

# LU-Net: Invertible Neural Networks Based on Matrix Factorization

Sarina Penquitt<sup>1</sup>, Robin Chan<sup>2</sup>, and Hanno Gottschalk<sup>3</sup>

<sup>1</sup> IZMD, University of Wuppertal

<sup>2</sup> Machine Learning Group, Bielefeld University

<sup>3</sup> Institute of Mathematics, Technical University Berlin



## Abstract

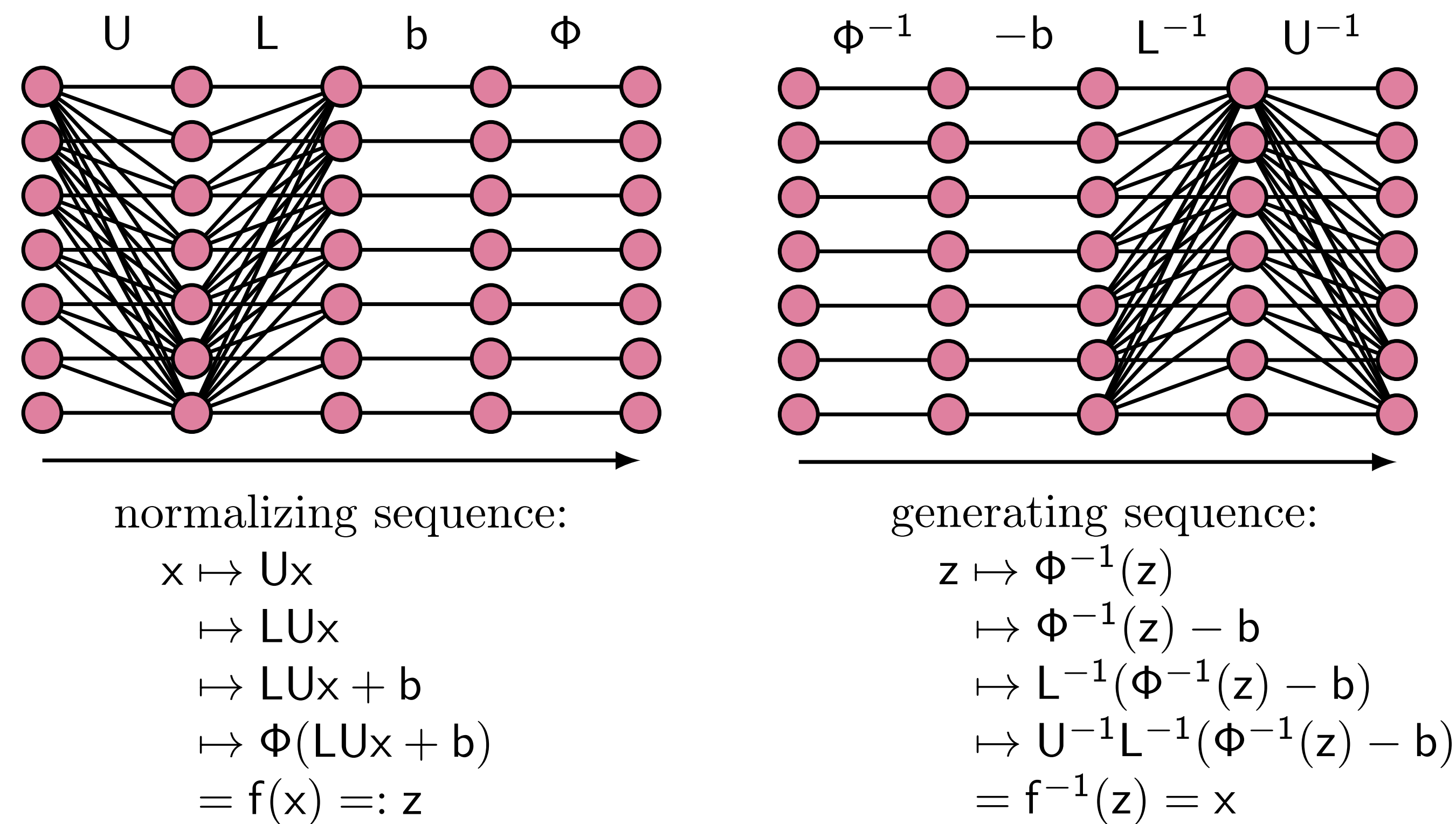
LU-Net is a simple and fast architecture for invertible neural networks (INNs) that is based on the factorization of quadratic weight matrices  $A = LU$ , where  $L$  is a lower triangular matrix with ones on the diagonal and  $U$  an upper triangular matrix. Instead of learning a fully occupied matrix  $A$ , we learn  $L$  and  $U$  separately. If combined with an invertible activation function, such a layer can easily be inverted whenever the diagonal entries of  $U$  are different from zero. Also, the computation of the determinant of the Jacobian matrix is cheap. Consequently, the LU-Net architecture allows for cheap likelihood computation via the change of variables formula and can be trained according to the maximum likelihood principle.

## Training via Maximum Likelihood

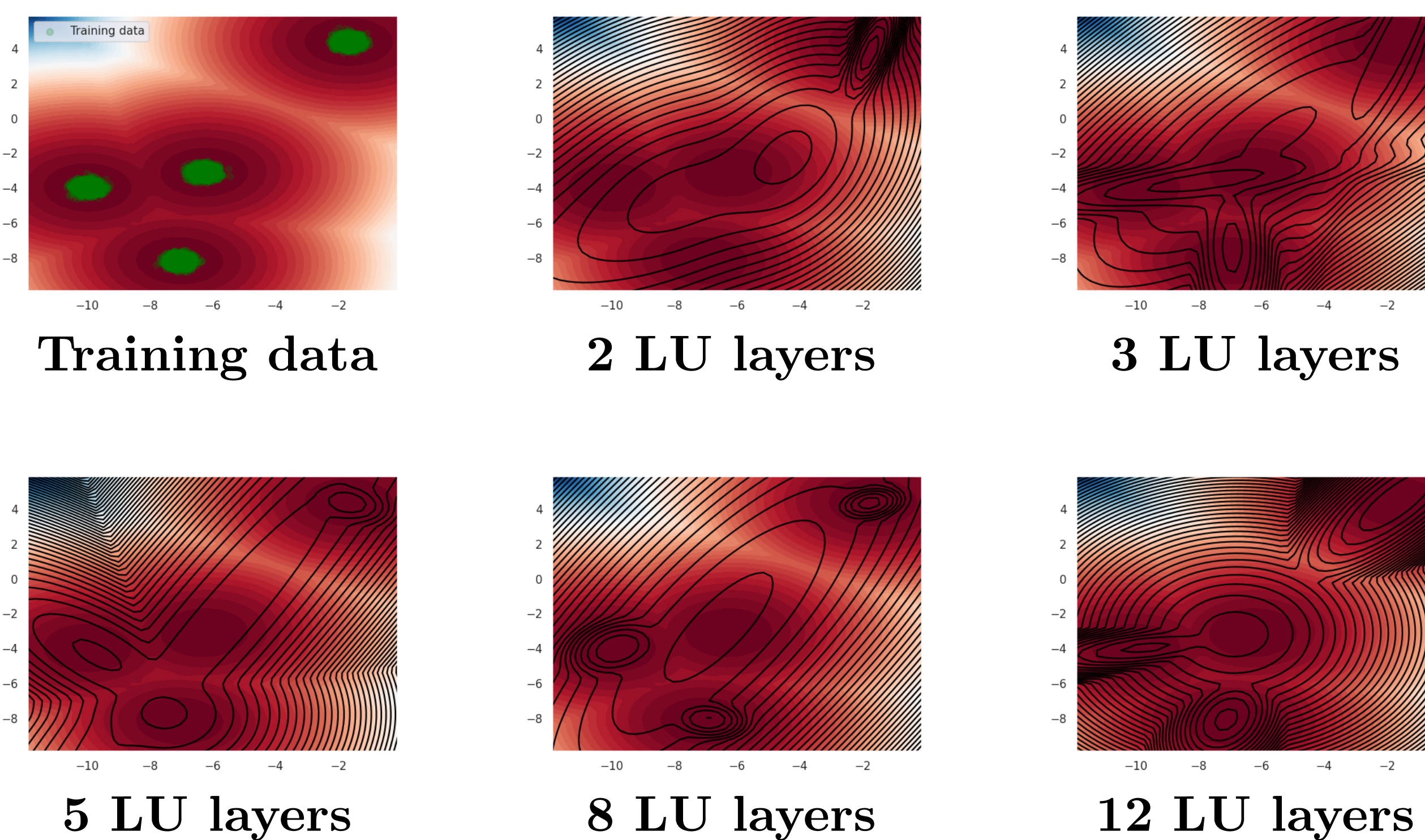
Let  $x \in \mathbb{R}^D$  denote some  $D$ -dimensional input and let  $M \geq 2$  specify the number of LU layers, where each layer of LU-Net is a map  $\mathbb{R}^D \rightarrow \mathbb{R}^D$ . Hence,  $f : \mathbb{R}^D \rightarrow \mathbb{R}^D$  denotes the output of LU-Net. Given a dataset  $\mathcal{D} = \{x^{(n)}\}_{n=1}^N$  and the set of model parameters  $\theta = \{U^{(m)}, L^{(m)}, b^{(m)}\}_{m=1}^M$ , our training objective is to maximize the likelihood on  $\mathcal{D}$ . By using the change of variables formula, the chain rule of calculus and given the fact that the determinant of a triangular matrix is the product of its diagonal entries, we obtain the following expression for the negative log likelihood as training loss function:

$$-\ln \mathcal{L}(\theta|\mathcal{D}) = \frac{1}{2} \cdot N \cdot D \cdot \ln(2\pi) + \frac{1}{2} \sum_{n=1}^N \sum_{d=1}^D f_d(x^{(n)}|\theta)^2 - \sum_{n=1}^N \sum_{m=1}^M \sum_{d=1}^D \ln \phi^{(m)} \left( (L^{(m)}U^{(m)}x^{(n)})_d + b_d^{(m)} \right) - N \cdot \sum_{m=1}^M \sum_{d=1}^D \ln |u_{d,d}^{(m)}| \rightarrow \min$$

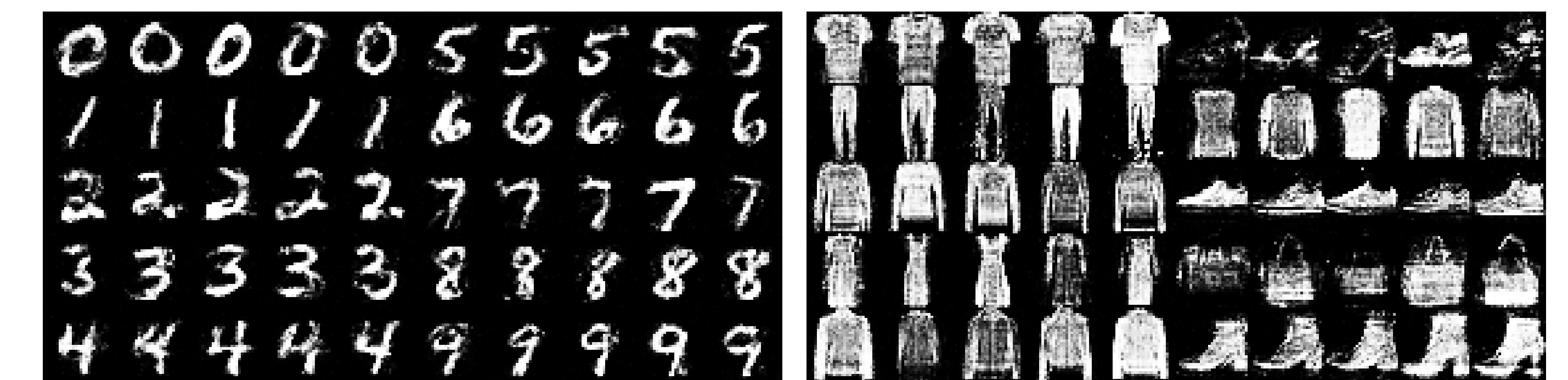
## Illustration of one LU layer



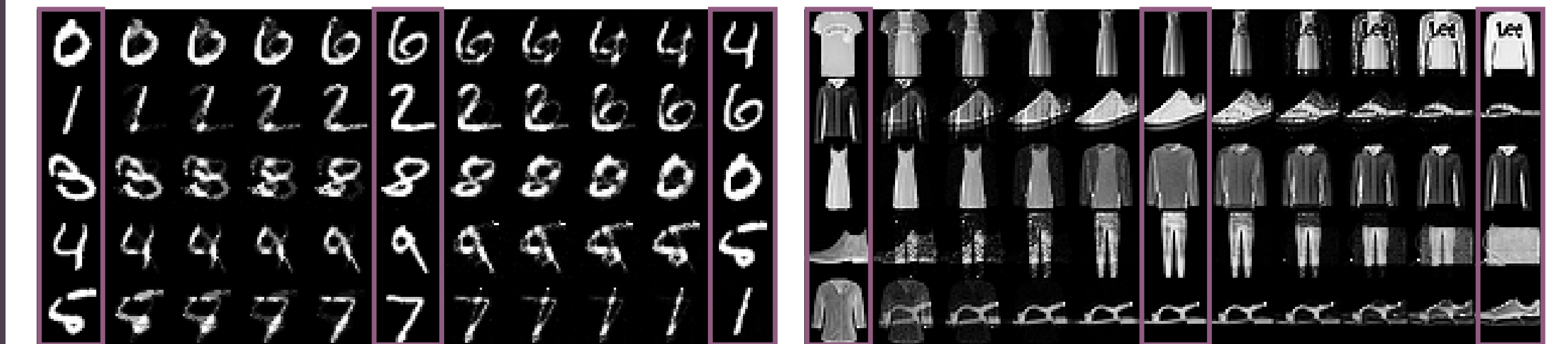
## Gaussian Mixture



## MNIST and Fashion MNIST



LU-Net: Randomly generated samples of MNIST and Fashion MNIST



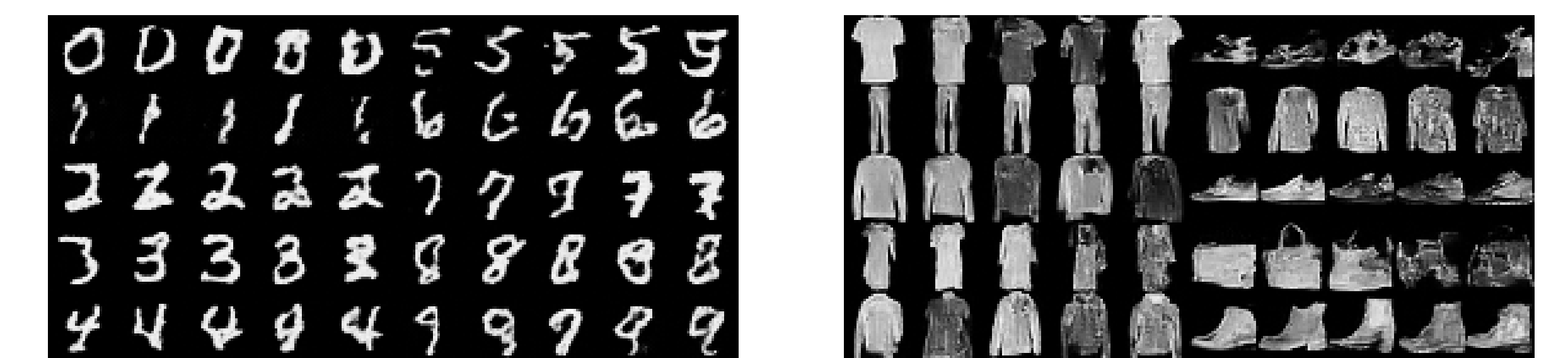
LU-Net: Samples of MNIST and Fashion MNIST generated by interpolating in latent space of LU-Net

## Comparison with RealNVP

model	num weight parameters	GPU memory usage	num epochs training	test NLL
LU-Net	4.92 M	1,127 MiB	40	3.2424 bits/pixel
RealNVP	5.39 M	3,725 MiB	100	5.6819 bits/pixel

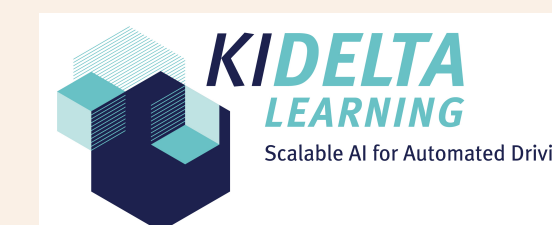
model	train epoch	optimization step	density per image	sampling per image
LU-Net	7.32 sec	1.2 ms	37.10 ms	45.15 ms
RealNVP	99.88 sec	56.0 ms	259.15 ms	1.03 ms



RealNVP: Randomly generated samples of MNIST and Fashion MNIST

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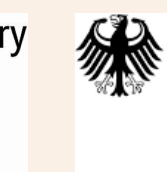
*Contact.* <sup>1</sup>penquitt@uni-wuppertal.de, <sup>2</sup>rchan@techfak.uni-bielefeld.de, <sup>3</sup>gottschalk@math.tu-berlin.de  
*Code.* <https://github.com/spenquitt/LU-Net-Invertible-Neural-Networks>



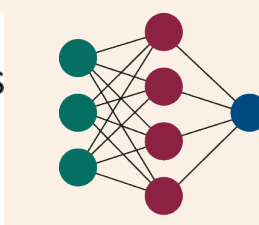
Ministry of Culture and Science of the State of North Rhine-Westphalia



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