

Siddhant Mishra-Sharma (MIT/AI FI) | AI FI Summer School

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Simple objectives as a weighted sum of ELBOs

Kingma et al (2023) showed that common objectives can be written as a weighted sum
(across different noise levels) of ELBOs

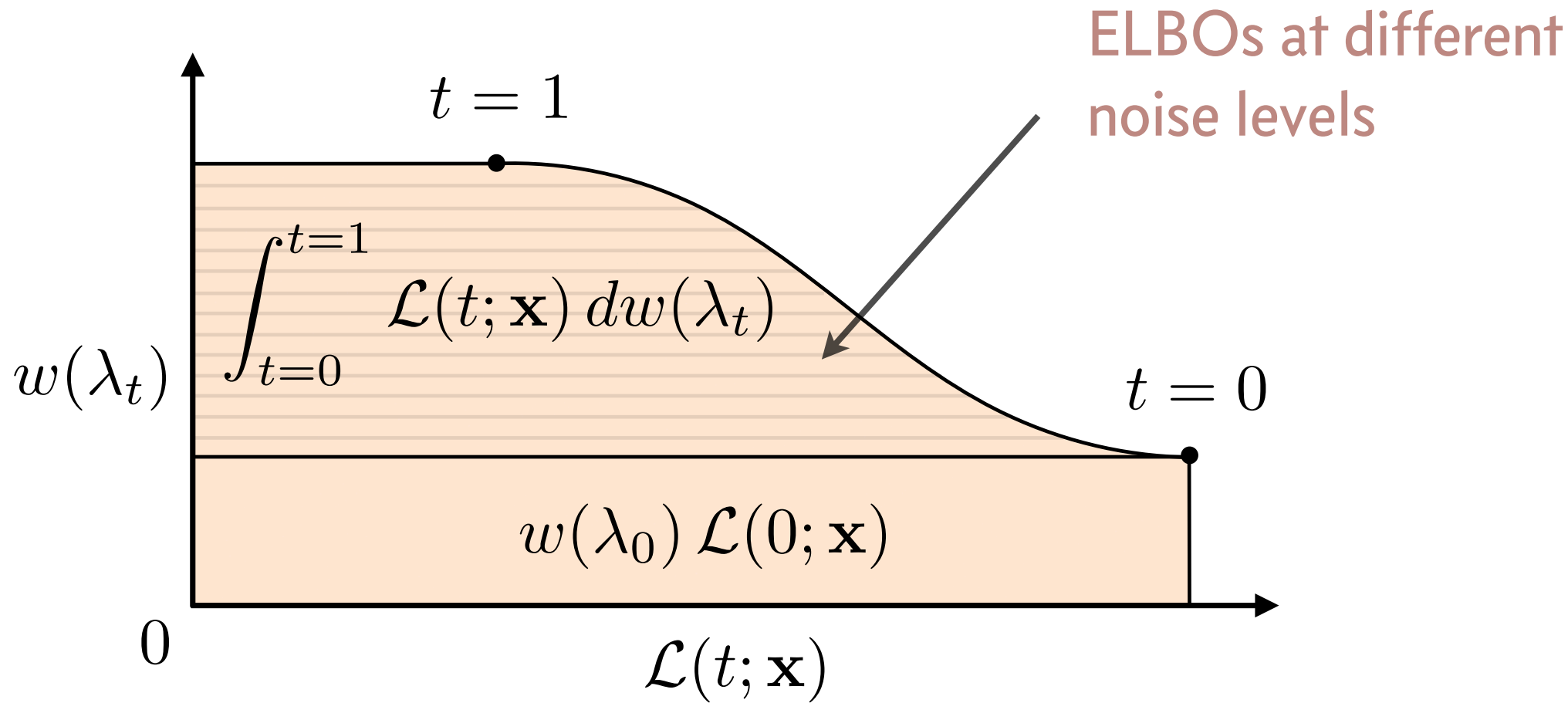
$$L_w(x) = \left\langle \textcolor{green}{w}(t) \cdot \textcolor{red}{w}_{\text{ML}}(t) \left\| \epsilon - \hat{e}_{\theta}(x_t, t) \right\|^2 \right\rangle$$

Additional weighting
(w_{ML}^{-1} for ϵ -prediction)

Weighting for ELBO/
ML objective

$$L_w(x) = \left\langle \left\| w_{\text{ML}}(t) \left(\epsilon - \hat{e}_{\theta}(x_t, t) \right) \right\|^2 \right\rangle_{p(w)}$$

Importance weighting
of different noise levels

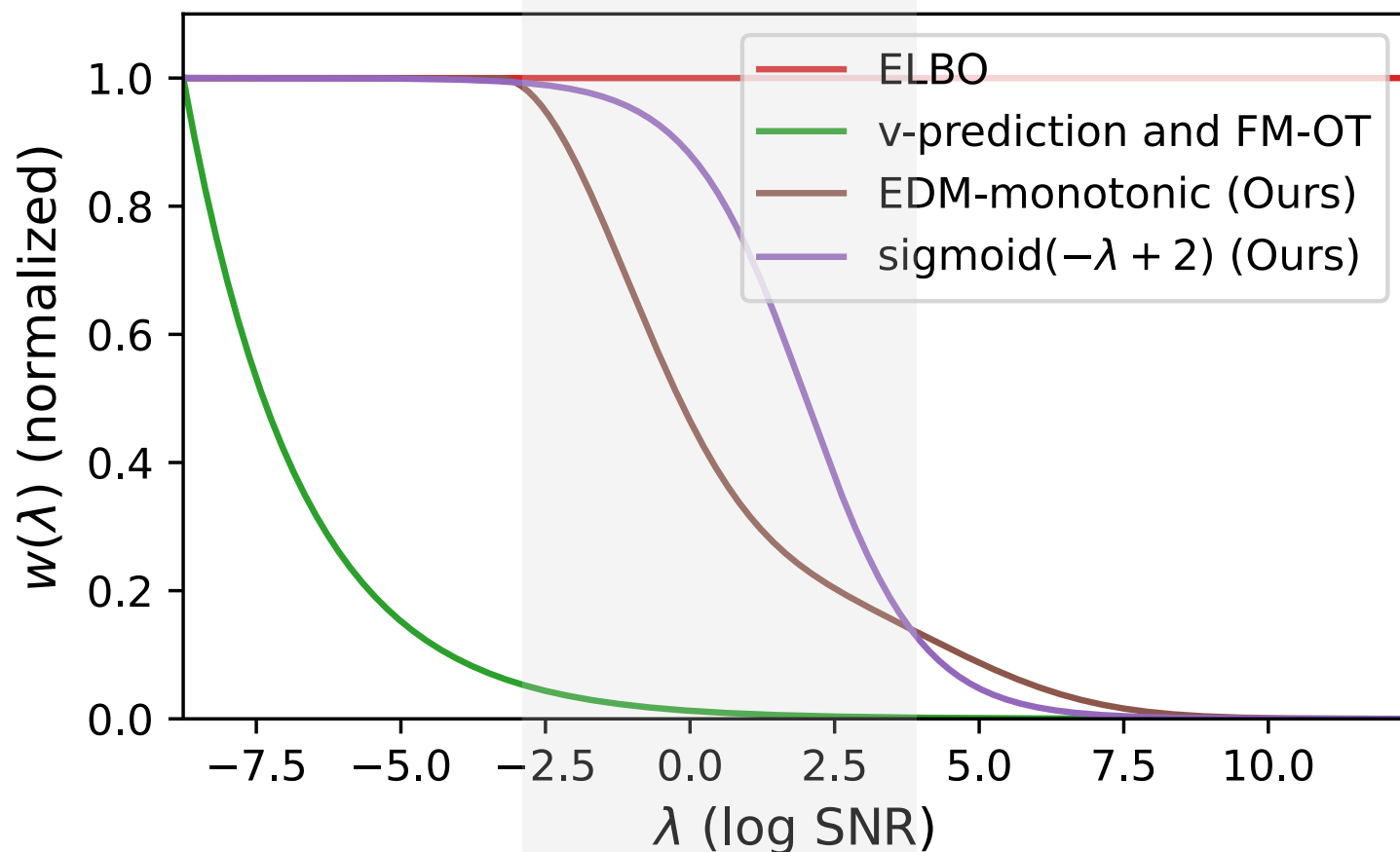


Interpretation: data augmentation with additive Gaussian noise /

data-distribution smoothing

More important
for perceptual
quality?

Monotonic weighting functions



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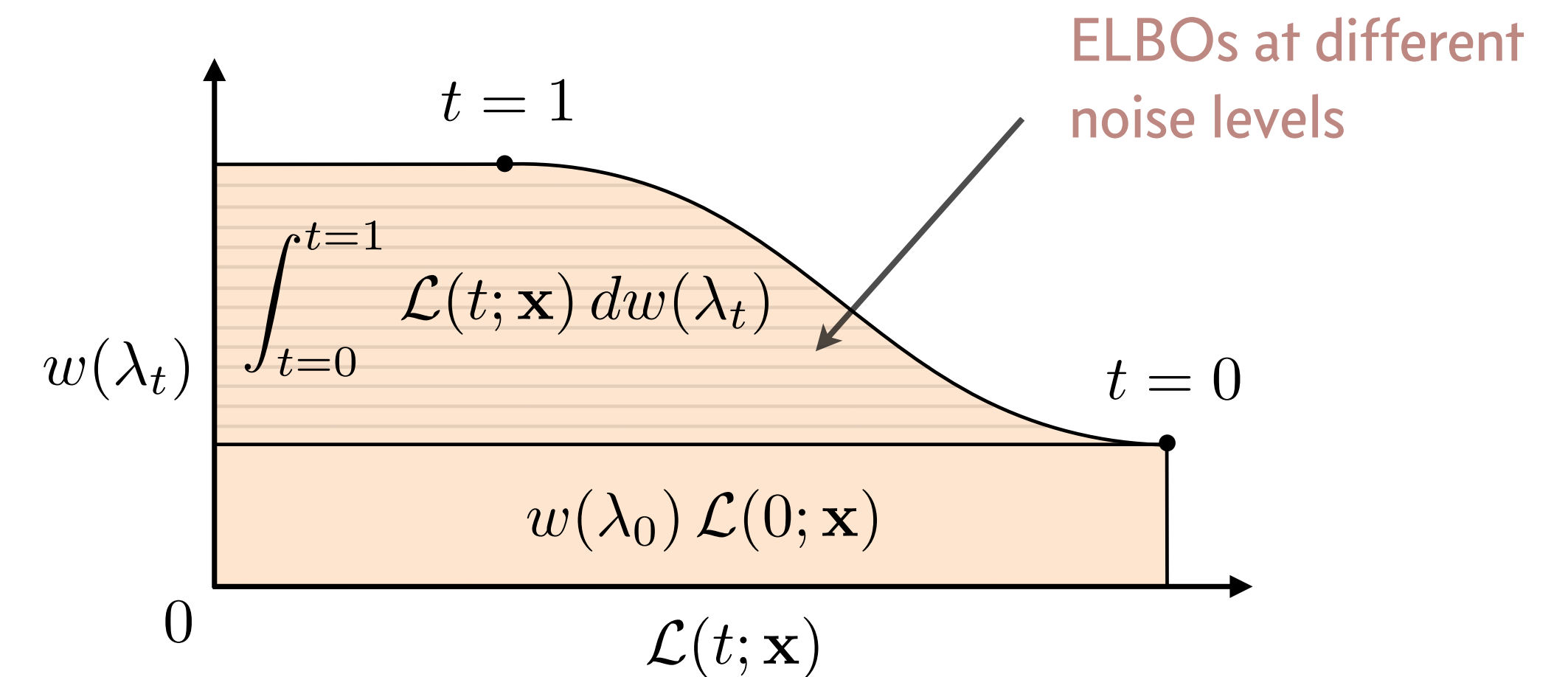
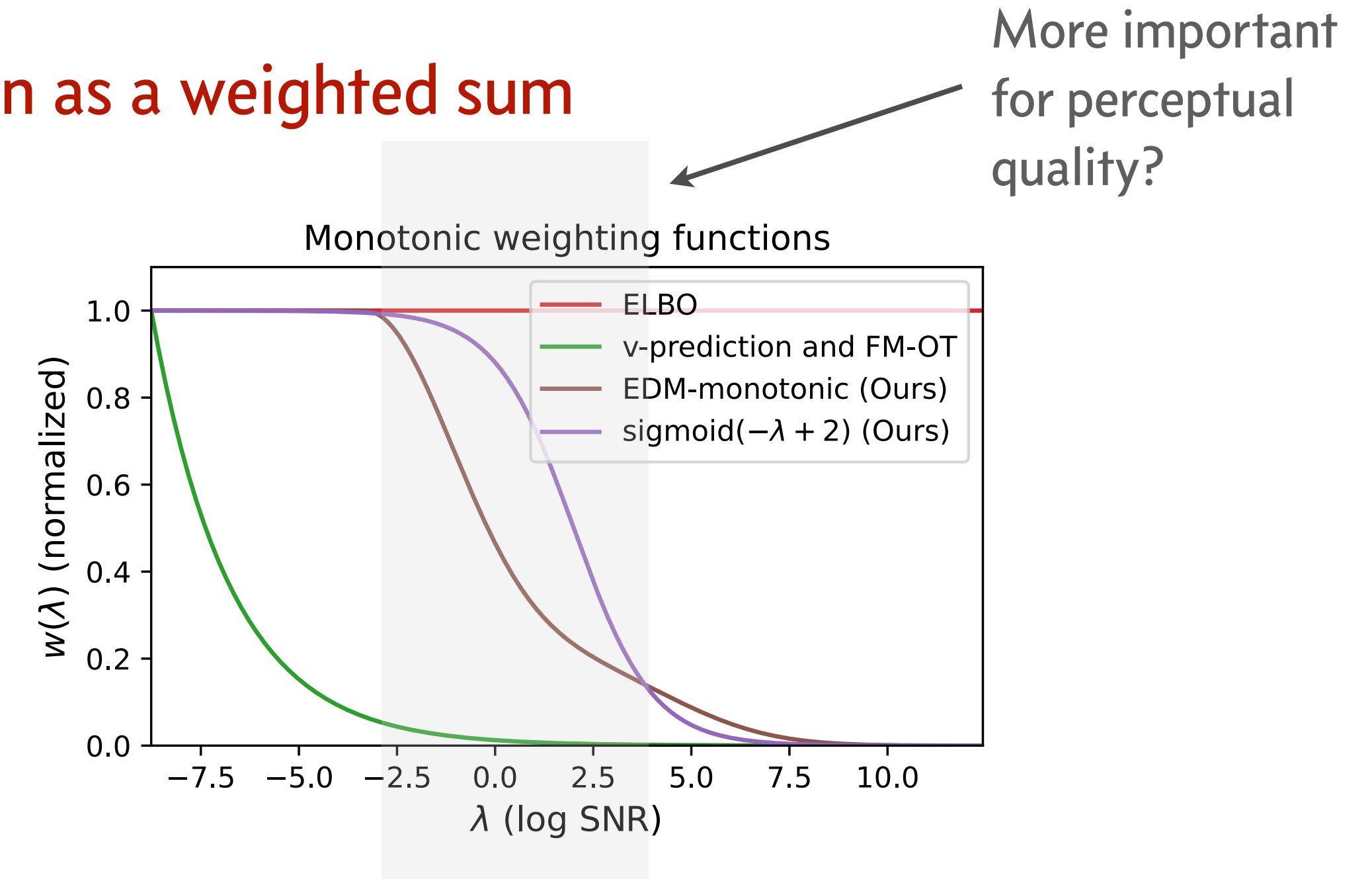
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Continuous-time/SDE formulation

In the limit of infinite time steps, $\Delta_t \rightarrow 0$ and the forward diffusion process can be written as

$$\begin{aligned}x_t &= \sqrt{1 - \beta(t)\Delta_t}x_{t-1} + \sqrt{\beta(t)\Delta_t}\mathcal{N}(0, \mathbb{I}) \\&\approx x_{t-1} - \frac{\beta(t)\Delta_t}{2}x_{t-1} + \sqrt{\beta(t)\Delta_t}\mathcal{N}(0, \mathbb{I})\end{aligned}$$