawn at random according to the current posterior probability distribution. Surprisingly, it can be shown that under certain conditions the expected misclassification error for the Gibbs algorithm is at most twice the expected error of the Bayes optimal classifier (Haussler et al. 1994). More precisely, the expected value is taken over target concepts drawn at random according to the prior probability distribution assumed by the learner. Under this condition, the expected value of the error of the Gibbs algorithm is at worst twice the expected value of the error of the Bayes optimal classifier. This result has an interesting implication for the concept learning problem described earlier. In particular, it implies that if

the learner assumes a uniform prior over  $H$ , and if target concepts are in fact drawn from such a distribution when presented to the learner, then classifying the next instance according to a hypothesis drawn at random from the current version space (according to a uniform distribution), will have expected error at most twice that of the Bayes optimal classifier. Again, we have an example where a Bayesian analysis of a non-Bayesian algorithm yields insight into the performance of that algorithm.

#### References:

1. <http://profsite.um.ac.ir/~monsefi/machine-learning/pdf/Machine-Learning-Tom-Mitchell.pdf>
2. <https://www.mit.edu/~ilkery/papers/GibbsSampling.pdf>
3. <https://stats.stackexchange.com/questions/325696/explanation-regarding-gibbs-sampling>
4. <https://kieranrcampbell.github.io/blog/2016/05/15/gibbs-sampling-bayesian-linear-regression.html>
5. <https://stats.stackexchange.com/questions/325696/explanation-regarding-gibbs-sampling>