

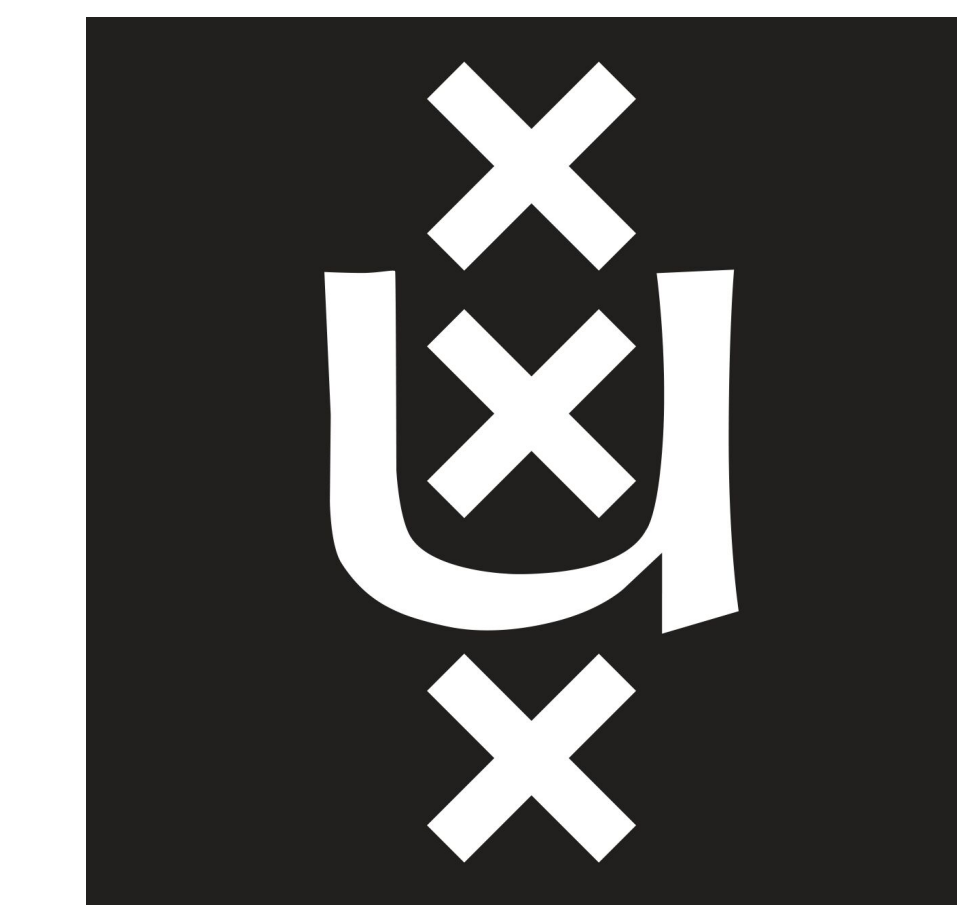
Nested Variational Inference

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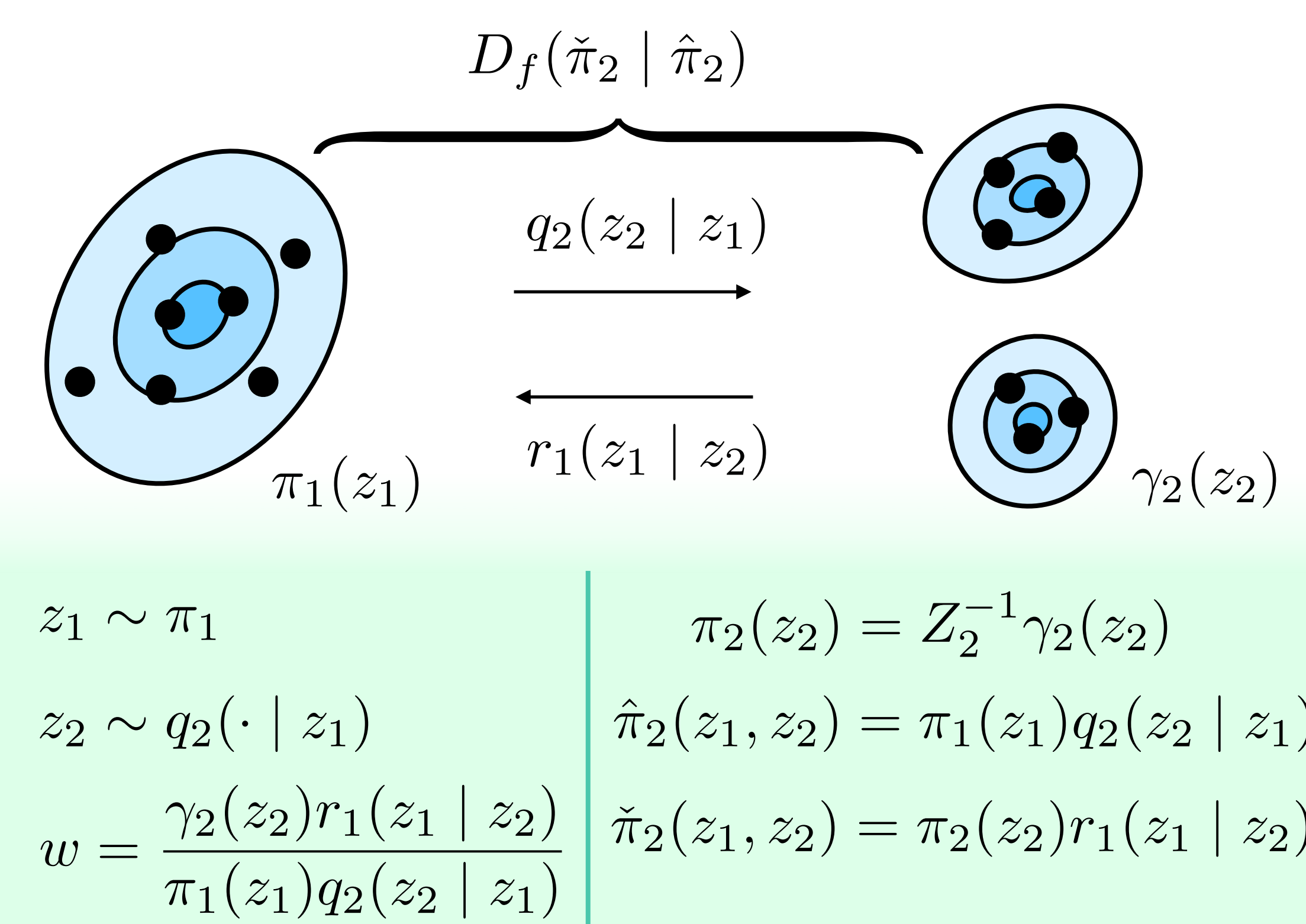
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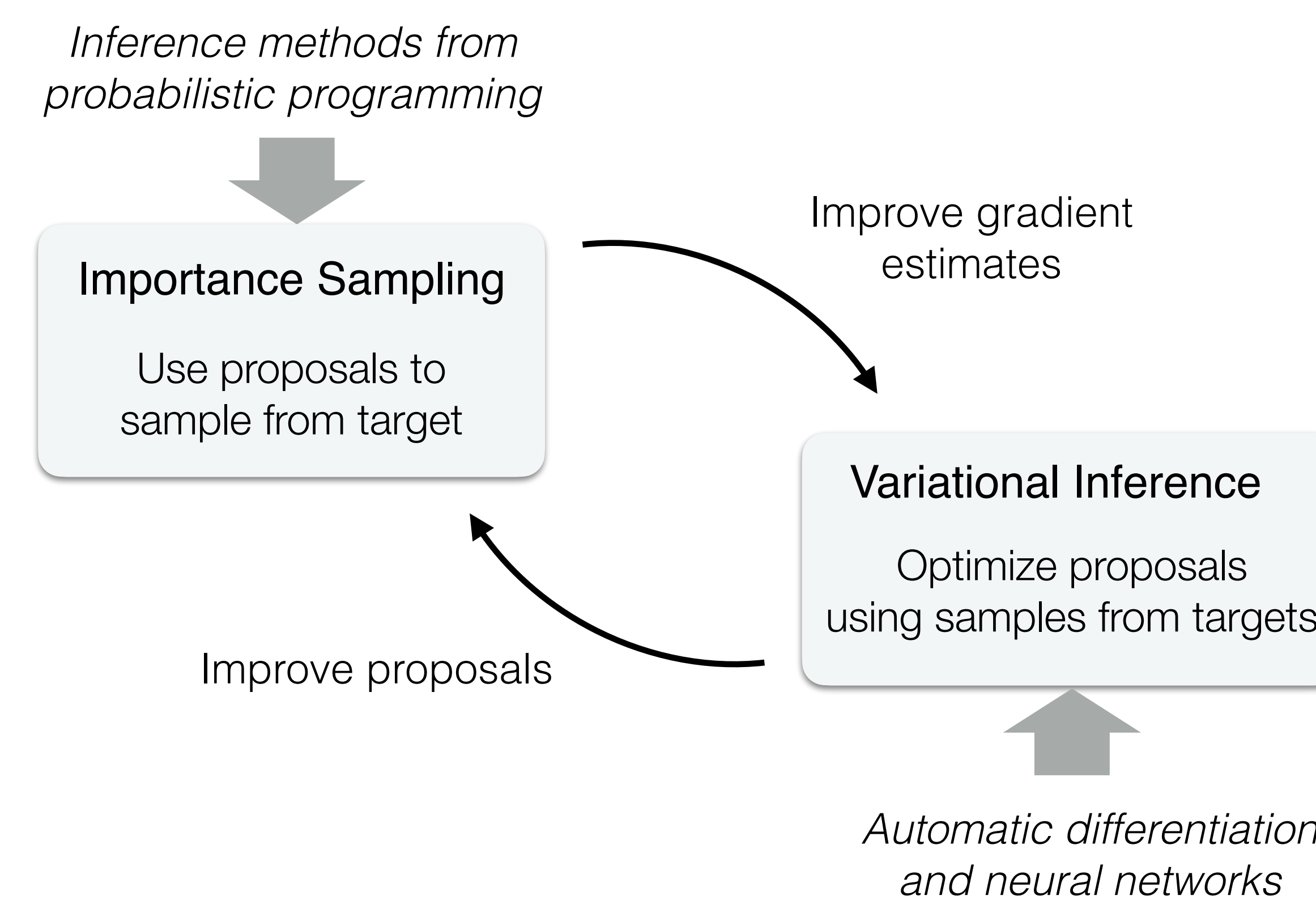
Shortcomings of standard VI

- Potentially hard one-step learning problem
- For mode-covering divergences, the variance of weights and gradient estimates is high due to initially bad samples
- For mode-seeking divergences, variational distribution might not capture all modes



Combining Importance Sampling with VI

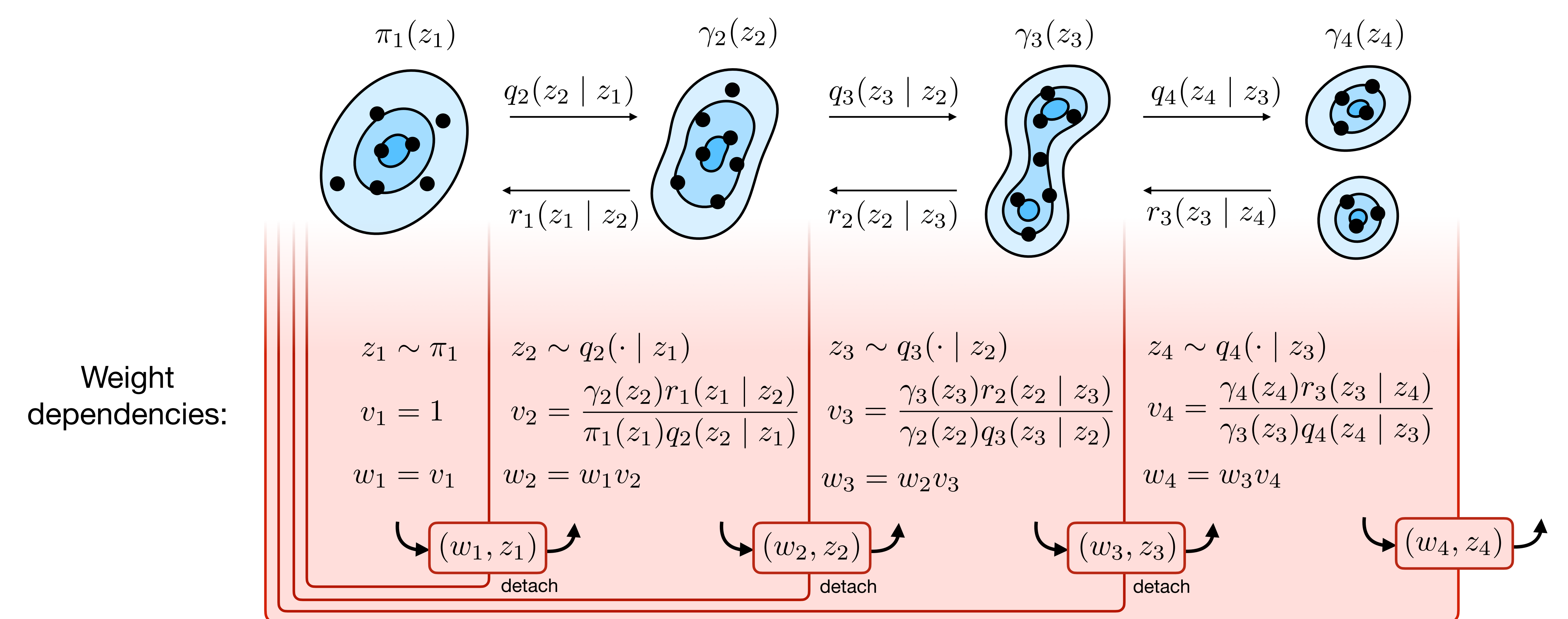
- Break problem into sequence of easier problems
- Initial samples are good enough to make progress on early stages; Optimizing earlier stages improves samples for later stages
- Samples/Optimization can be guided by choice of intermediate distributions



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Nested Variational Inference

Inference Objective: $D_f(\tilde{\pi}_2 | \hat{\pi}_2) + D_f(\tilde{\pi}_3 | \hat{\pi}_3) + D_f(\tilde{\pi}_4 | \hat{\pi}_4)$



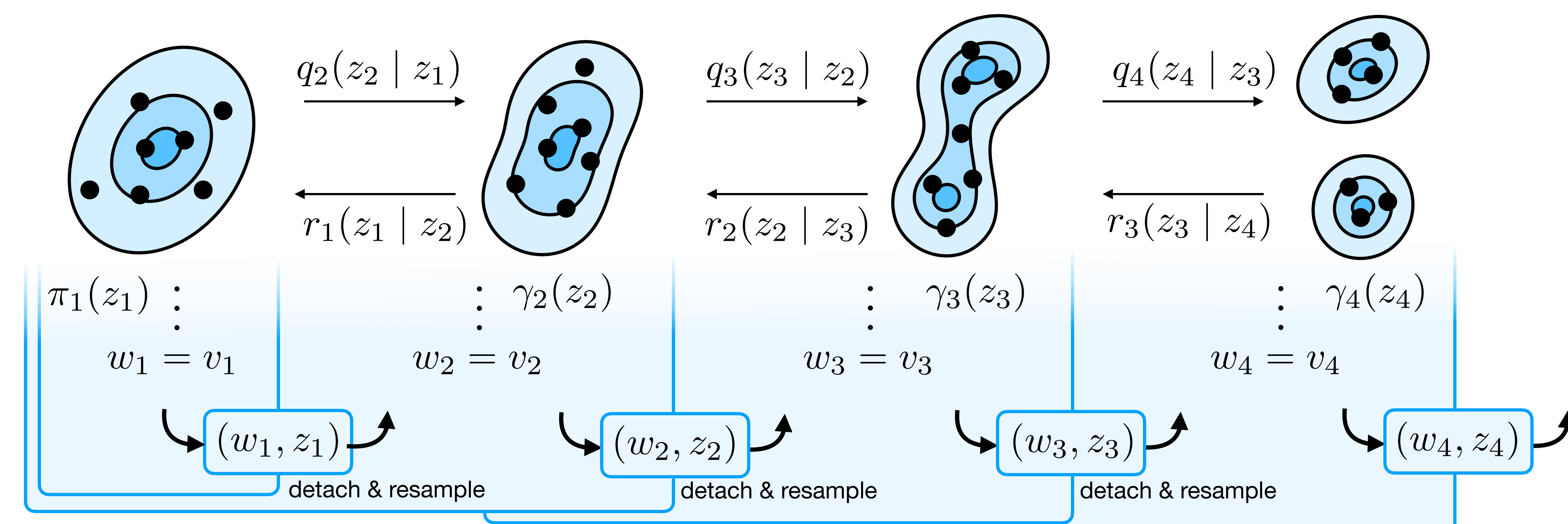
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Proper Weighting and Resampling

Proper weighting Let π be a probability density. For some constant $c > 0$, a random pair $(w, z) \sim \Pi$ is properly weighted (p.w.) for an unnormalized probability density $\gamma \equiv Z\pi$ if $w \geq 0$ and for all measurable functions g

$$\mathbb{E}_{w, z \sim \Pi} [w g(z)] = c \int dz \gamma(z) g(z) = c Z \mathbb{E}_{z \sim \pi} [g(z)].$$

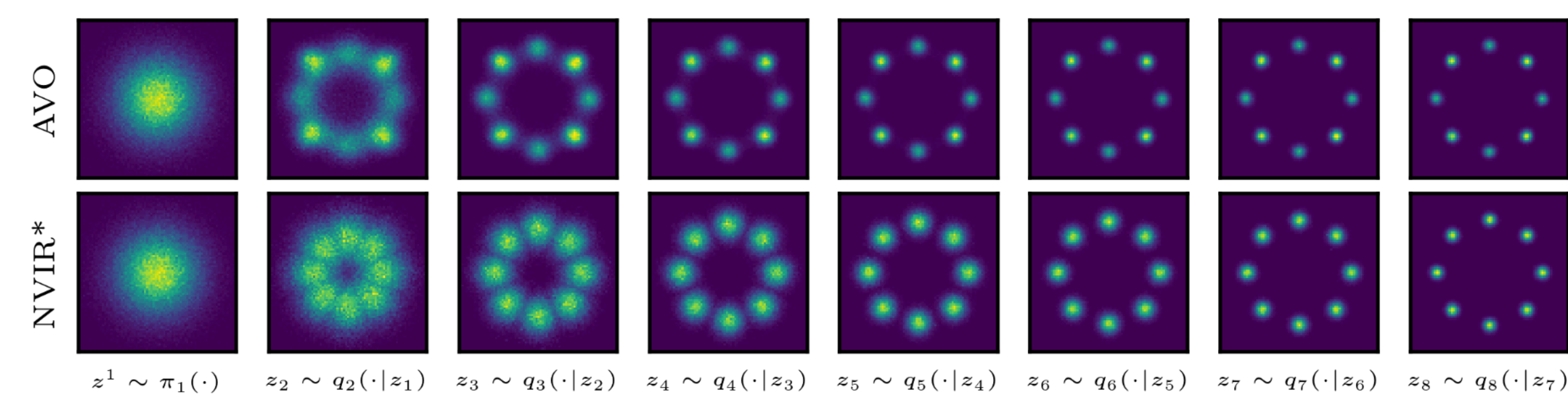
We can propose from any sampler as long as it produces properly weighted samples for the proposal density of interest. **Resampling preserves proper weighting.**



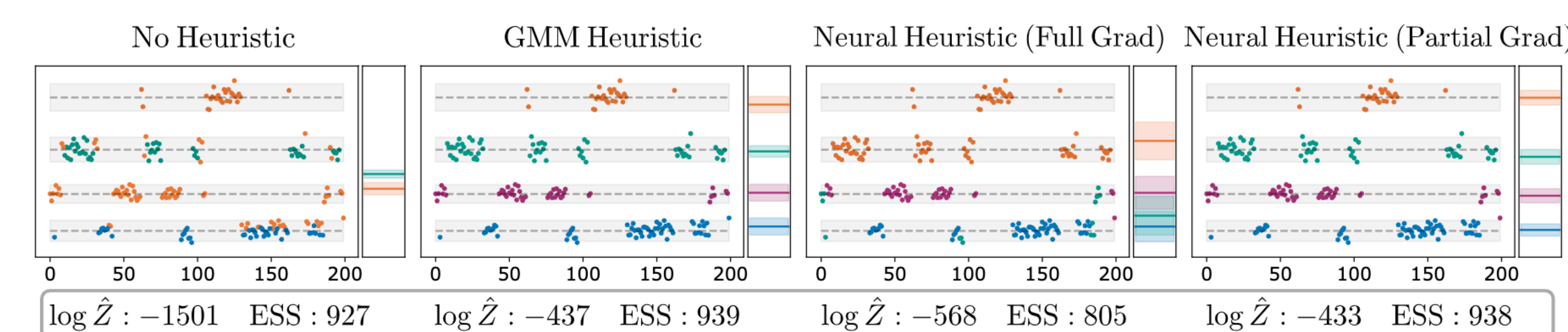
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Experiments

Training Annealed Samplers

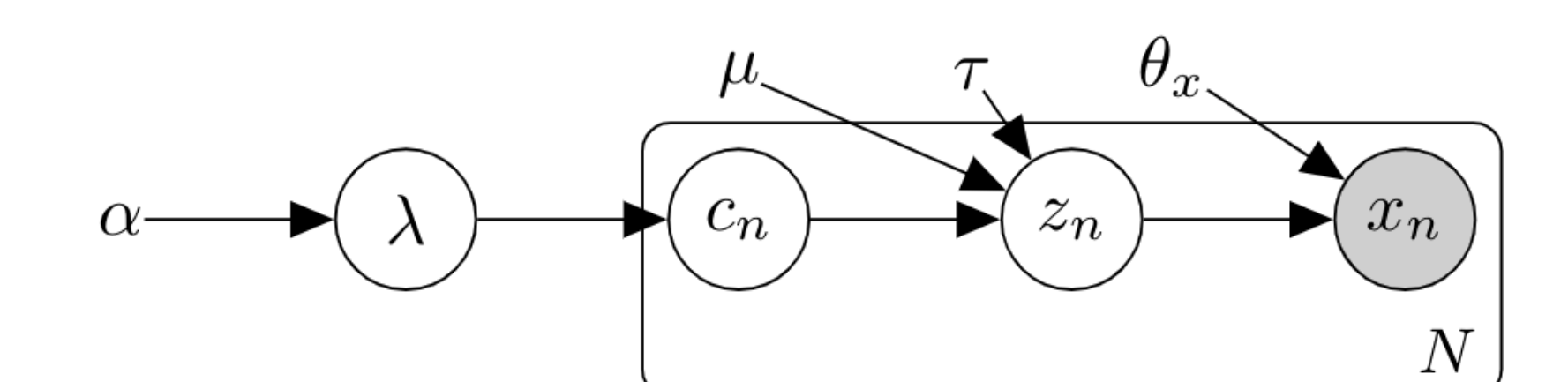


Time Series Model



Deep Generative Model

Generative Model:



Inference Model:

