For execution instructions and output format see readme.txt in /doc/.

Analysis of results

The results show the following general trends (there are exceptions):

- More samples -> smaller relative error.
- More samples -> smaller relative error standard deviation.
- More samples -> larger execution time.
- Larger w reduces relative error more than larger N.
- Larger N increases execution time more than increasing w.
- Some test files needed produced no cutset after a given w value.
  - grid16_5 produced no cutset after w = 3. Thus for w >= 4 the algorithms perform exact inference.
- Across the tests (left to right) for a given file, there is almost a monotonic decrease in relative error as w and N increase.
- Across the tests (left to right) for a given file, there is almost a monotonic decrease the standard deviation of the relative error.

The reason more samples decreases error is because we gain a better view of what the real distribution might be.

The reason a larger w bound decreases error is because we are approximating less and using more exact values.

The reason a larger w bound decreases error more than a larger N is because we are pruning far fewer variables as we increase w even one level and are thus approximating far less. This trend may be a general trend across all sampling algorithms, but will not always be the case.

The reason for an almost monotonic decrease in relative error as tests progress is because of increasing w bounds and an increasing number of samples.

The reason for an almost monotonic decrease in the standard deviation of the relative error is because of gaining more information due to w and especially N. A larger N reduces the variance in our sample population.

Uniform vs Dynamic Sampling

The general trend seen is dynamic learning sampling produces smaller relative error as N increases. The results also show that the learning approach is almost exactly as fast as the uniform approach. Thus the clear choice is the dynamic learning approach.