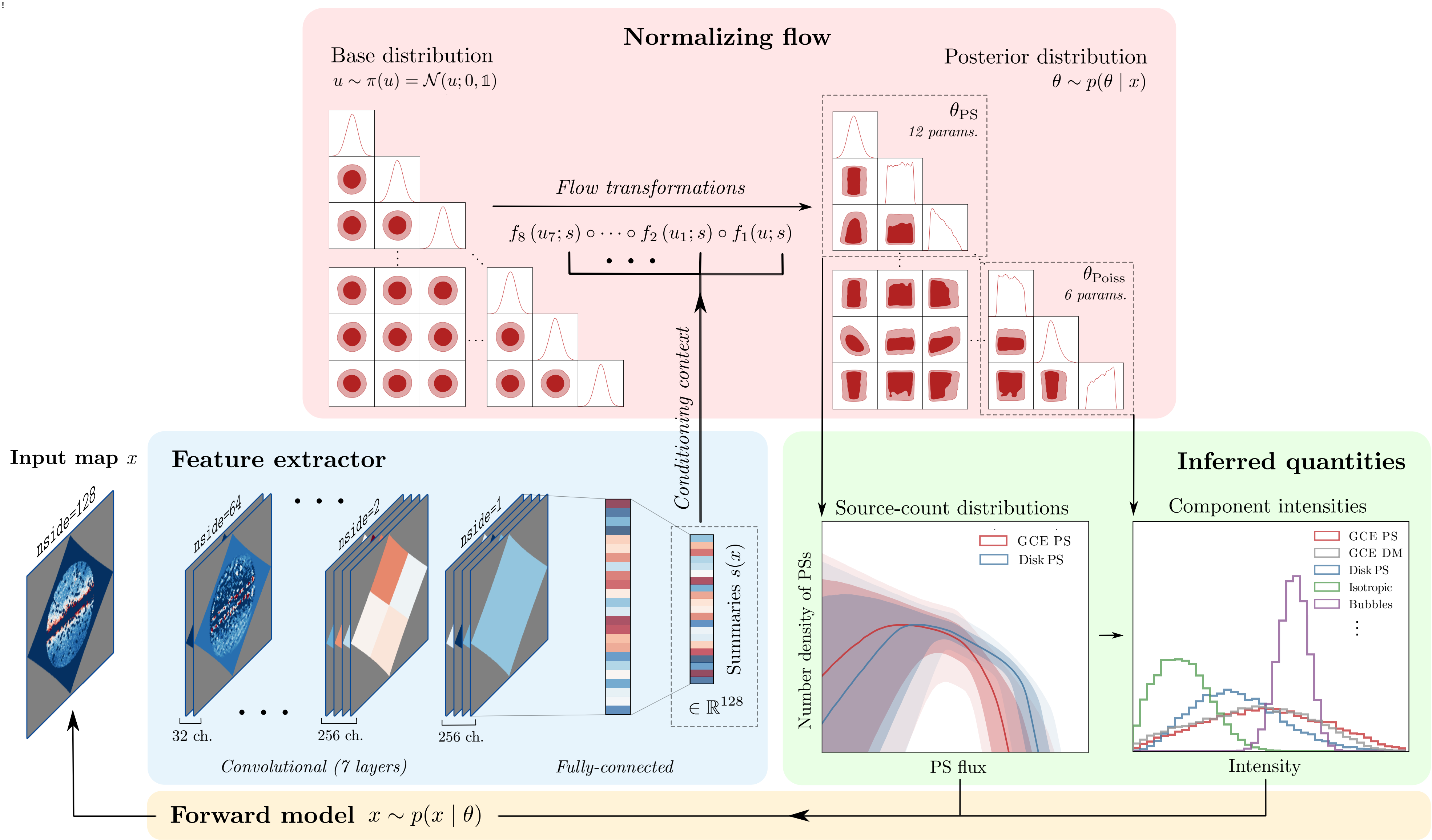# Siddharth Mishra-Sharma (MIT/IAIFI) | IAIFI Summer School
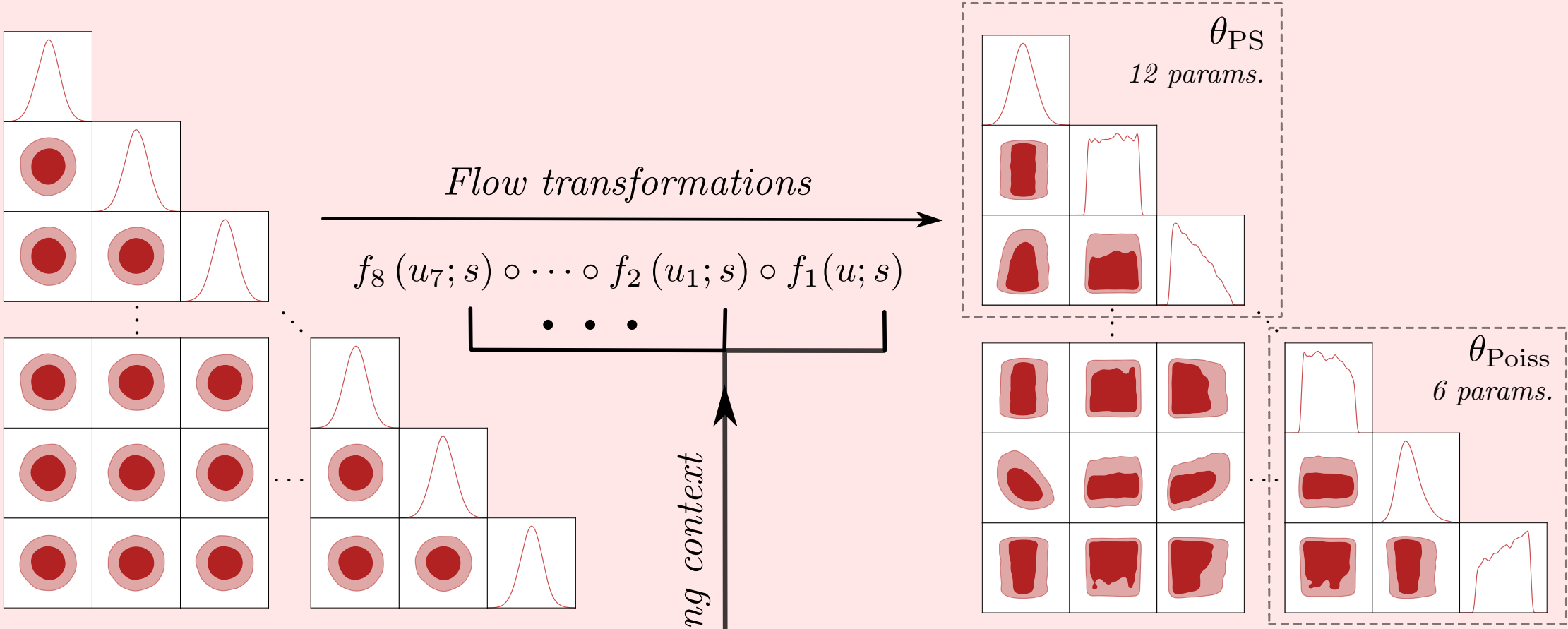
Flows in simulation-based inference: an application to γ-ray data

Normalizing flow

Base distribution
$u \sim \pi(u) = \mathcal{N}(u; 0, \mathbb{1})$

Posterior distribution
$\theta \sim p(\theta \mid x)$

θ_{PS}
12 params.

θ_{Poiss}
6 params.

Flow transformations

$f_8(u_7; s) \circ \cdots \circ f_2(u_1; s) \circ f_1(u; s)$

Conditioning context

Input map x

Feature extractor

$nside=128$

$nside=64$

$nside=2$

$nside=1$

Summaries $s(x)$

$\in \mathbb{R}^{128}$

32 ch.

256 ch.

256 ch.

Convolutional (7 layers)

Fully-connected

Inferred quantities

Source-count distributions

Number density of PSs

- GCE PS
- Disk PS

PS flux

Component intensities

- GCE PS
- GCE DM
- Disk PS
- Isotropic
- Bubbles

Intensity

Forward model $x \sim p(x \mid \theta)$

Normalizing flow
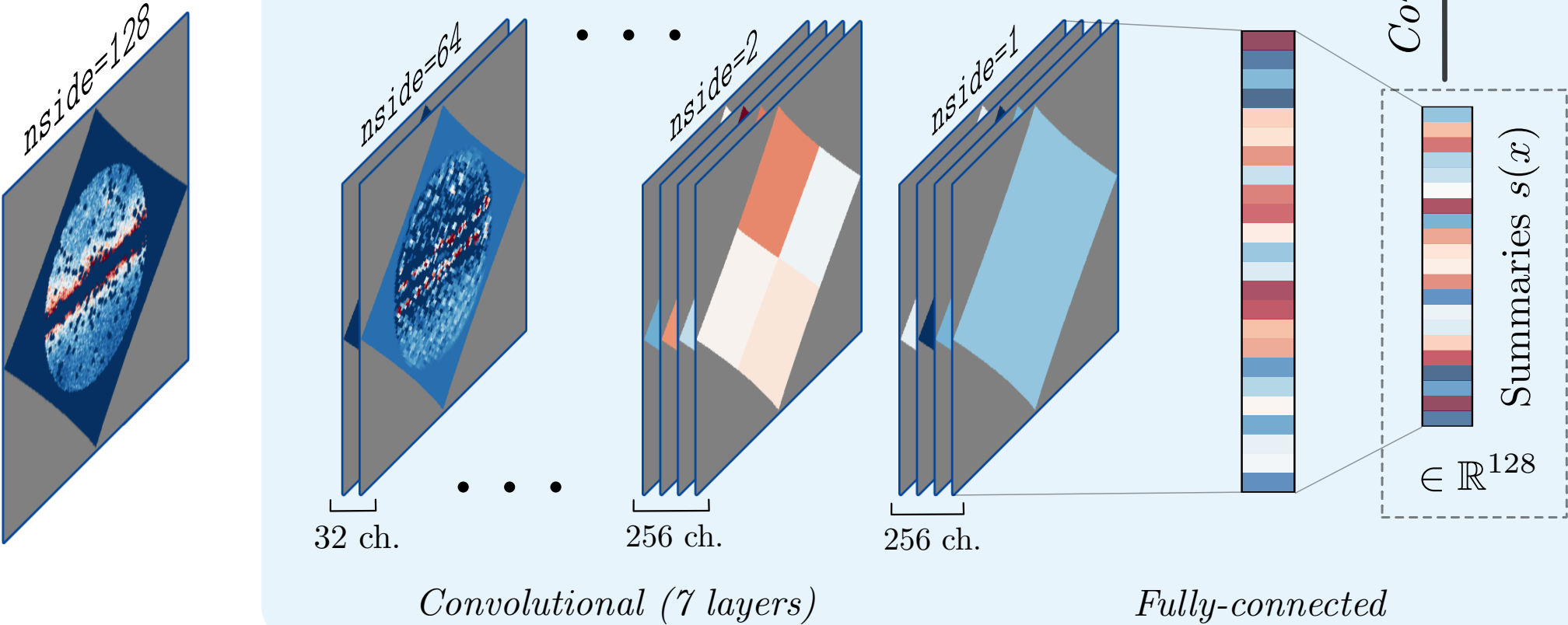
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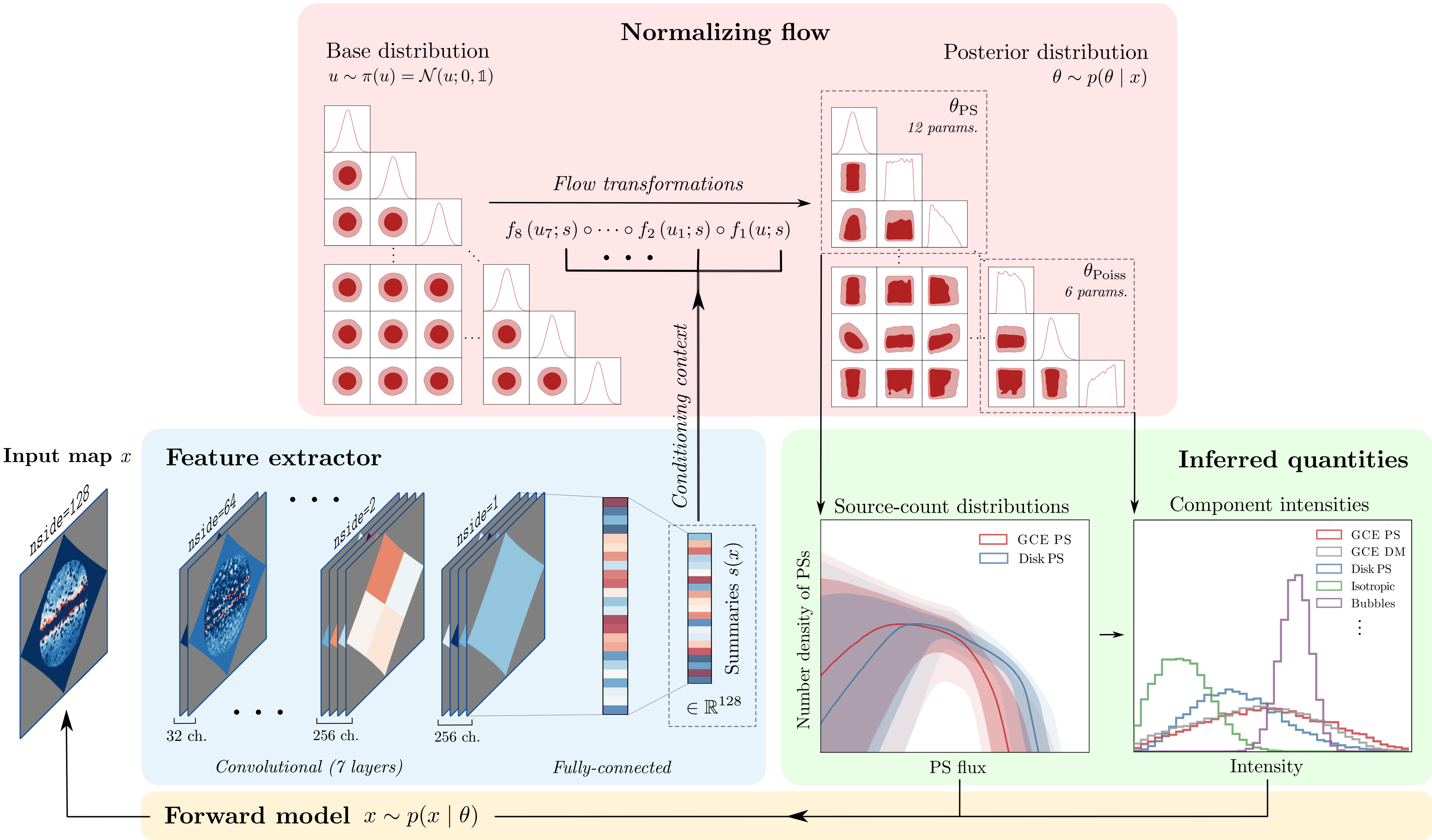
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Back to diffusion: the *probability flow ODE*

For any diffusion process, there exists a corresponding deterministic process whose trajectories share the same marginal probability densities $p(x_t)$ as the SDE [Song et al 2021]