Deep Neural Maps

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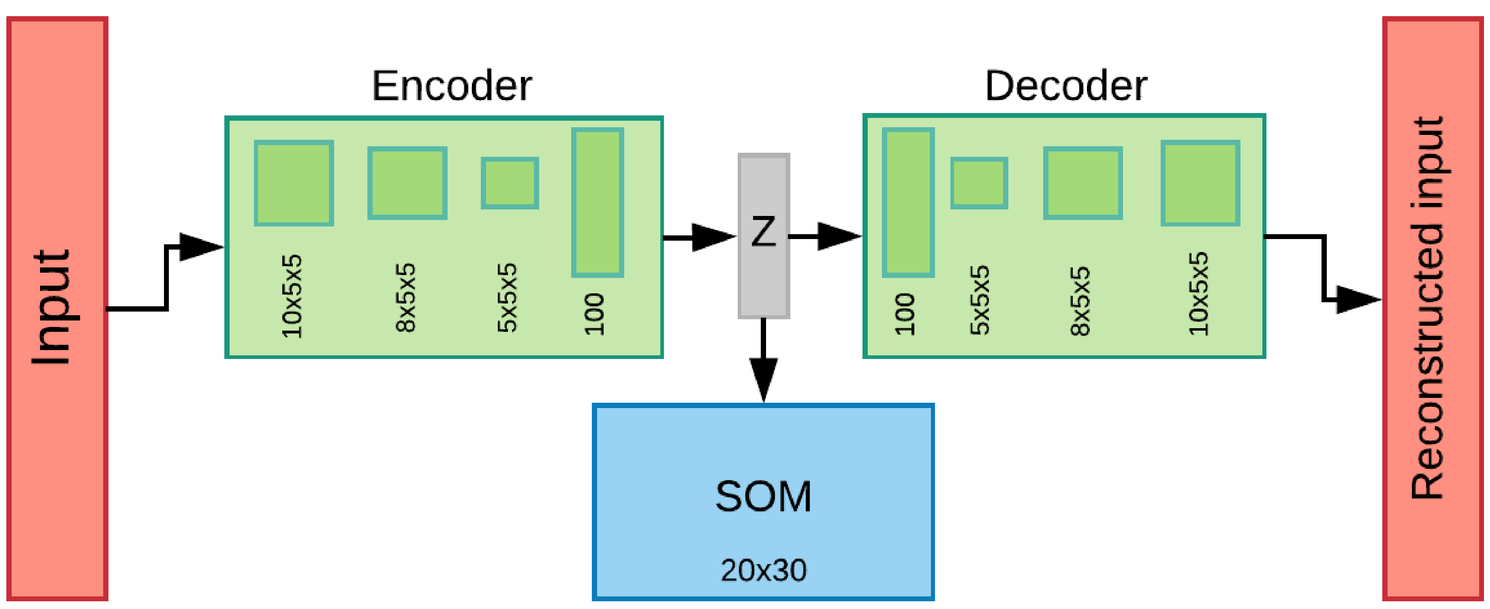
Introduction

Representation learning algorithms, whose goal is to capture the principal factors of the observed data [1], are a common technique for dimensionality reduction. However, the majority of these methods aim to yield an embedding of the data that are only efficient for clustering or classification [2, 3]. Hence, in order to interpret the embedding space, there is a need for an additional algorithm, such as t-SNE.
In this study, we introduce a method to learn and optimize an embedding space for visualization, called Deep Neural Maps (DNM).

DNM model

DNM model architecture:



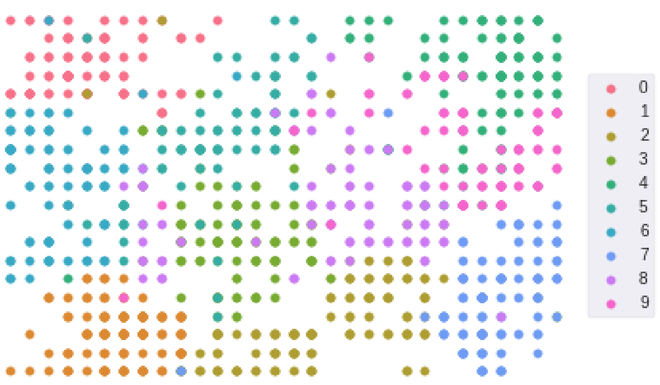
- The DNM model consists of a convolutional auto-encoder ($\mathcal{E}_\theta : X \rightarrow Z$, $\mathcal{D}_\phi : Z \rightarrow \widehat{X}$) and an SOM [4] ($\mathbf{W} = [w_j]$ for $j = 1, 2, ..., l$).
- The goal of DNM is to optimize θ and w_j such that $||Z_i - w_j||$ is minimized for all Z_i.

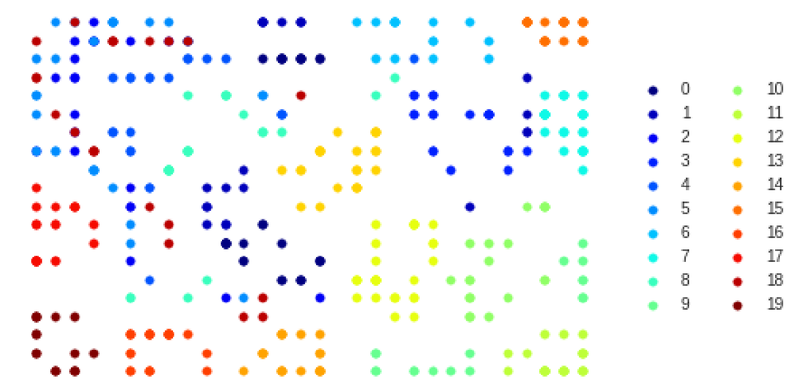
Experiments and results

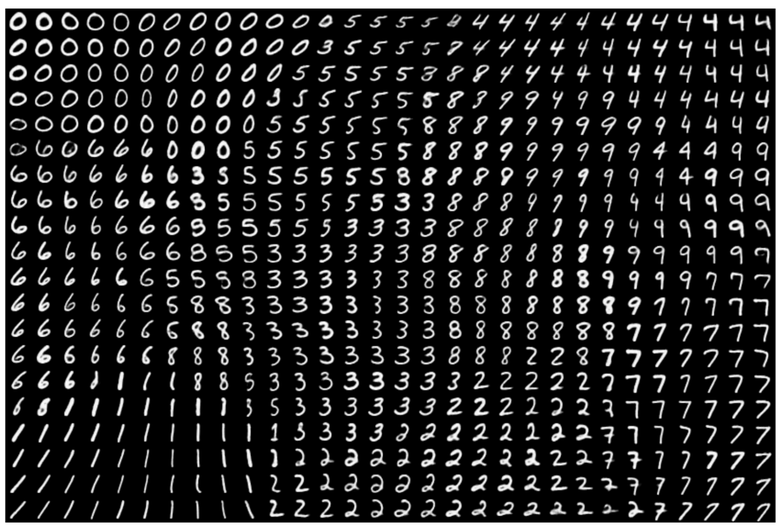
The auto-encoder filter dimensions are set to $(10 \times 5 \times 5)$-$(8 \times 5 \times 5)$-$(5 \times 5 \times 5)$-$dense100$ symmetrically for encoder and decoder. We set the lattice size of the SOM to 20×30, and pre-trained the auto-encoder and the SOM for 500 and 10000 iterations, respectively. We trained the DNM model on the following datasets:

- MNIST: Normalized, 60000 train and 10000 test images of handwritten digits of size 28×28 (a).
- COIL-20: Normalized, 1000 train, 440 test images of 20 objects re-sized to 64×64 (b).

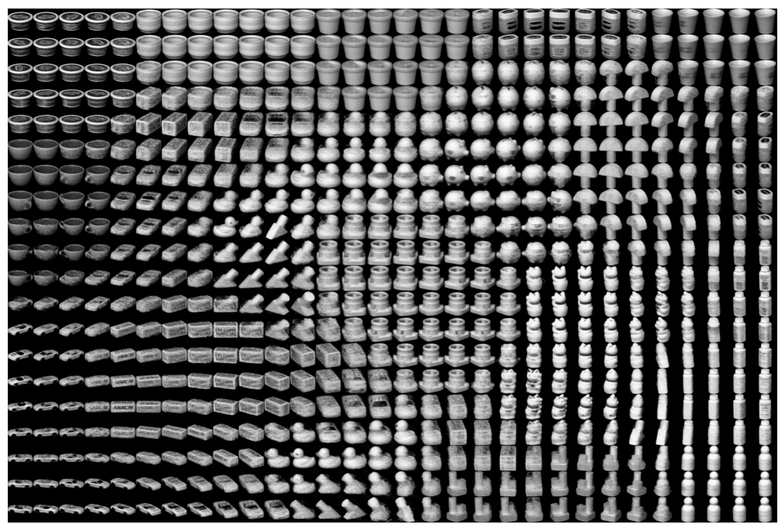
The DNM has separated each class of the data and mapped it to a particular location on the lattice, as seen as clear color separation. Moreover, it captured the variations within each class of data and mapped them to their corresponding location.







a



b

Pre-training

- Train the auto-encoder, $\mathcal{E}_\theta, \mathcal{D}_\phi$, on training dataset
- Compute the embedding Z using $\mathcal{E}_\theta$
- Train SOM weights $\mathbf{W}$ on Z
- Initialize the final model with θ, ϕ and $\mathbf{W}$

Training algorithm

Input: $\mathcal{D} \leftarrow$ training dataset, **epochs**
Output: $\mathcal{E}_\theta, \mathcal{D}_\phi, \mathbf{W} : [w_j]\ for\ j = 1, 2, ..., l$
Initialize $\theta, \phi, \mathbf{W}$ from pre-trained models
$\alpha \leftarrow 2000$, $\sigma_0 \leftarrow 10$, $\eta_0 \leftarrow 0.3$
for $n = 0$ to **epochs do**
  for each minibatch $\mathcal{B}$ in $\mathcal{D}$ **do**
    for each Z_i in $\mathcal{E}_\theta(\mathcal{B})$ **do**
      $u \leftarrow argmin||Z_i - \mathbf{W}||$
      $\sigma(n) = \sigma_0 exp\left(-\frac{n}{\alpha}\right)$
      $H_u(n) = exp\left(-\frac{||p_{w_j} - p_u||^2}{2\sigma^2(n)}\right)$
      $\eta_n = \eta_0 exp\left(-n/\alpha\right)$
      $q_{ij} = \frac{\left(1+||Z_i - w_j||^2\right)^{-1}}{\sum_{j'}\left(1+||Z_i - w_{j'}||^2\right)^{-1}}$,
      $p_{ij} = \frac{q_{ij}^2 / \sum_i q_{ij}}{\sum_{j'} q_{ij'}^2 / \sum_i q_{ij'}}$
      $\mathbf{W}^{n+1} = \mathbf{W}^n + \eta_n H_u(n)(Z_i - \mathbf{W}^n)$
    end for
    $g \leftarrow grad(KLD(P||Q) + \gamma||X - \widehat{X}||_2^2 + \beta||\theta||_2)$
    $\theta, \phi \leftarrow Adam(g, \theta, \phi)$
  end for
end for

Acknowledgements

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References

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