You are an expert in Bayesian Networks and Propbabilistic Programming with Pyro and PGMPy. When you write math use plain or inline notation. Never use LaTEX. You are also a swing trader who likes quantitative methods to build weekly porfolios. Your asset universe is composed of FOREX, Indices and commodities for a total of 52 assets in the universe. You trade only through CFD. Let's delineate the procedure: I want to build a long-short portfolio on a weekly basis, entering on monday and exiting on Friday. I would like to build a quantitative model done like that: A dynamic bayesian network in the first step and applying a hierarchical clustering in the second step to determine the long-short portfolio for the week. For the moment I would like to use only the following data: hourly and daily data and not more that 3 technical indicators. I want to use SVI to perfom bayesian inference.

Weaknesses:

Single-Asset Focus. If your ultimate goal is to build a “weekly long–short portfolio” across many instruments, you will need a multi-asset framework or (at least) a post-hoc correlation step. Right now the model is effectively for one time series (daily\_close plus its hourly decomposition). In a real multi-asset environment with 52 instruments, you likely need either:

– A shared latent factor or correlation structure across assets, or

– A method to combine each instrument’s latent in a second-stage hierarchical model,

– Or both, so that the dynamic Bayesian network captures cross-asset relationships rather than ignoring them.

• Weekly vs. Daily/Hourly Horizon. As you described, you want to enter positions on Monday and exit on Friday. However, the model is pitched at a daily/hourly timescale. That is not necessarily a problem, but at some point you need to connect each week’s predicted direction or expected return to the daily latent states. For example, you might:

– Aggregate the daily\_latent predictions for the next week and convert them into a weekly signal, or

– Shift the model itself to a weekly-latent timescale (still possibly using daily/hourly data for more frequent updates).

• Limited Feature Set. You mentioned you only want to use up to 3 technical indicators for the moment. The current code snippet does not show any direct incorporation of indicators (e.g., RSI, moving averages, etc.). You would need to incorporate them into the model as additional latent or observed inputs—perhaps letting them drive daily\_latent[t] or adjusting the observation distributions. Without these indicators, your model is basically just a time-series filter that extracts a hidden factor, so it may or may not be sufficient to generate an alpha signal on its own.

• Ignoring Volatility Dynamics. Although using StudentT helps with heavy tails, you still may want to capture time-varying volatility (for example, with a GARCH-like or stochastic volatility extension). This is especially relevant if you plan on a systematic trading approach that tries to size positions or weigh risk across multiple instruments.

• Factorized Guide Ignores Markov Dependencies. In the guide, daily\_latent\_t is sampled from an independent Normal ignoring the Markov chain structure that is explicitly modeled. This can sometimes lead to an underestimation or misestimation of uncertainty in the latent states. If you really need a better posterior on daily\_latent[t], you might consider a more structured approximate posterior.

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• No Direct Long–Short Mechanism in the Model. This is purely a state-space time-series model. To get from there to a long–short set of positions, you will still need:

– A method to transform the latent states and any subsidiary parameters into a directional or “z-score” type signal,

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