

Preferential Normalizing Flows

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Goal: Learn a probability density from preference data (comparisons or rankings).



Examples:

- <u>Prior elicitation</u>: joint prior distribution from expert comparisons
- Al alignment: probabilistic reward model from human preferences
- Density estimation: when the target density cannot be sampled or evaluated
 - E.g. LLM's belief density from rankings







Learn the probability density $p(\mathbf{x})$ from...

- **>** Density estimation: Samples from density, $\mathbf{x} \sim p(\mathbf{x})$
- > VI, MCMC: (unnormalized) Density evaluations, $p(\mathbf{x})$

Our setting:

Preferences (comparisons or rankings), "x is preferred to x'" or "x is more probable than x'", which means in a noise-free setting p(x) > p(x')



What?

- Works with any flow as longs as the density is fast to compute; we use RealNVP and Neural Spline Flow
- Choices are generated by a random utility model (RUM) with exponentially distributed noise and utility function log p(x)

Density estimation using Real NVP [Dinh *et al.*, ICLR17] Neural Spline Flows [Durkan *et al.*, NeurIPS19] 

What?



What is the training objective? How about maximizing the likelihood of the preference data? Failure modes:





(a) Collapsing probability

(b) Diverging probability







Our objective is the function-space maximum a posteriori estimate,

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p(f \mid D) \propto p(D \mid f)p(f),
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where f is the flow log-density.

- We introduce the empirical functional prior p(f) that allocates probability mass to high-density points
 - Building on a limit theorem, the prior can be made consistent with the underlying decision-model (RUM)

Should we learn most likely functions or parameters? [Qiu *et al.*, NeurIPS23] Probabilistic choice with an infinite set of options [Malmberg&Hössjer, 2014]







With the prior:





(c) 10 rankings, k = 5

(d) 100 rankings, k = 5