## Extra sparse dimensionality reduction



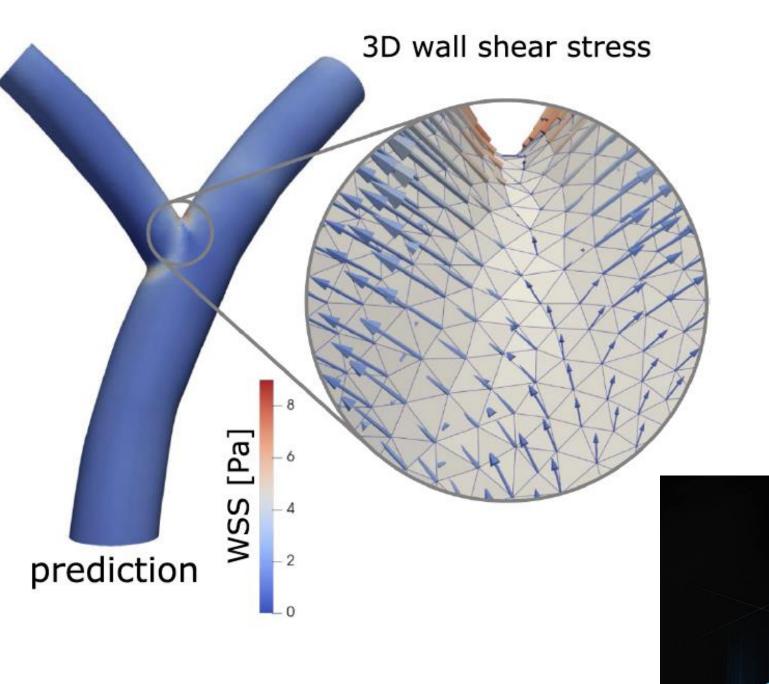
Tjeerd Jan Heeringa, Christoph Brune, Mengwu Guo

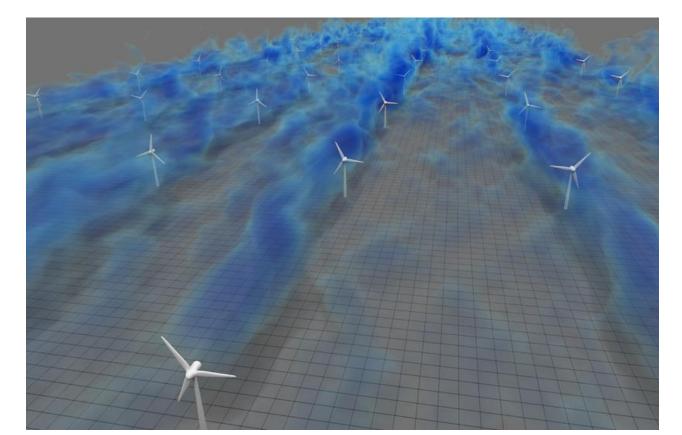
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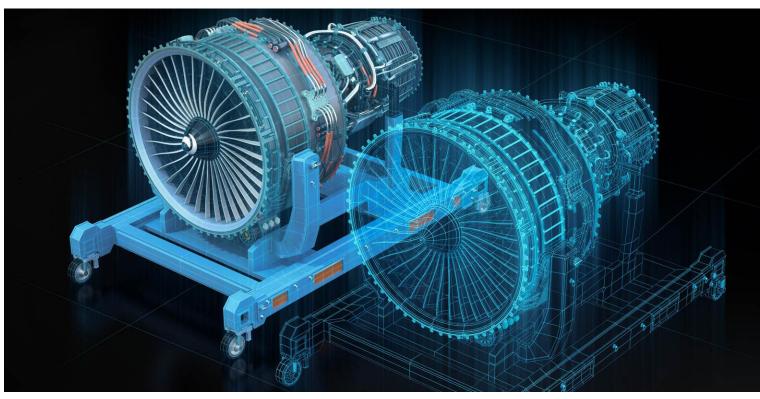
## What we want

Many problems require computationally expensive problem









To remedy this, we want

- 1) to find a **small** set of representative variables
- 2) that accurately describes the full solution
- 3) and allows for **fast** computing of the full solution.

## The optimisation problem

We look for the best parameters  $\theta$  for an autoencoder  $\phi_{\theta} =$  $\phi_{\theta,dec} \circ \phi_{\theta,enc}$  using

$$\theta^{\dagger} \in \arg\min_{\theta} \sum_{i} \|x_{i} - \phi_{\theta}(x_{i})\|_{2}^{2} + \lambda \left(\sum_{\ell=1}^{L} \|W^{\ell}\|_{1,2} + \|W^{L_{enc}}\|_{*}\right)$$
Accurate
fast

We solve this using Linearized Bregman iterations

$$v^{(k+1)} = v^{(k)} - \eta \nabla L(\theta^{(k)})$$
$$\theta^{(k+1)} = prox_R(v^{(k+1)})$$

where

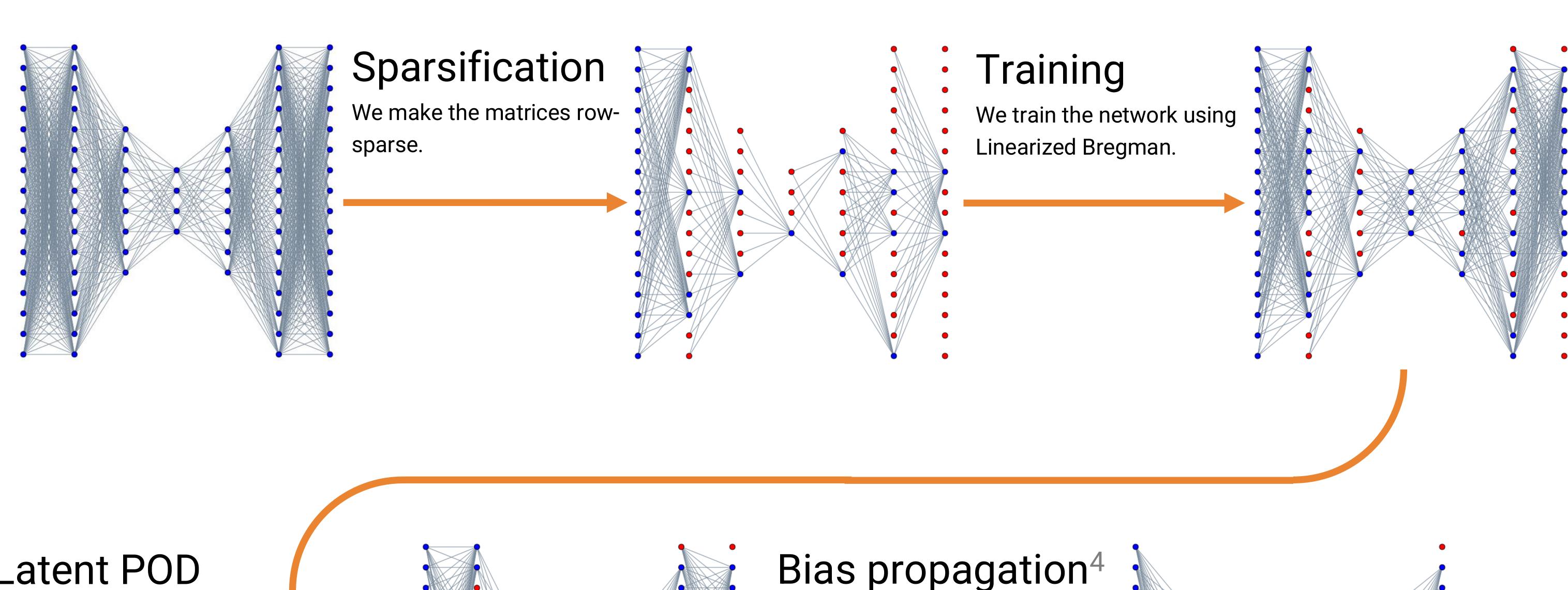
$$prox_R(v) = \arg\min_{\theta} \frac{1}{2} ||v - \theta||_2^2 + R(\theta)$$

$$L(\theta) = \sum_{i} \|x_{i} - \phi_{\theta}(x_{i})\|_{2}^{2}$$

$$\text{Last layer of the encoder}$$

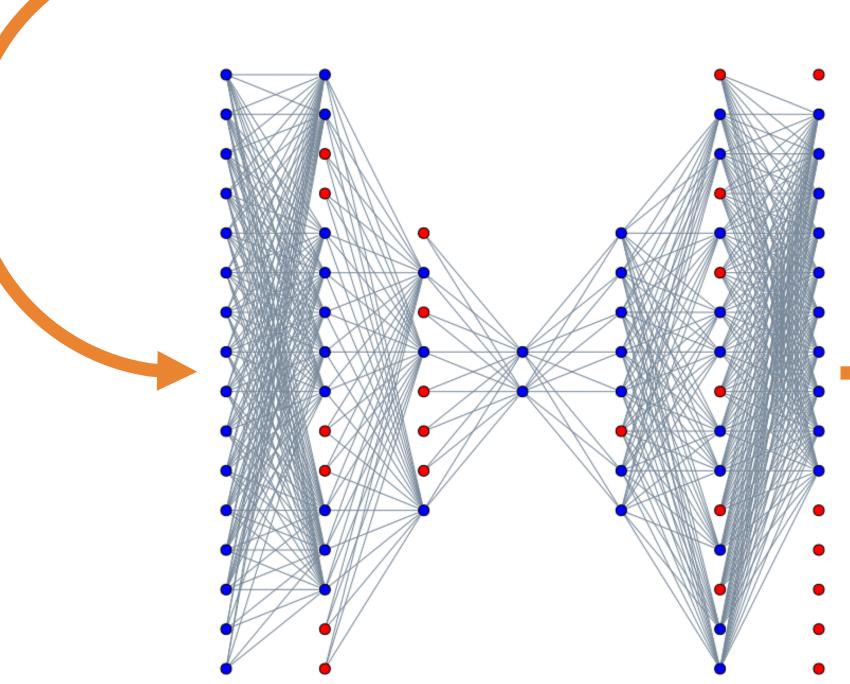
$$R(\theta) = \lambda(\sum_{i} \|W^{\ell}\|_{1,2} + \|W^{L_{enc}}\|_{*})$$

## Similar accuracy Sparser network and smaller latent dimensionaility

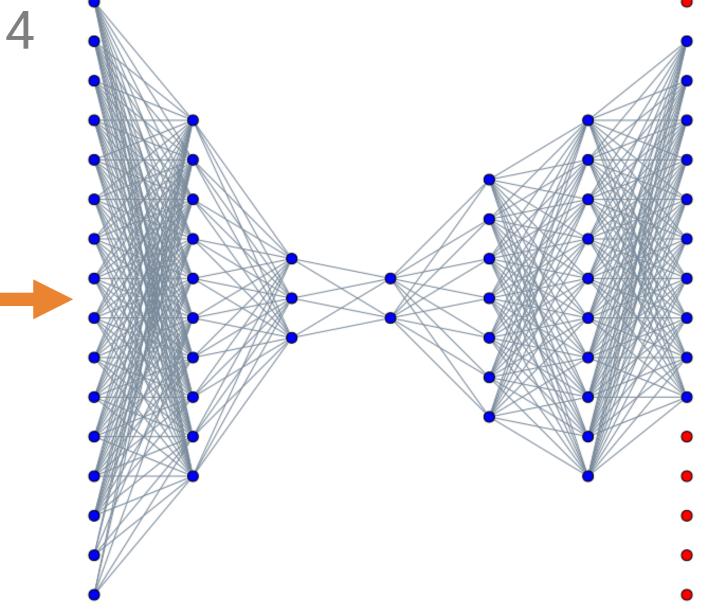


We use POD to truncate the

number of latent variables.



We move all the biases corresponding to matrices with zero-rows to the next layer.



- 1. Suk et al., <a href="https://doi.org/10.1007/978-3-030-93722-5\_11">https://doi.org/10.1007/978-3-030-93722-5\_11</a>
- https://www.aip.org/publishing/journal-highlights/wind-energy-grid-checkerboard
- https://www.atriainnovation.com/en/digital-twins-what-are-they-advantages-and-applications
- Simplify, <a href="https://doi.org/10.1016/j.softx.2021.100907">https://doi.org/10.1016/j.softx.2021.100907</a>