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Gibbs Sampling

Gibbs sampling works as follows:

In step 1, we start with a network that has known and unknown nodes.

In step 2, we initialize every unknown node using the local classifier to obtain the local posterior probabilities P(c equal to k), with k ranging from 1 to m, with m the number of classes.

In step 3, we sample the class value of each node according to the posterior probabilities P(c equal to k). This basically works as follows: Suppose the probability of fraud equals 0.80. We then draw a random number between 0 and 1. If the value obtained is less than 0.80, the node is labeled as fraudulent. If it's above 0.80, the node is labeled as non-fraudulent. In step 4, we then generate a random ordering for the unknown nodes.

In step 5, for each node i in the ordering, we do the following: Apply the relational learner to node i to obtain the new posterior probabilities P(c equal to k), and sample the class value of each node according to the new probabilities P(c equal to k).

Step 6 repeats step 5 for 200 iterations without keeping any statistics. This is what we refer to as the burn-in period.

In step 7, we repeat step 5 for 2000 iterations, thereby counting the number of times each class is assigned to a particular node. We then normalize these counts to obtain the final class probability estimates.

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