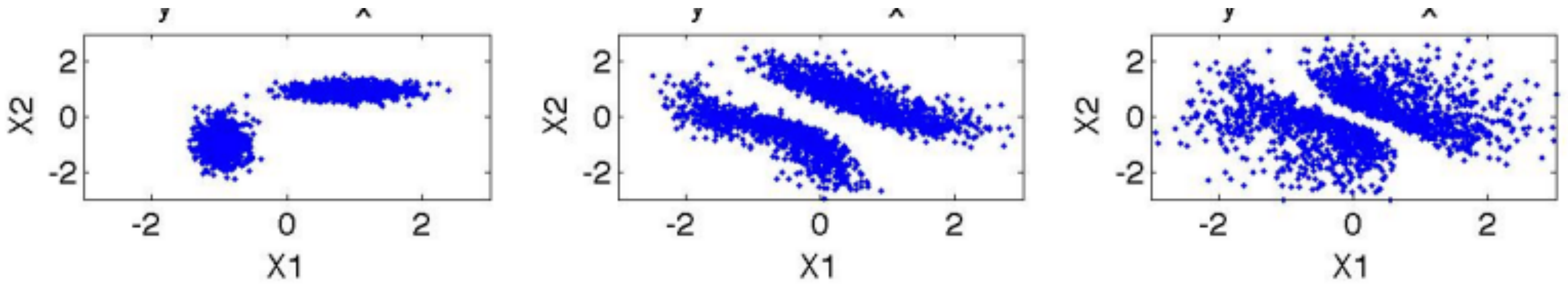
Normalizing Flow history



2010
Tabak, Esteban G., and Cristina V. Turner.
"A family of nonparametric density estimation algorithms."

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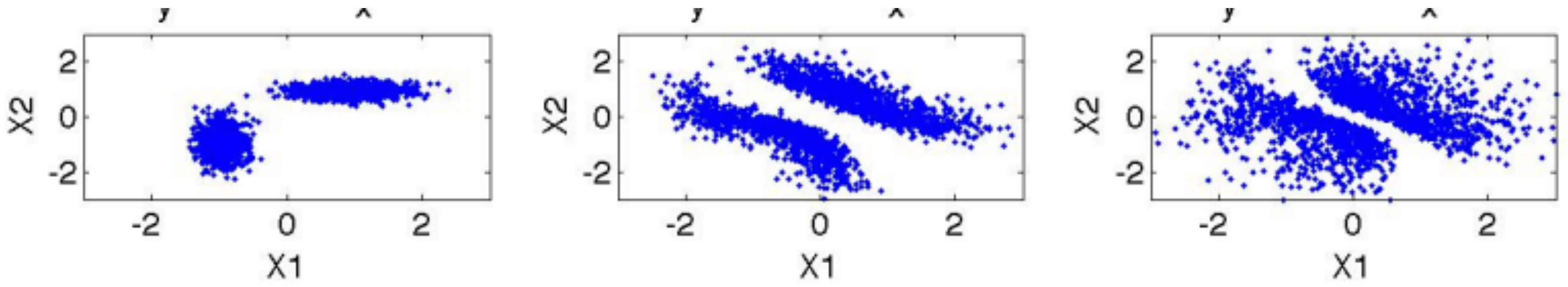

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"A family of nonparametric density estimation algorithms."

3.1 Regularizing the Transformations

We will train the model on data by minimizing an objective composed of several parts:

Divergence Penalty $\mathcal{D}(\boldsymbol{\Psi})$: This determines the fit of the current encoding transformation. It forces the marginal densities of the empirical distribution of the representation-space data to match a target distribution of our choice, by penalizing divergence from it.

Invertibility Measure $\mathcal{I}(\boldsymbol{\Theta})$: This ensures the invertibility of $\boldsymbol{f}_{\boldsymbol{\Theta}}(\cdot)$ by penalizing poorly-conditioned transformations.

Reconstruction Loss $\mathcal{R}(\boldsymbol{\Theta}, \boldsymbol{\Psi})$: This jointly penalizes the encoder $\boldsymbol{g}_{\boldsymbol{\Psi}}(\cdot)$ and decoder $\boldsymbol{f}_{\boldsymbol{\Theta}}(\cdot)$ to ensure that $\boldsymbol{g}_{\boldsymbol{\Psi}}(\boldsymbol{y}) \approx \boldsymbol{f}_{\boldsymbol{\Theta}}^{-1}(\boldsymbol{y})$ on the data.

Each of these participates in the overall objective given by:

$$C(\boldsymbol{\Theta}, \boldsymbol{\Psi}) = \mu_{\mathcal{D}}\mathcal{D}(\boldsymbol{\Theta}) + \mu_{\mathcal{I}}\mathcal{I}(\boldsymbol{\Psi}) + \mu_{\mathcal{R}}\mathcal{R}(\boldsymbol{\Theta}, \boldsymbol{\Psi}) \ , \tag{6}$$

where $\mu_{\mathcal{I}}, \mu_{\mathcal{D}}, \mu_{\mathcal{R}} \in \mathbb{R}$ are the weights of each term. We will examine each of these terms in more detail in the proceeding sections.

2013
Rippel, Oren, and Ryan Prescott Adams.
“High-dimensional probability estimation with deep density models."