Deriving Disease Modules from the Compressed Transcriptional Space Embedded in a Deep Autoencoder

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Abstract

Disease modules in molecular interaction maps have been useful for characterizing diseases. Yet biological networks, that commonly define such modules are incomplete and biased toward some well-studied disease genes. Here we ask whether disease-relevant modules of genes can be discovered without prior knowledge of a biological network, instead training a deep autoencoder from large transcriptional data. We hypothesize that modules could be discovered within the autoencoder representations. We find a statistically significant enrichment of genome-wide association studies (GWAS) relevant genes in the last layer, and to a successively lesser degree in the middle and first layers respectively. In contrast, we find an opposite gradient where a modular proteinprotein interaction signal is strongest in the first layer, but then vanishing smoothly deeper in the network. We conclude that a data-driven discovery approach is sufficient to discover groups of disease-related genes. Code: gitlab.com/Gustafsson-lab. Full Paper: www.nature.com/articles/s41467-020-14666-6

1. Paper Summary

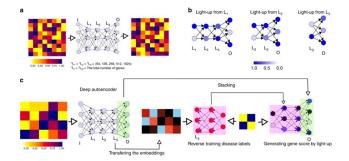


Figure 1. Schematic diagram of interpreting an autoencoder and defining the disease modules. a Training an autoencoder. b The steps of light-up method used for interpreting the hidden layer nodes in terms of PPI and pathways. c Depicts the steps of predicting the disease gene using transcriptomics signals and autoencoder.

References

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