Autoencoders and their applications

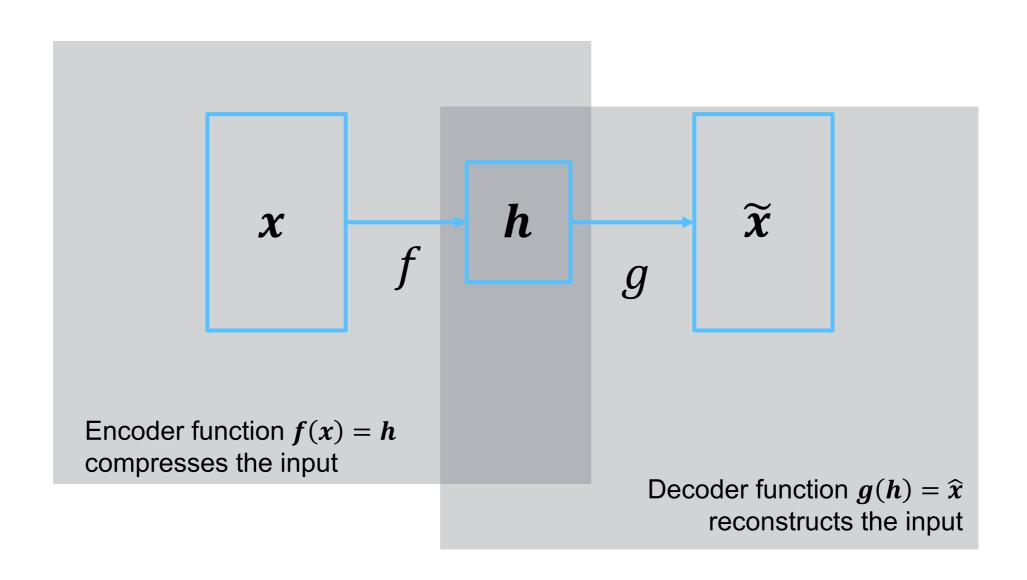
in computational biology

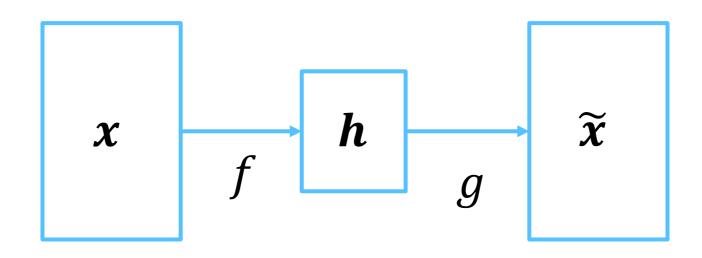
Marianna Rapsomaniki Computational Systems Biology group IBM Research Zurich

contact: <u>aap@zurich.ibm.com</u>

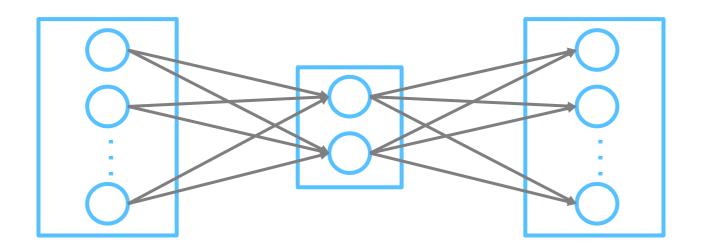
Overview

- Intro to autoencoders
- Main variations examples
- Applications in single-cell analysis
- Hands-on exercise



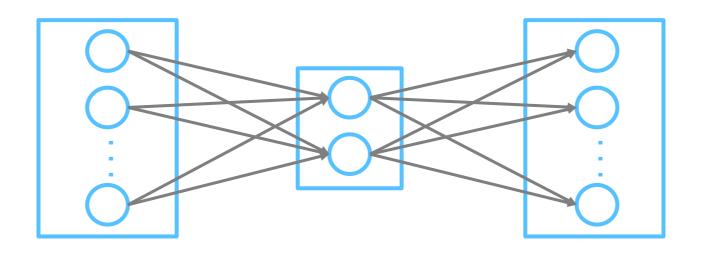


- Non-linear activation functions → complex relationships
- Lossy reconstruction → most salient features of the data



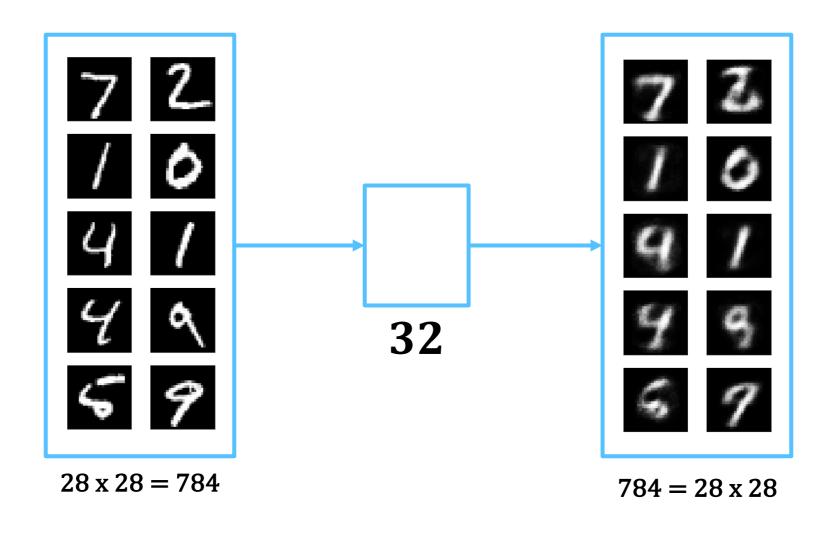
Trained using backpropagation

$$mse = \frac{1}{n} \sum_{i=1}^{n} (x_i - \tilde{x}_i)^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - g(f(x_i)))^2$$

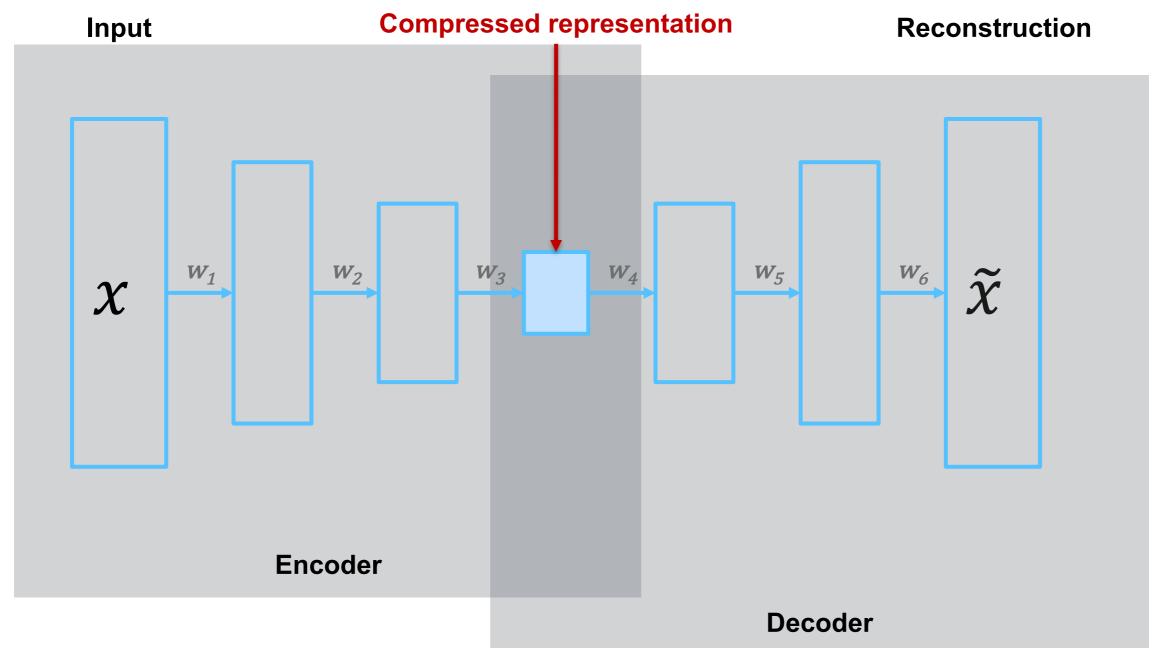


- → Data compression
- → Experiment reconstruction
- → Dimensionality reduction

Example 1: simple AE

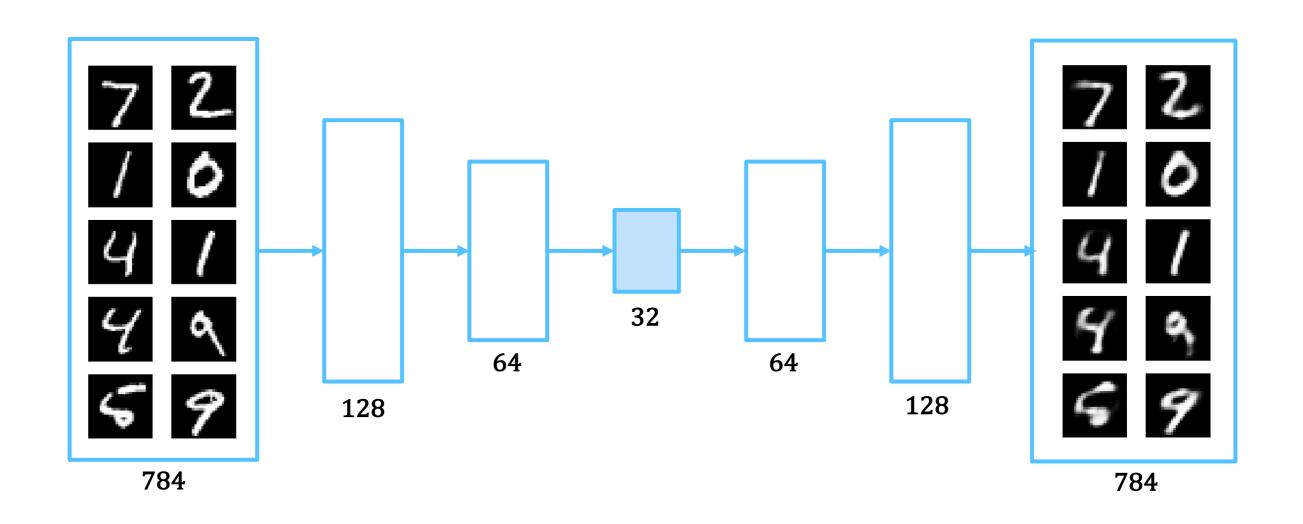


Deep autoencoders

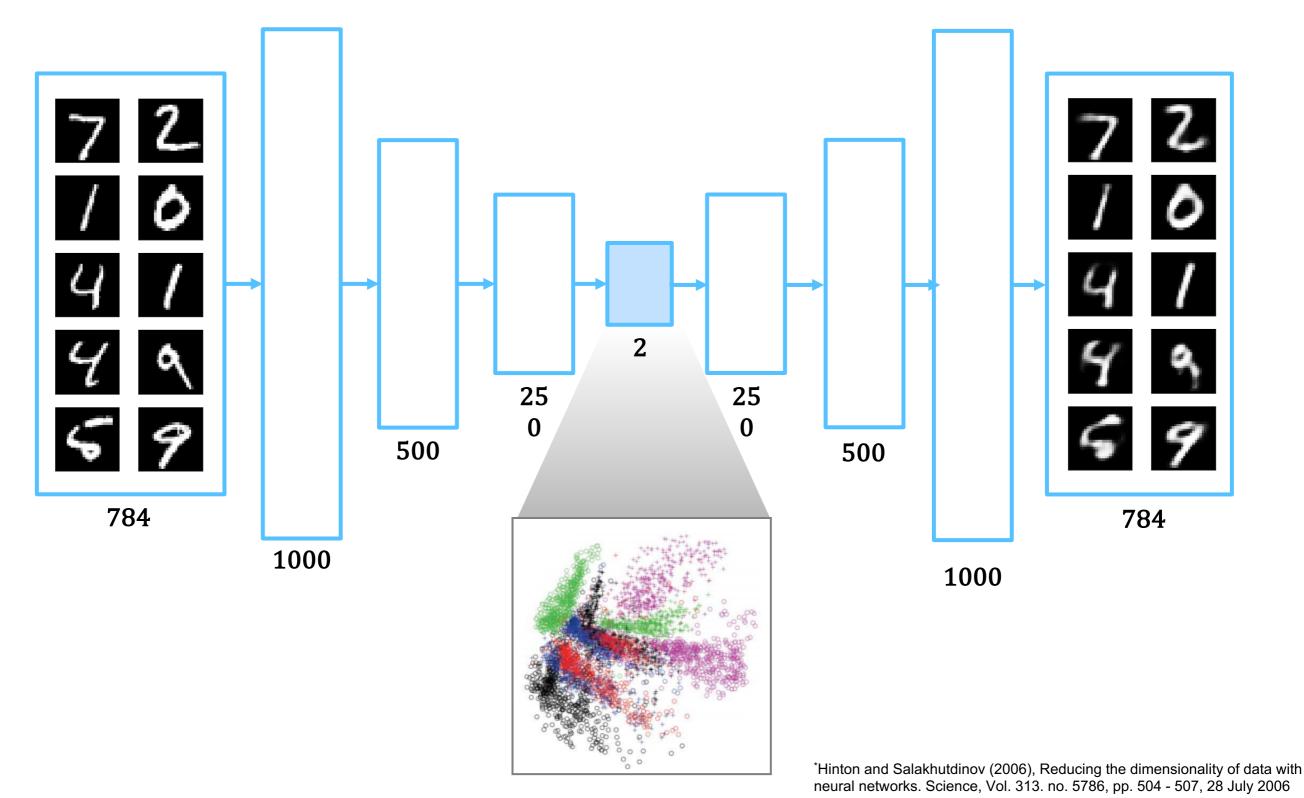


Hierarchy of representation Stacking – pretraining*

Example 2: deep AE



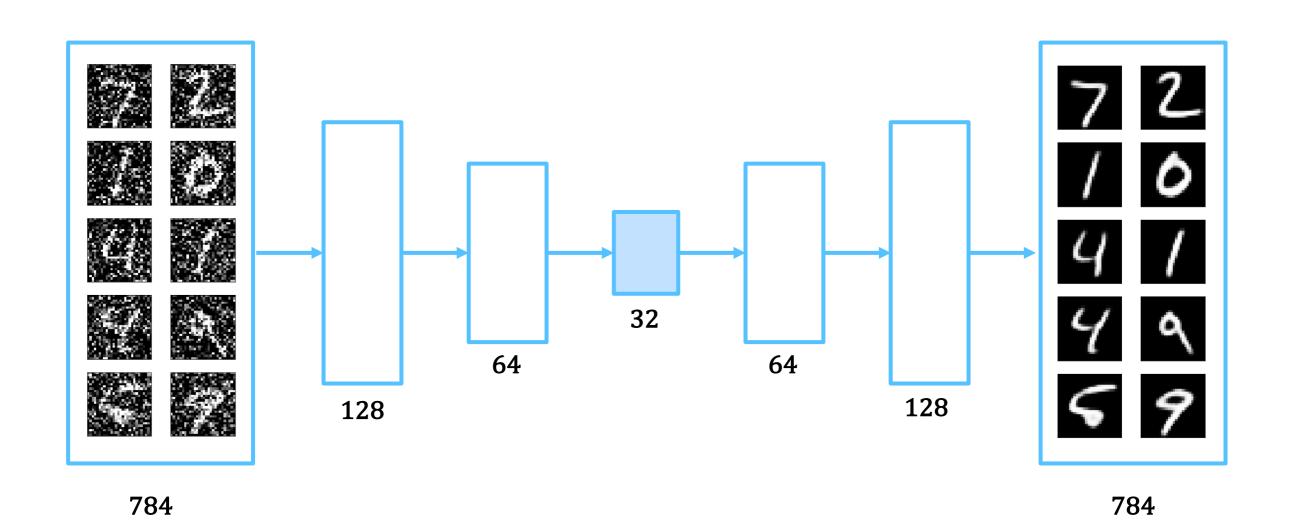
Example 3: deep AE + dimensionality reduction



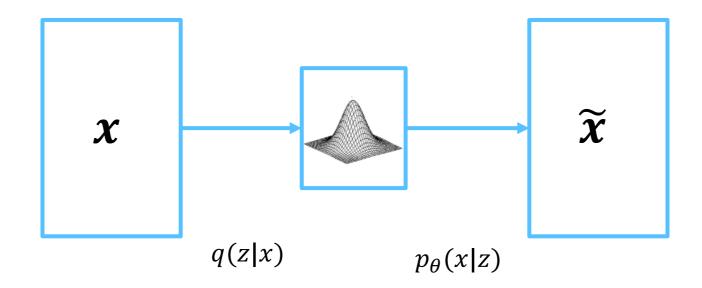
Different flavors

- Undercomplete: the "vanilla" flavor
- Convolutional: convolutions as hidden layers
- Sparse: impose sparsity constraint on hidden units
- Denoising: corrupt input with noise to increase robustness
- Variational: generative models, probabilistic spin

Example 4: denoising AE



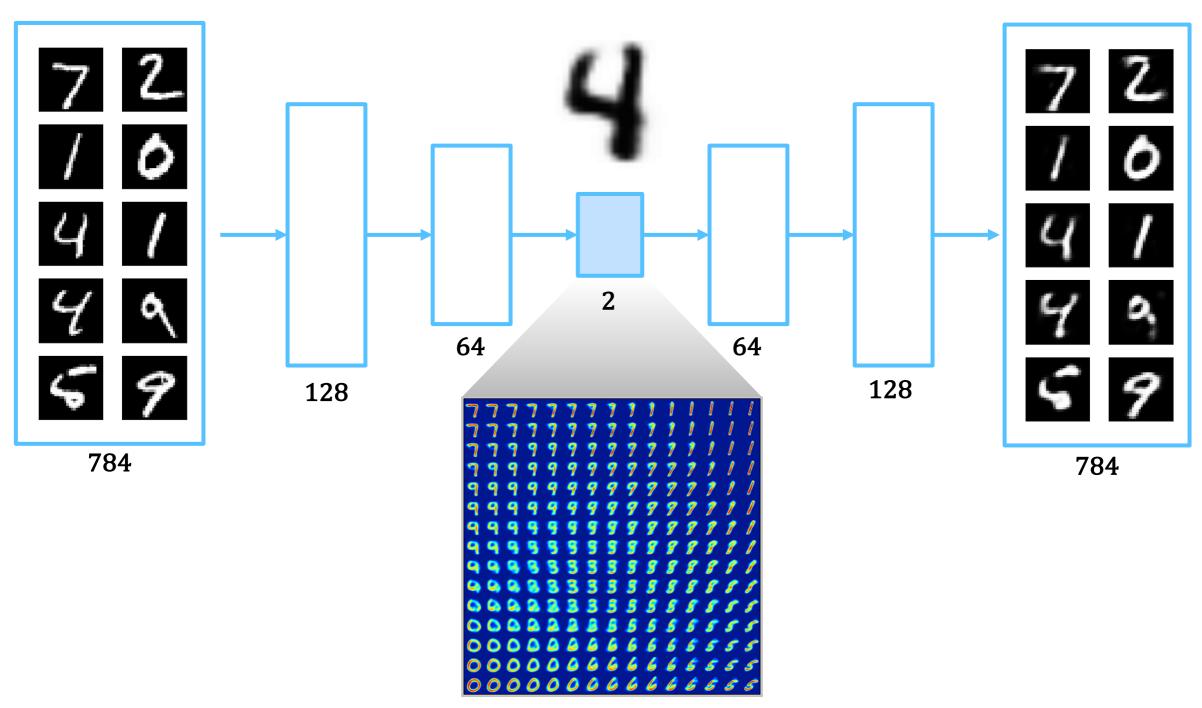
Variational Autoencoders



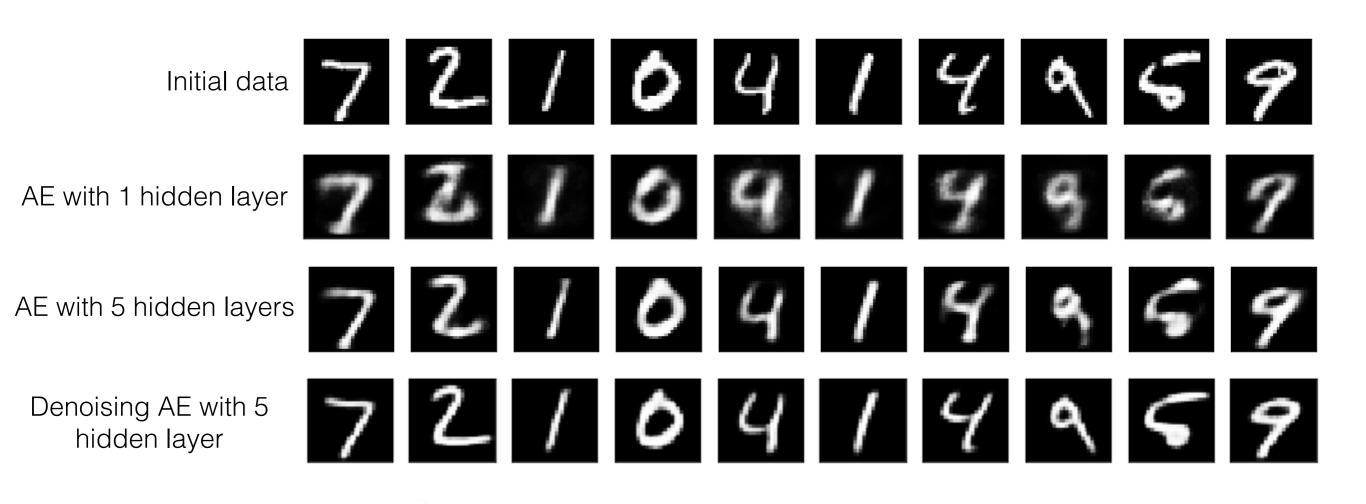
Encoder: maps input to posterior distributions over latent space

Decoder: maps coordinates back to distributions over the original space

Example 5: variational AE



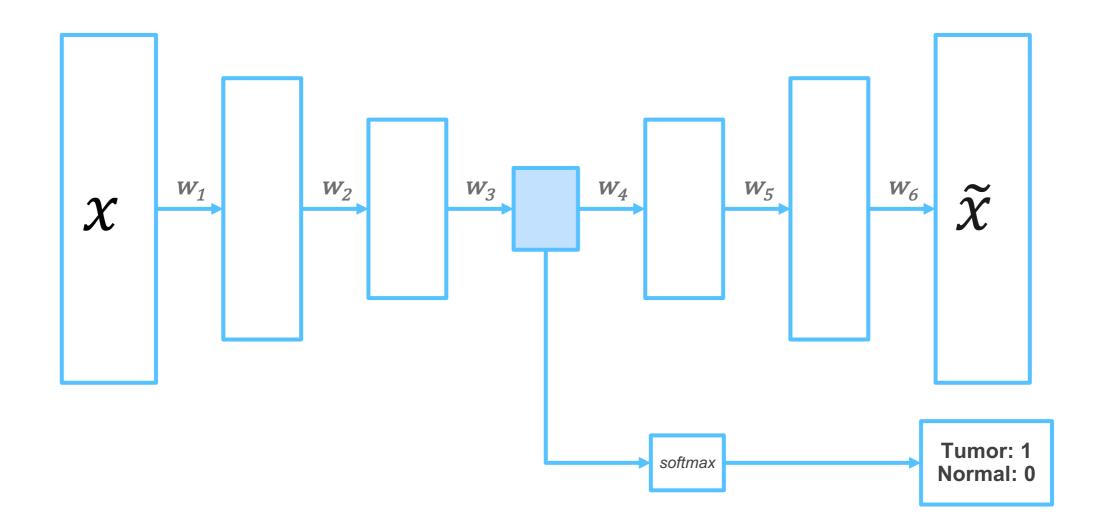
Comparison



Variational

Extensions

Modified network architectures allow for hybrid unsupervised and supervised learning



Autoencoders for automatic gating

DeepCyTOF: Automated Cell Classification of Mass Cytometry Data by Deep Learning and Domain Adaptation

Huamin Li 1, Uri Shaham 2, Yi Yao 3, Ruth Montgomery 3, and Yuval Kluger 1,4,5

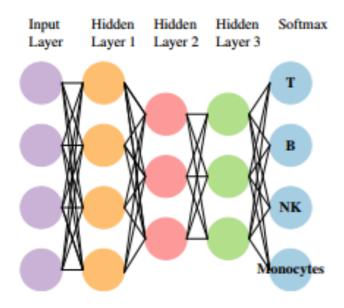


Figure 1: Stacked autoencoder for gating cell populations

Table 2: Summary of results for the cell identification challenge. The numbers in parentheses represent 95% confidence intervals

$F = \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$	Stacked autoencoder	Competition's winner
GvHD ^a	0.98 (0.97,0.99)	0.92 (0.88,0.95)
DLBCL	0.97 (0.95, 0.99)	0.95 (0.93, 0.97)
HSCT	0.98 (0.96, 0.99)	0.98 (0.96, 0.99)
WNV	0.98 (0.97, 0.99)	0.96 (0.94, 0.97)
ND	0.98 (0.96, 0.99)	0.94 (0.92, 0.95)

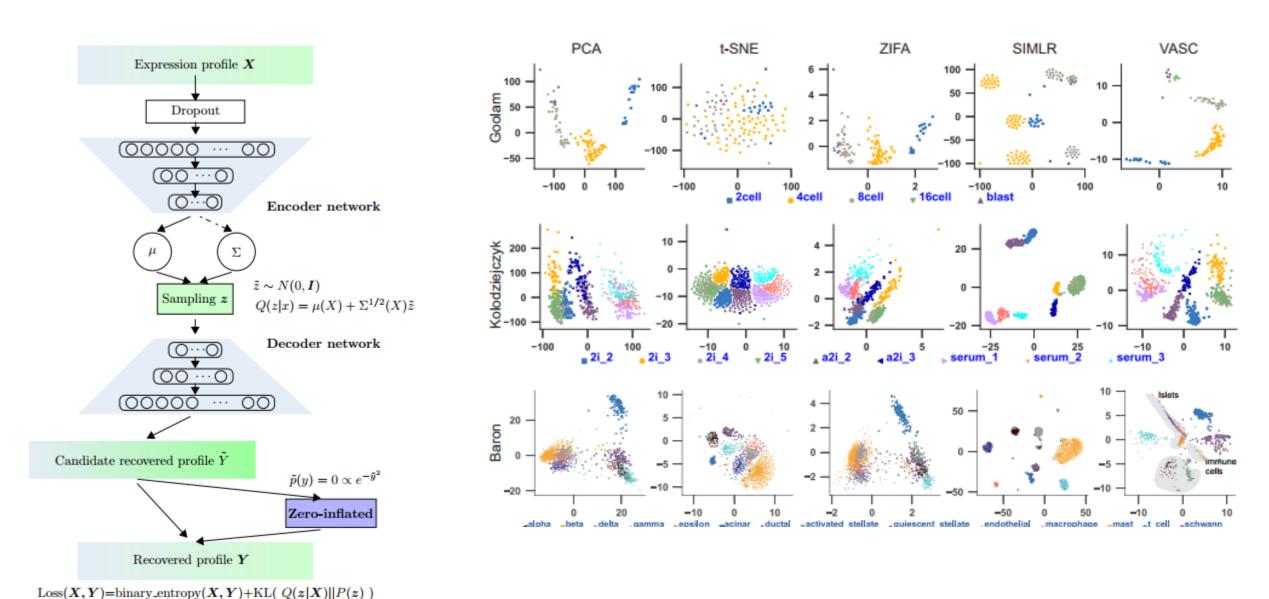
^a Datasets: graft-versus-hist disease (GvHD); diffuse large B-cell lymphoma (DLBCL); symptomatic West Nile virus (WNV); normal donors (ND); hematopoietic stem cell transplant (HSCT).

Autoencoders for unsupervised learning

VASC: dimension reduction and visualization of single cell RNA

sequencing data by deep variational autoencoder

Dongfang Wang1, Jin Gu1,#



Hands-on exercise

- Characterizing cell populations from single-cell mas cytometry data
- Open your jupyter notebook ae.ipynb

Learning resources

Papers and blogs:

- Review: http://msb.embopress.org/content/12/7/878
- Awesome list: https://github.com/terryum/awesome-deep-learning-papers
- Variational Bayes: https://arxiv.org/pdf/1312.6114.pdf
- Sparse autoencoders: https://web.stanford.edu/class/cs294a/sparseAutoencoder.pdf
- Colah's blog: http://colah.github.io

Tutorials:

https://blog.keras.io/building-autoencoders-in-keras.html

Courses:

- http://cs231n.github.io/neural-networks-1/
- https://stats385.github.io/readings
- http://slazebni.cs.illinois.edu/spring17/#resources
- https://www.udacity.com/course/deep-learning-nanodegree-foundation--nd101