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Continuous-time normalizing flows

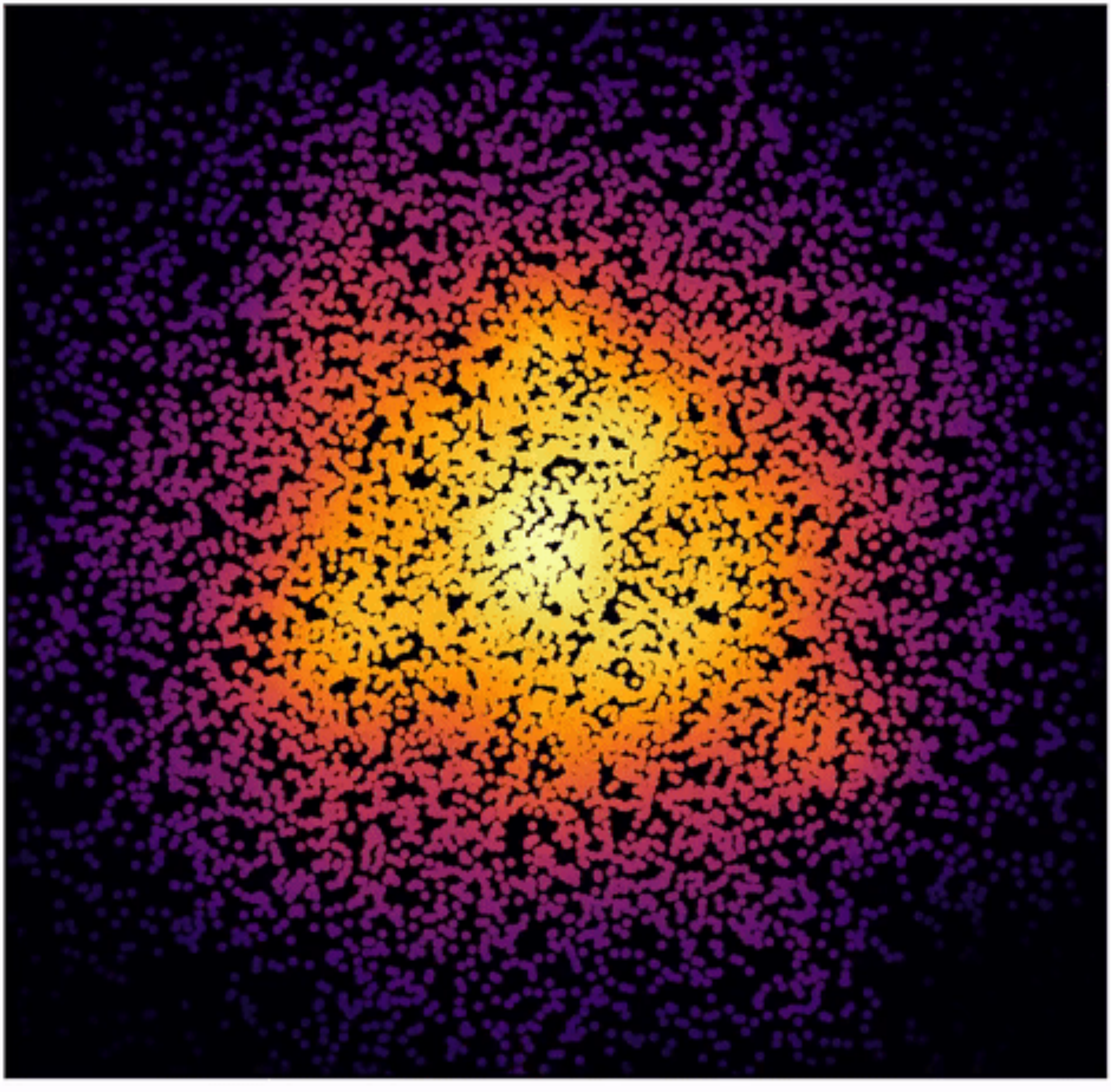
Parameterize the transformation by a neural ODE

Instantaneous change-of-variable formula

$$\frac{\mathrm{d}\log p(z(\mathrm{d}t))}{\mathrm{d}t} = -\,\mathrm{Tr}\left(\frac{\mathrm{d}f}{\mathrm{d}z(t)}\right)$$

ODE with reversible dynamics

$$\frac{\mathrm{d}z}{\mathrm{d}t} = f\big(z(t)\big)$$

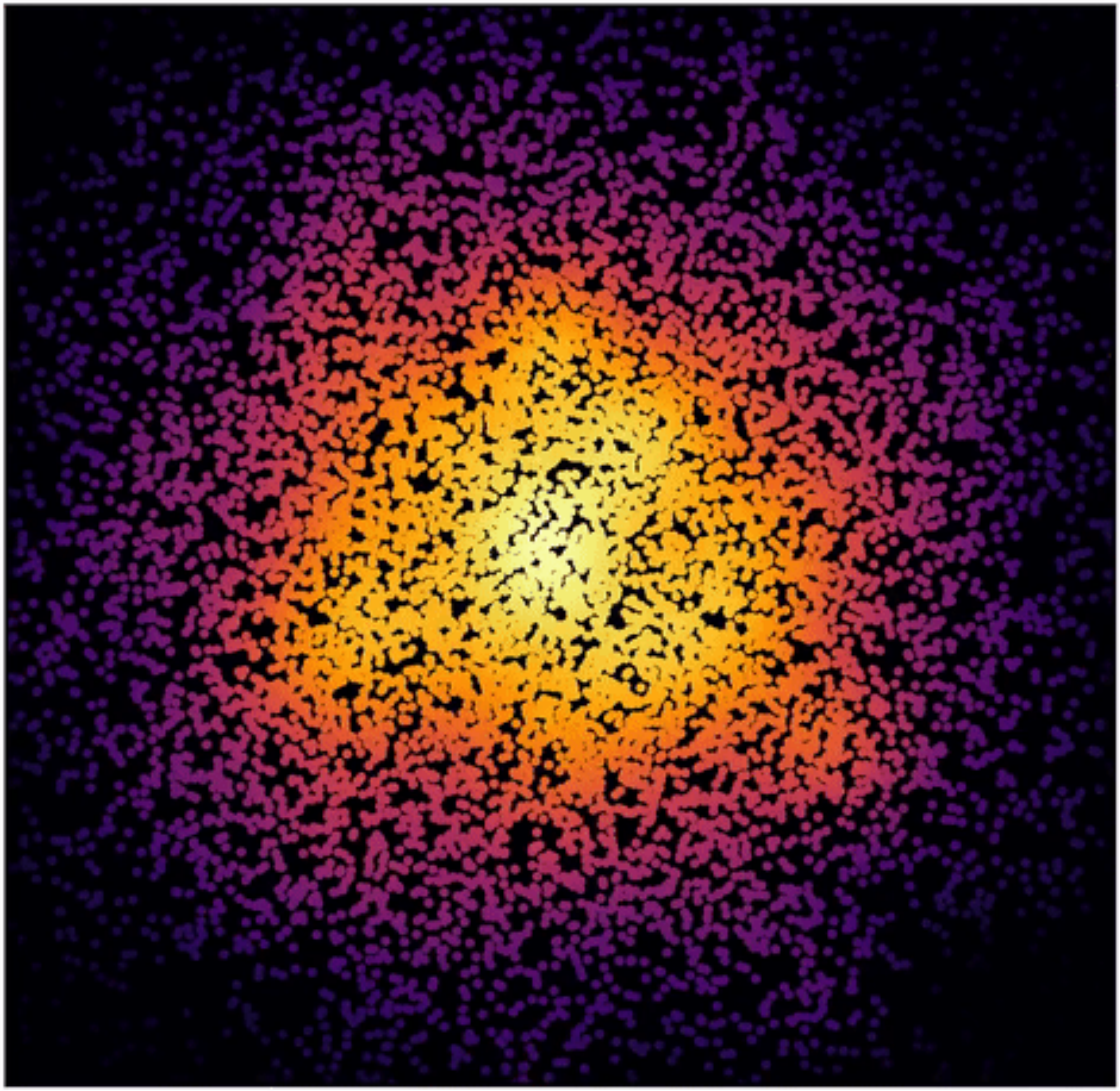


Cons 😵‍💫

- Need for efficient trace calculation
- Solving an ODE and backpropping through the solution can make for cumbersome training

Pro ✅

Unrestricted form of transformation $f(z)$!



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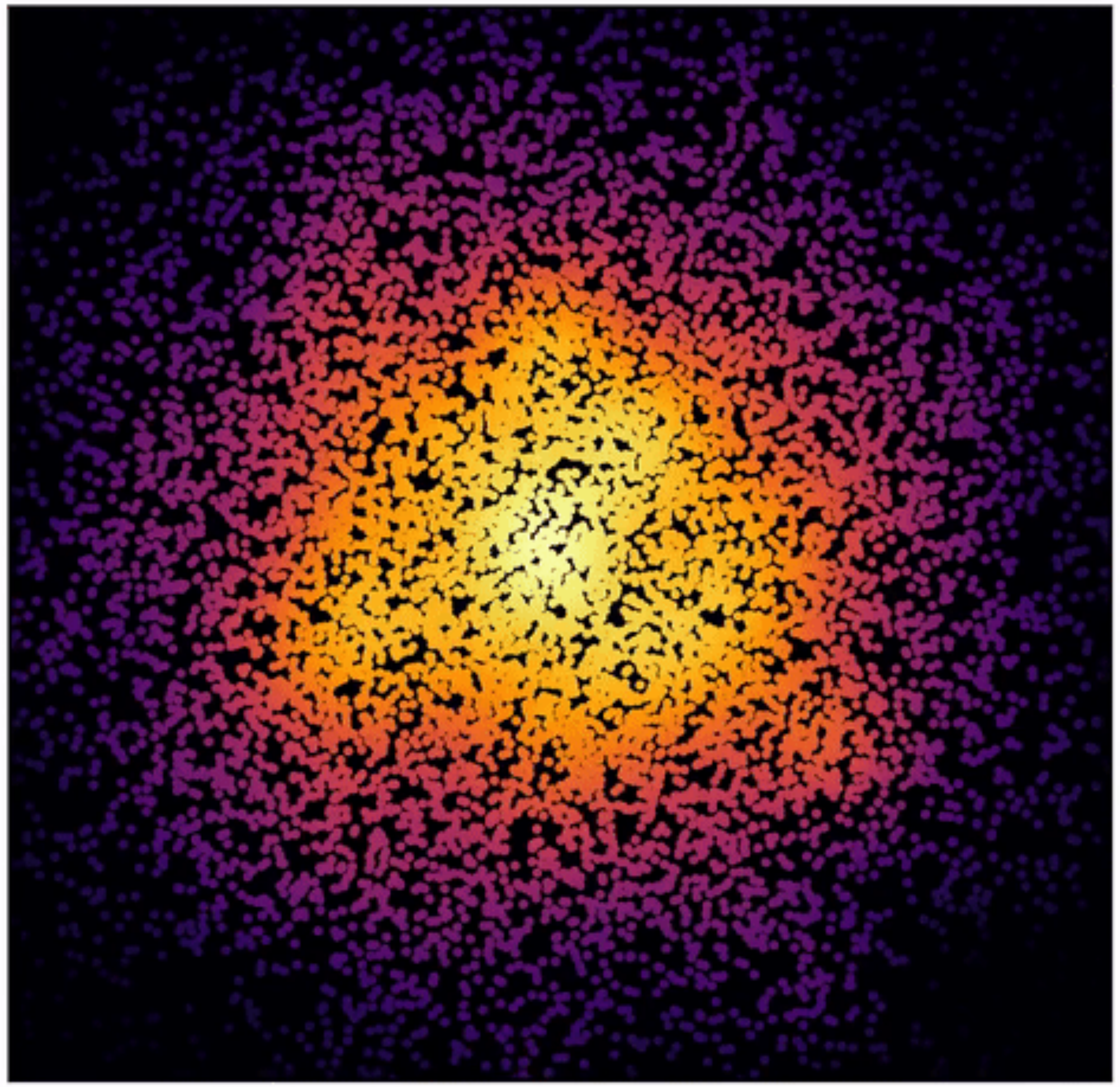

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Flows in *simulation-based inference*

Flows are commonly employed as *conditional posterior density estimators* in simulation-based inference

Data

$$x$$

$$p(x \mid \theta) \cdot p(\theta) \longrightarrow \theta$$

Parameters