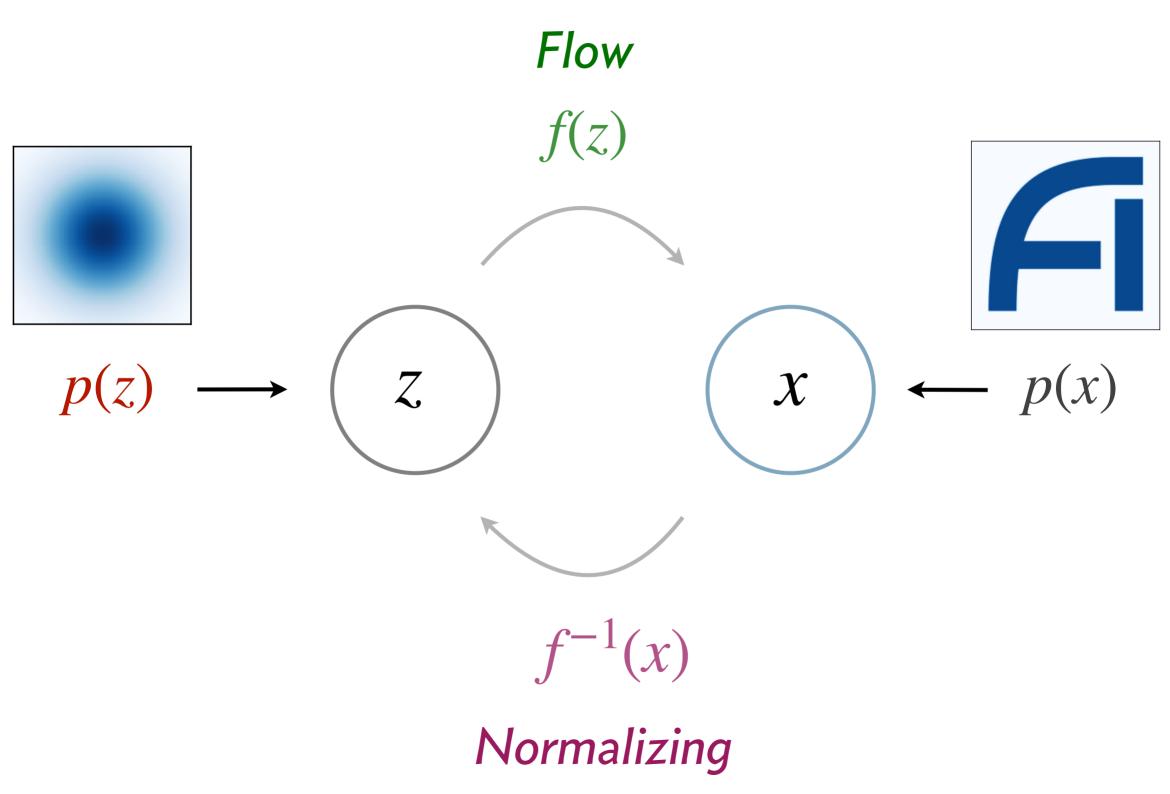
Siddharth Mishra-Sharma (MIT/IAIFI) | IAIFI Summer School



Normalizing flows



The distribution p(z) should

- Have an easy-to-evaluate density
- Be easy to sample from $z \sim p(z)$

Typically

$$p(z) = \mathcal{N}(0, \mathbb{I})$$

The function *f* should be

- One-to-one
- Differentiable
- Invertible
- Tractable f^{-1} and $\det \nabla f$



- Constrained form of the transformation can limit the expressivity of flows compared to e.g. diffusion models.
- However, for certain physics applications the transformation

can be restricted in a specific, desired way; see Miranda Cheng's lectures on Wednesday!

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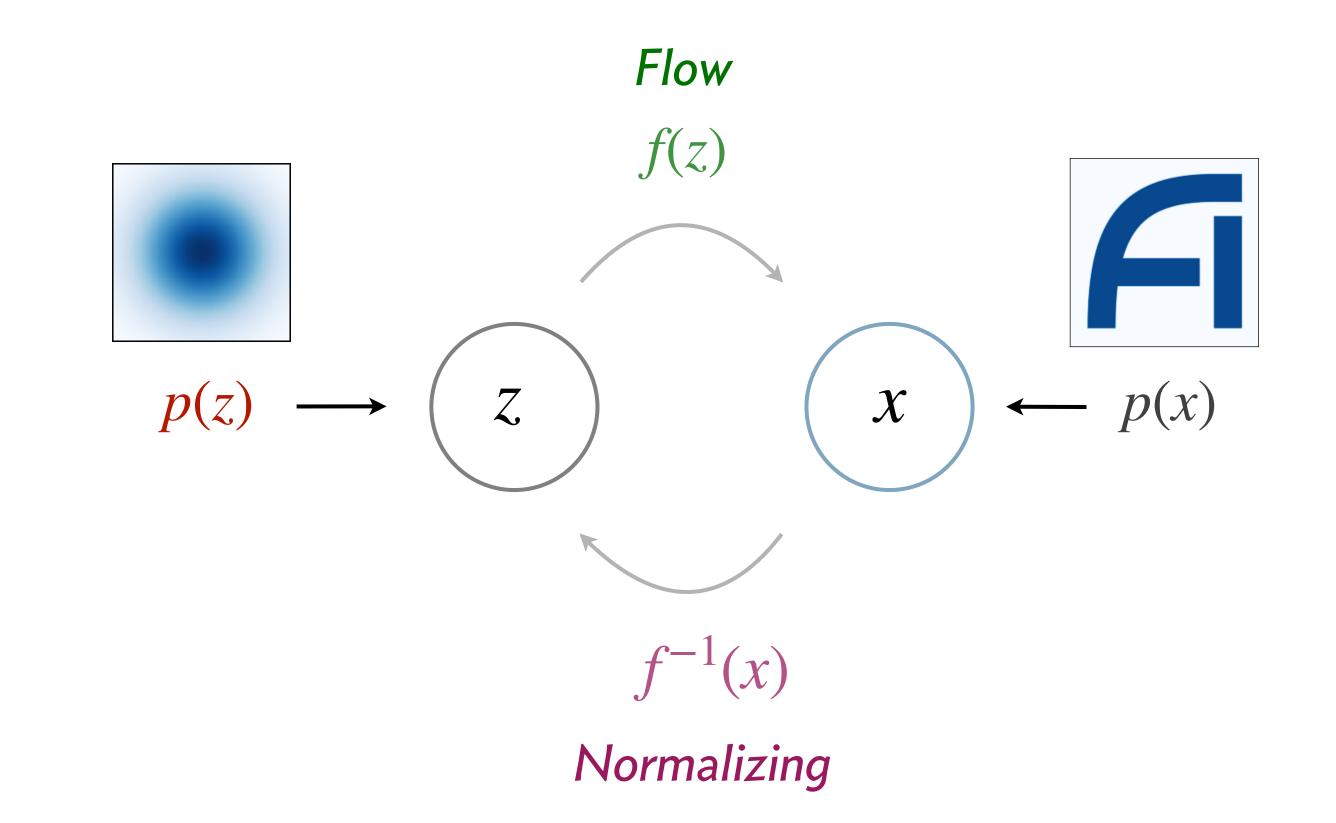
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Diffeomorphism

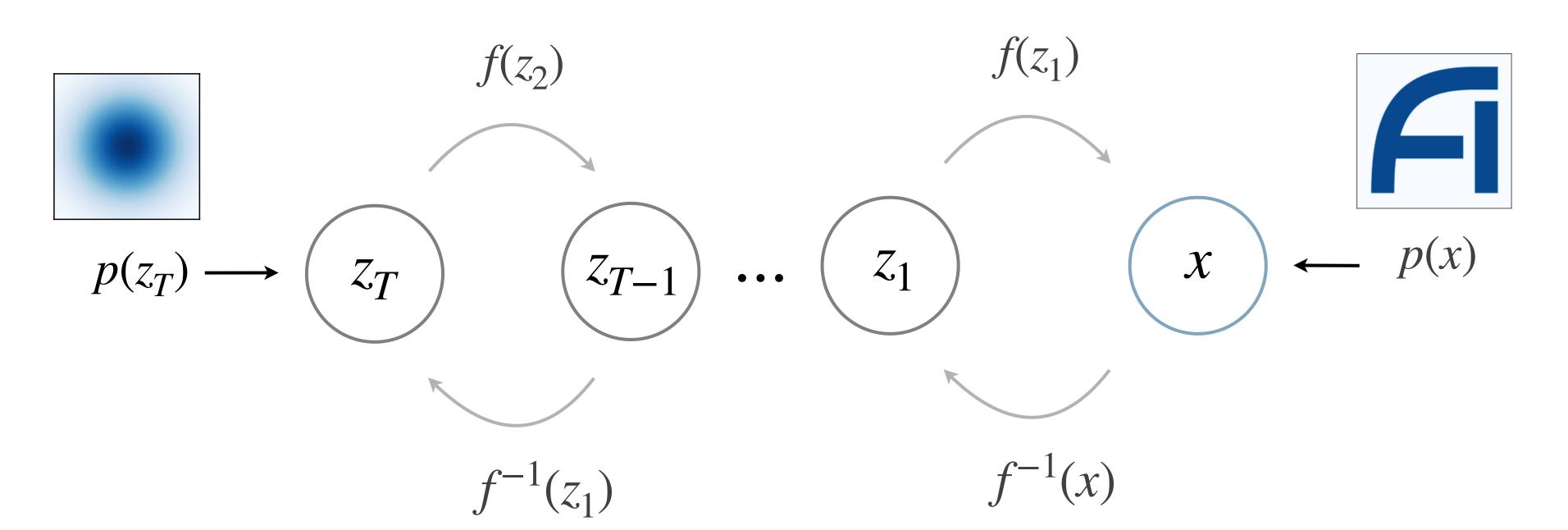
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Normalizing flows

Multiple flow transformation can be easily composed for e.g. expressivity



Computing p(x): change-of-variables formula

$$\int p(x)dx = \int p(z)dz = 1$$

$$p(x) = \pi(z) \left| \frac{dz}{dx} \right| = p\left(f^{-1}(x)\right) \left| \frac{df^{-1}}{dx} \right| = p\left(f^{-1}(x)\right) |\det \nabla f|^{-1}$$

Train using maximum-likelihood objective

$$\varphi^* = \left\langle \arg \max_{\varphi} p\left(f_{\varphi}^{-1}(x)\right) | \det \nabla f_{\varphi}|^{-1} \right\rangle_{x \sim p(x)}$$