

Wednesday, April 21, 2021 10:15 AM

Lecture 24Last time (Clandius)

- Idea of density estimation - learn $p(x)$ from data

- Simple approaches

- histograms
- KDE
- GMM

- Modern approaches — Normalizing Flows

$z, x \in \mathbb{R}^d$

$z \xrightarrow{f} x$
 "base" dist'n
 e.g. $z \sim N(\theta, \Sigma)$
 or $\text{unif.}(0, 1)$

"target" dist'n
 $x \sim p_{\text{data}}(x)$

$$p(x) = p(z) \left| \det \frac{\partial f}{\partial z} \right|^{-1}$$

f must be piecewise diff.
invertible

Wednesday, April 21, 2021 10:30 AM

If we have $\begin{cases} f: z \rightarrow x \rightarrow \text{sample} \\ f^{-1}: x \rightarrow z \rightarrow \text{density estimation} \\ \text{(assuming } \left| \frac{df^{-1}}{dx} \right| \text{)} \end{cases}$

NEED: - f invertible
 - $\det J$ fast compute Jacobian
 \downarrow \downarrow
 $d \times d$ matrix fastest algo $\sim d^3$.

Recent breakthroughs (2015+)

- f 's can be composed! $f = f_1 \circ f_2 \circ f_3 \dots$ still bijective

$$\det J_f = (\det J_{f_1} \cdot \det J_{f_2} \dots)$$

could try to build expressions f out of simple ones (flow idea)

Wednesday, April 21, 2021 10:37 AM

e.g.

- planar flow

$$f(z) = z + u \cdot h(w^T z + b)$$

\nwarrow nonlinearity like tanh.
 \nearrow $\in \mathbb{R}$
 \nwarrow weights $\in \mathbb{R}^d$

Jacobian is not d^3 , fast
invertible given some conditions on h .

- radial flow

$$f(z) = z + \beta \frac{z - z_0}{\alpha + \|z - z_0\|}$$

\nwarrow $z - z_0$
 \nearrow learnable weights

good first step
not very expressive
not SOTA. for higher dim'l problems.



Wednesday, April 21, 2021 10:43 AM

Autoregressive flows

- First, solve $\mathcal{O}(d^3)$ det problem w/ following trick

$$x_1 = f_1(z_1)$$

$$x_2 = f_2(z_1, z_2)$$

$$\vdots$$

$$x_i = f_i(z_1, z_2, \dots, z_i)$$

$$\vdots$$

$$x_d = f_d(z_1, \dots, z_d)$$

Then $\frac{\partial f}{\partial \vec{z}} = \begin{pmatrix} \text{---} \\ \text{---} \\ \vdots \\ \text{---} \\ 0 \dots 0 \end{pmatrix}$

Jacobian is upper triangular!

$$\det J = \prod_{i=1}^d \frac{\partial f_i}{\partial z_i} \quad \text{now } \det J \sim \mathcal{O}(d) \text{ operations!}$$

Still need f to be invertible ... again make some simple choices for f .

Wednesday, April 21, 2021 10:47 AM

eg. -

$$x_i = z_i \sigma_i(x_{1:-i-1}) + \mu_i(x_{1:-i-1}) \quad \text{invertible} \quad z_i = \frac{x_i - \mu_i(x_{1:-i-1})}{\sigma_i(x_{1:-i-1})}$$

\swarrow could be NN's, \downarrow
 \swarrow $z_{1:-i-1}$ $\mu_i(x_{1:-i-1})$ $\sigma_i(x_{1:-i-1})$

Another perspective on Autoregressive Flows:

$$P(x_i | x_{1:-i-1}) = \mathcal{N}(x_i | \mu_i, \sigma_i) \quad \text{simple parametric density}$$

"mixture density network"

$$P(x) = \prod_{i=1}^d P(x_i | x_{1:-i-1})$$

- Problem w/ Auto. Flows is could depend heavily on ordering of x 's.
- Can chain together A.F.'s to build more complex transformations
- Can permute order of x 's b/w successive A.F.'s.

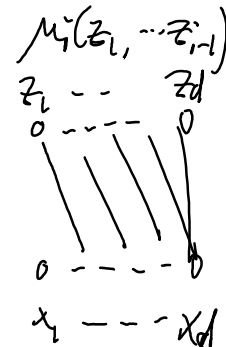
Wednesday, April 21, 2021 10:58 AM

Chang together successive AF's w/ normal dist's

→ "Masked Auto regressive Flows"
or "Inverse Auto regressive Flows"

dep. μ_i, σ_i are fns of x or z .

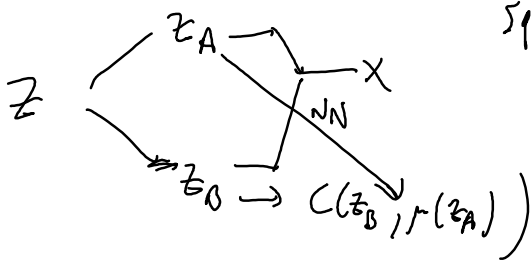
μ_i and σ_i are NN's



take ordinary DNN
apply binary masks to all weights
to enforce autoregressive
property.

"complexis"
C's: affine layer "ReLU NVP"
PW linear, quadratic, etc. "Neural Imp. Sampling"
rational quadratic spline "Neural spline Flows"

• Coupling Layers



Autoregressive!

split data into 2 groups

$$x_1 = z_1$$

$$\vdots$$

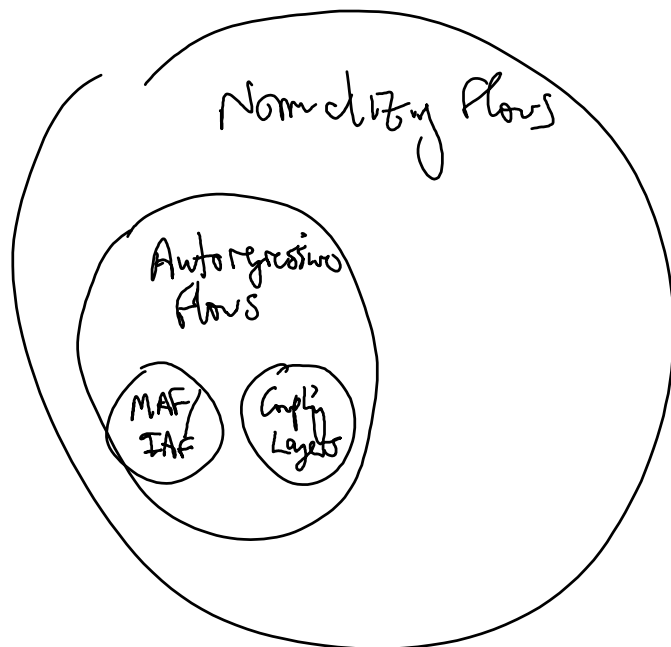
$$x_k = z_k$$

$$x_{k+1} = C_{k+1}(z_{k+1}, \mu_{k+1}(z_1, \dots, z_k))$$

$$\vdots$$

$$x_d = C_d(z_d, \mu_d(z_1, \dots, z_{d-1}))$$

Wednesday, April 21, 2021 11:06 AM



Training a density estimator $p(x|\theta)$

\downarrow

MLE: $\prod_{i=1}^{N_{data}} p(x_i|\theta)$

neg. log likelihood: $L = - \sum_{i=1}^{N_{data}} \log p(x_i|\theta)$

goal: $\min_{\theta} L$