

A photograph of three people in a modern office setting. On the left, a woman in blue scrubs is looking at a tablet. In the center, a woman in a white lab coat is looking at the tablet. On the right, a man in a blue blazer and glasses is looking at the tablet. They are standing in front of a large window with a view of a modern building and greenery. The image is overlaid with a semi-transparent white box containing text.

Neural Networks & Deep Learning

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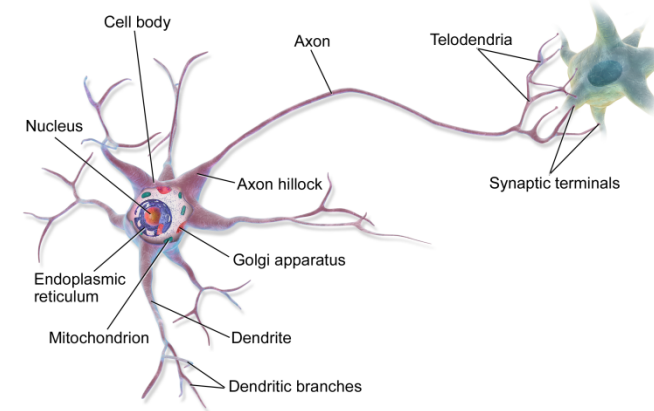
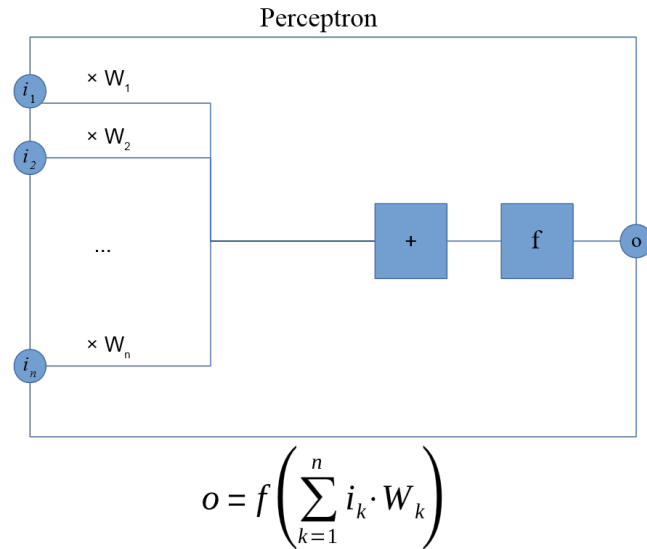
Disclosures

Financial disclosures:

- CureMetrix, Inc., co-founder with founder shares

Perceptron: An “artificial
neuron”

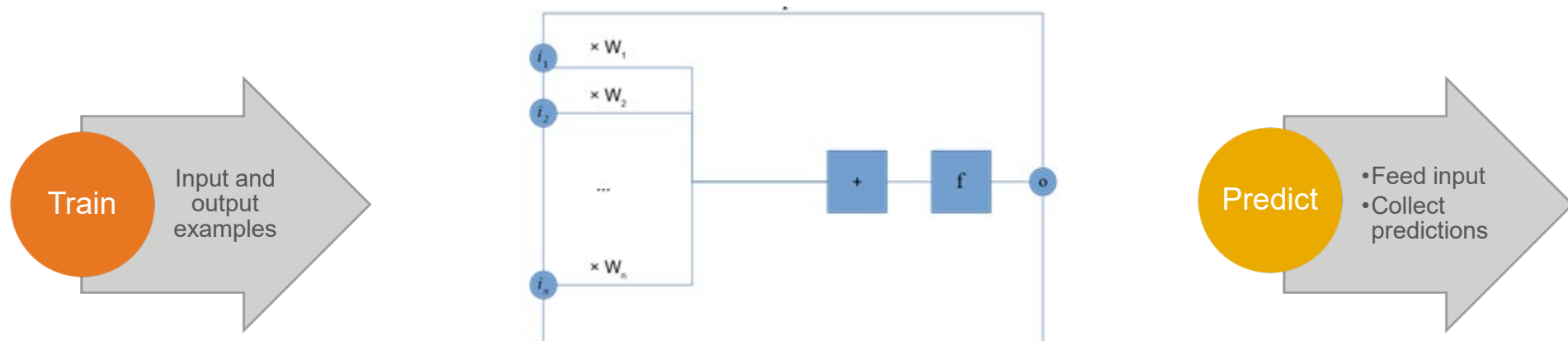
Perceptron & biological neuron



- Inspired by biological neural networks. Perceptron has several inputs.
- Multiple inputs are multiplied by weights assigned to that input.
- An offset (bias) is added to the weighted sum, which is passed to a function that provides the perceptron output.
- Dendrites receive signals, cell body processes them, and an axon sends signals to other neurons.
- Multiple inputs are multiplied by weights assigned to that input.
- If the output of a neuron surpasses a certain threshold, the neuron transmits this electrical signal along the axon.

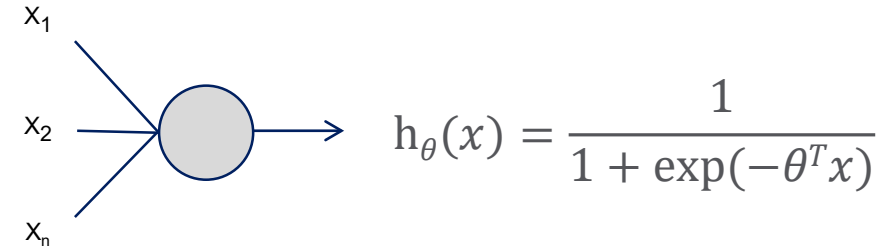
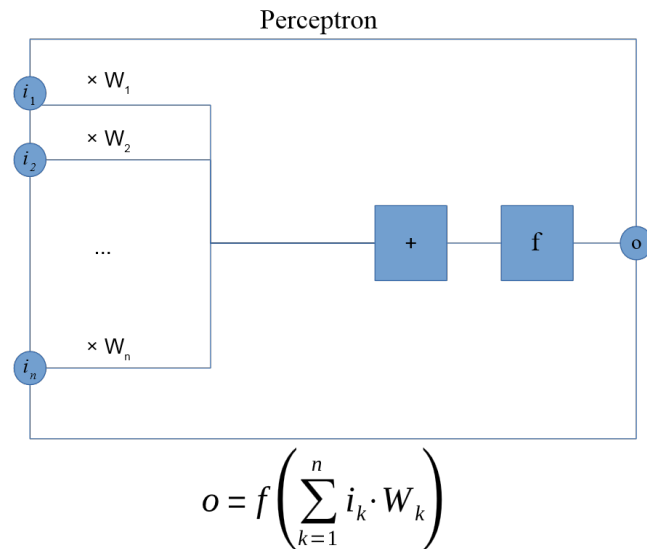
Perceptron is a linear classifier

- Perceptron is a **supervised learning** algorithm (trained on examples of data with known outcomes).
- Once trained, it is used to **classify** (or, predict) the outcome for new data.



- Perceptron is a **linear classifier** – it uses a linear prediction function (a sum of the product of weights and inputs).

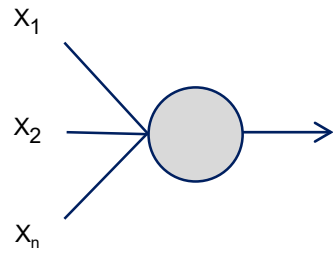
Perceptron & logistic regression



- Logistic regression is similar in structure, having one unit and multiple inputs, but logistic regression has probabilistic connotations.
- LR provides a measure of uncertainty in the occurrence of a binary outcome (0 or 1). The output is bounded asymptotically between 0 and 1.
- Both can be used as **building blocks** to create more complex classifiers.

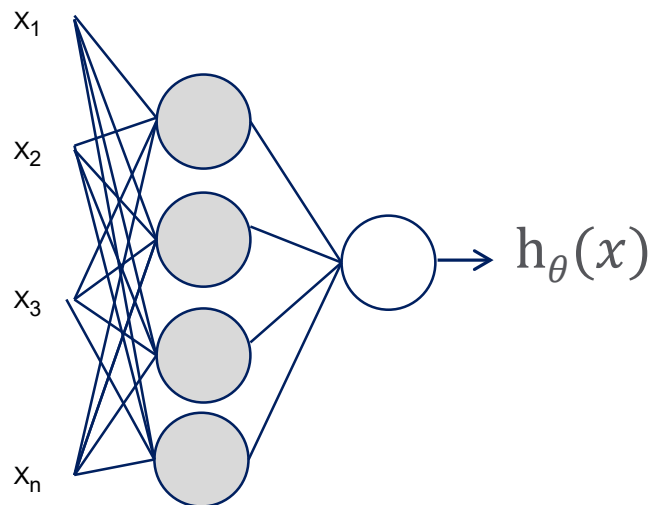
Logistic regression vs. artificial neural network (ANN)

LR:

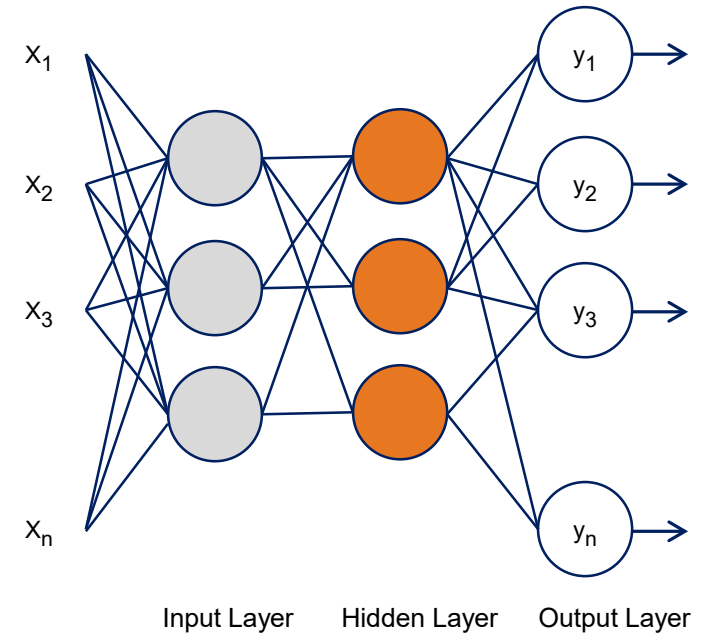


$$h_{\theta}(x) = \frac{1}{1 + \exp(-\theta^T x)}$$

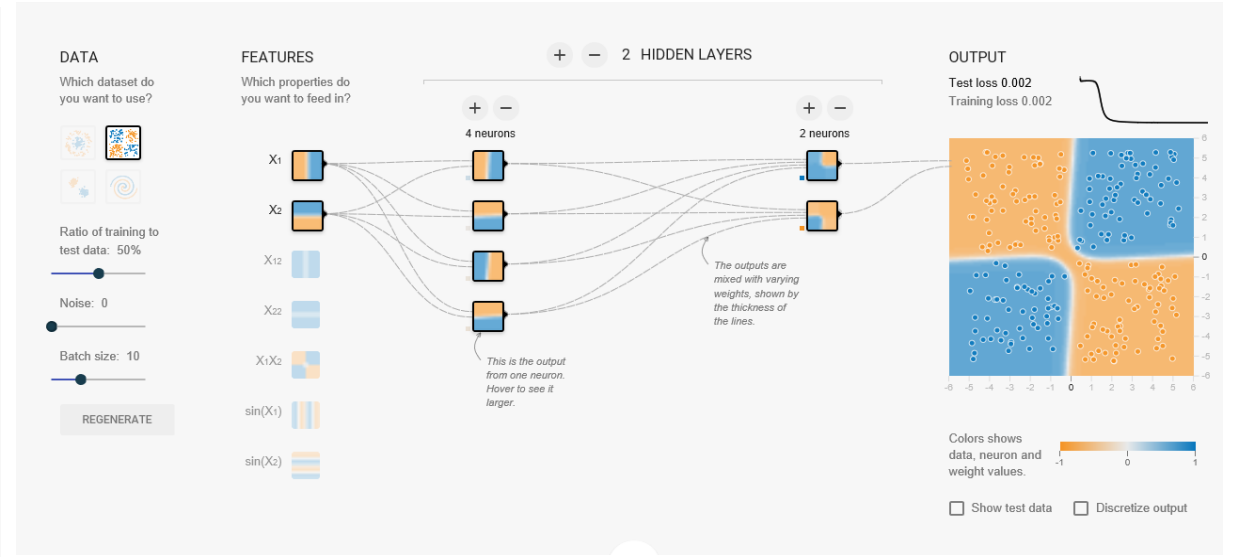
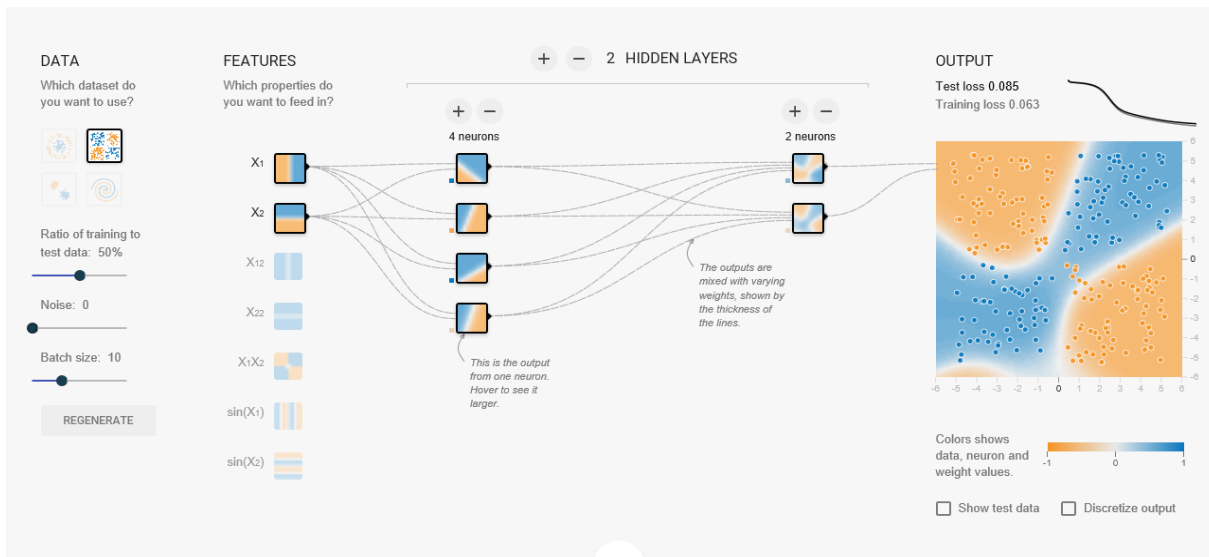
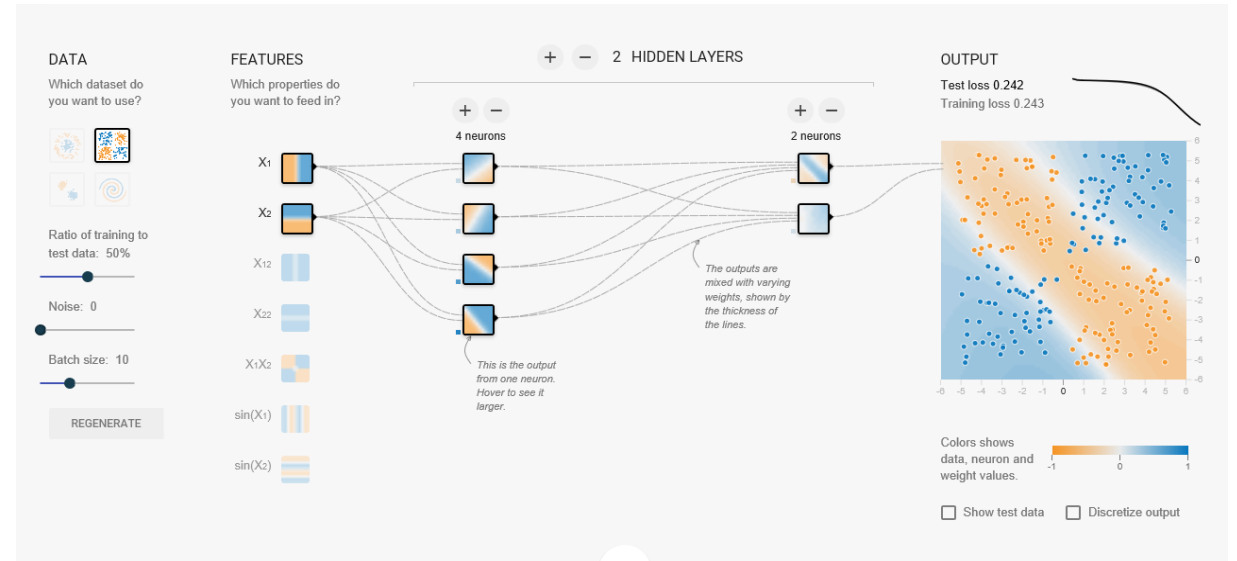
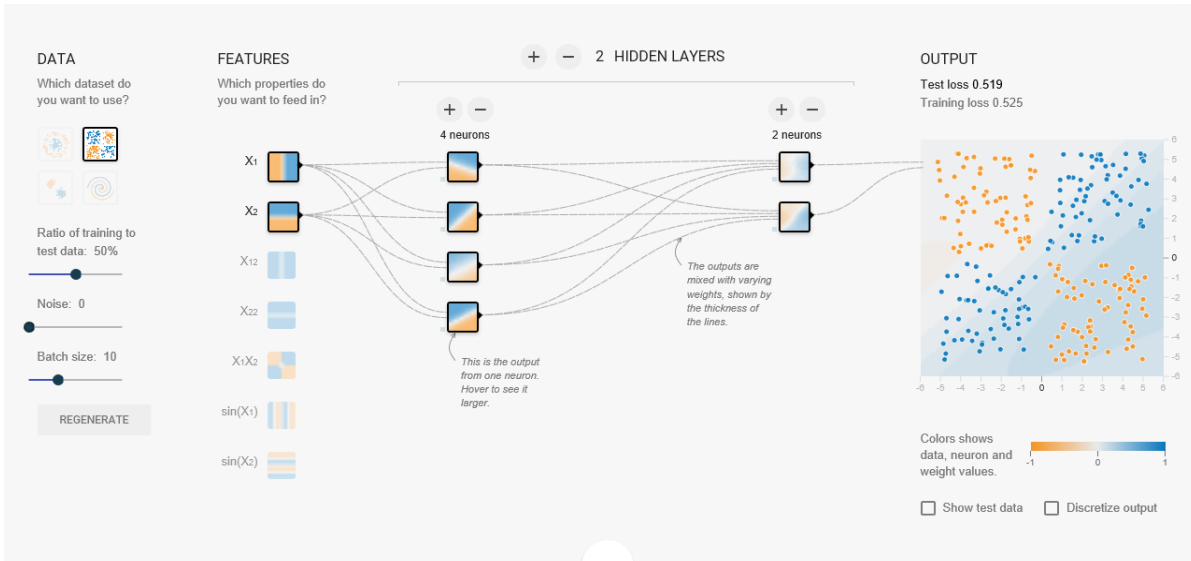
Several LR's strung together = ANN:



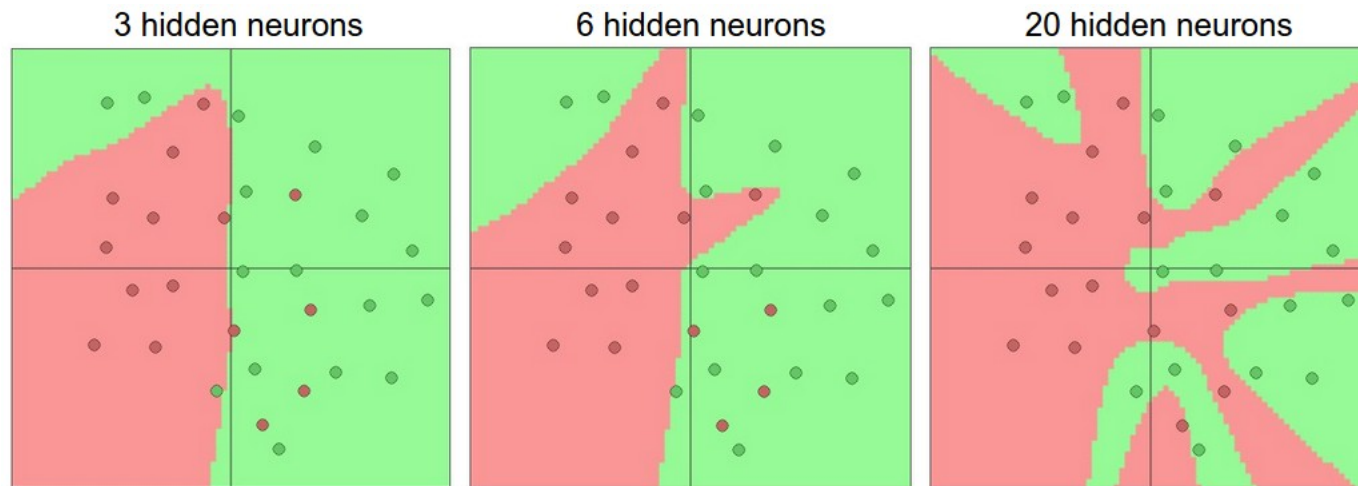
ANN with more layers/outputs:



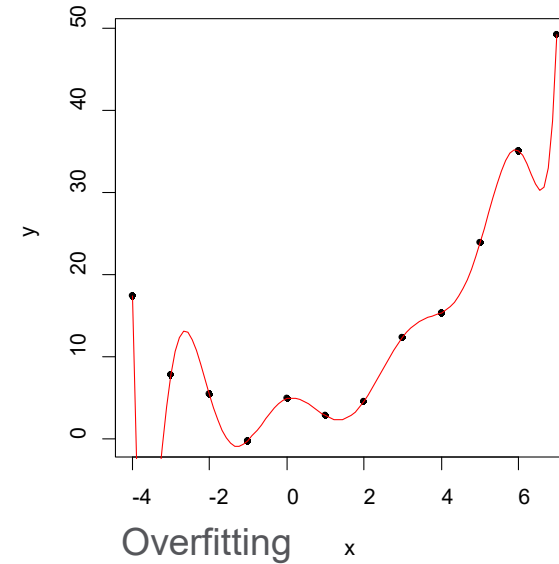
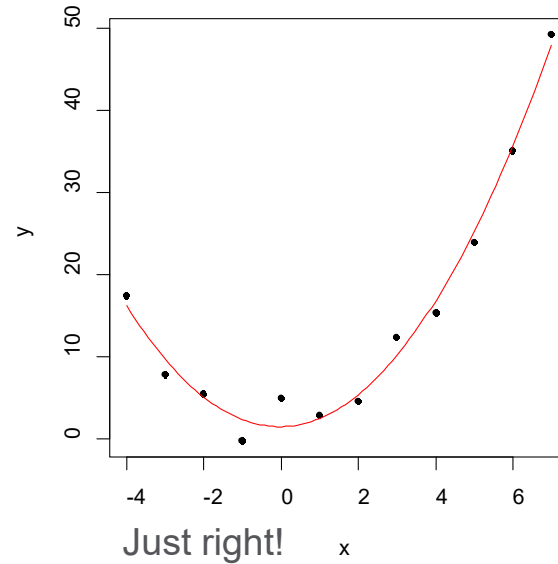
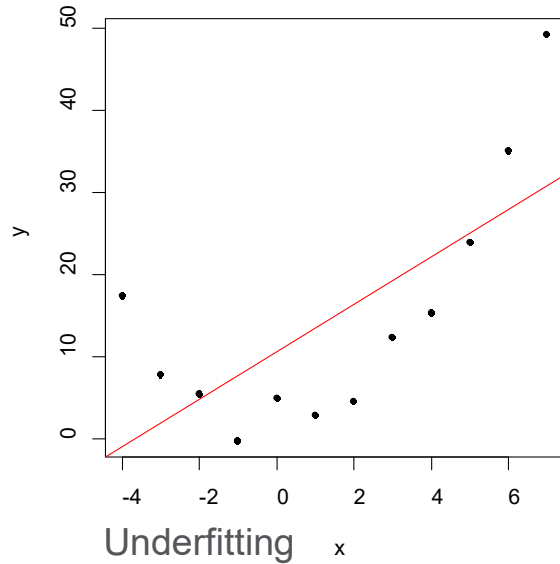
How do neural networks learn?



Nonlinearity to the rescue: Learning in complex domains



Tuning ANN: To learn every detail or not?

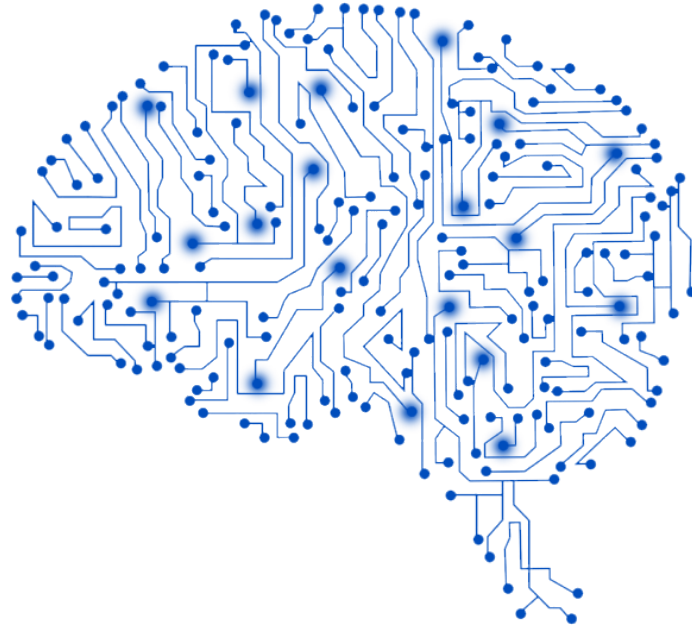


The goal: find the ANN with the best generalization properties and avoid underfitting or overfitting.

Deep learning

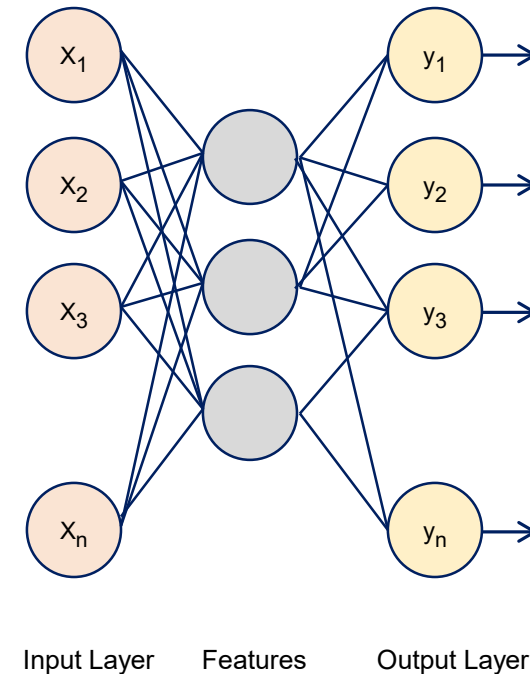
What are deep neural networks?

- Deep Neural Networks = neural networks with **several** hidden layers
- Deep Nets: **unsupervised** or **supervised**



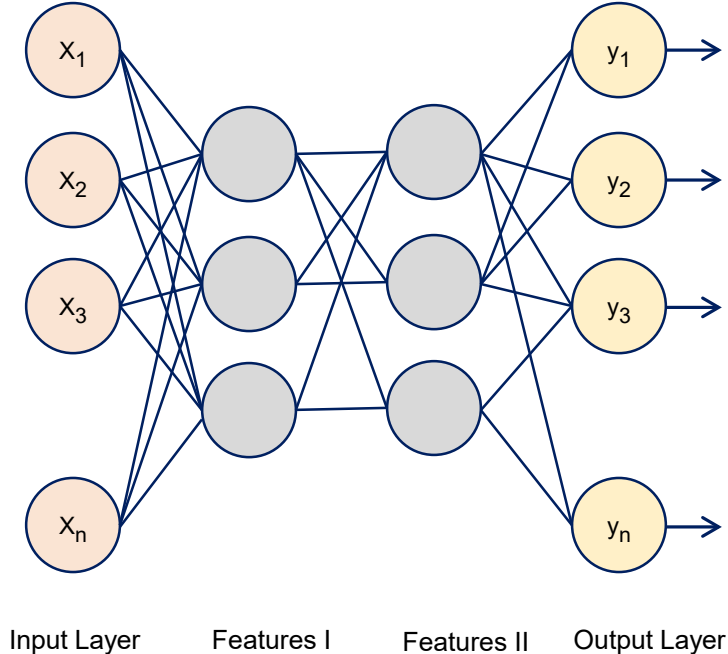
Autoencoder: An introduction

- A type of **unsupervised ANN** which tries to discover a compressed **representation** for a dataset
- Architecture:
 - an input layer
 - an output layer of the same size,
 - one or more hidden layers of different sizes connecting input to the output
- An autoencoder is trained to **reconstruct** its own inputs (hence the *auto*)

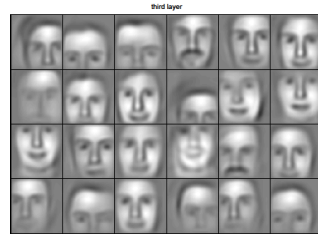


Stacked autoencoders

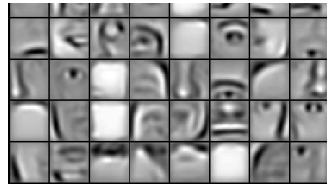
- Stack several autoencoders and train them using layer-wise training



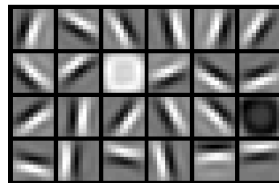
Feature hierarchies



images



combinations of edges



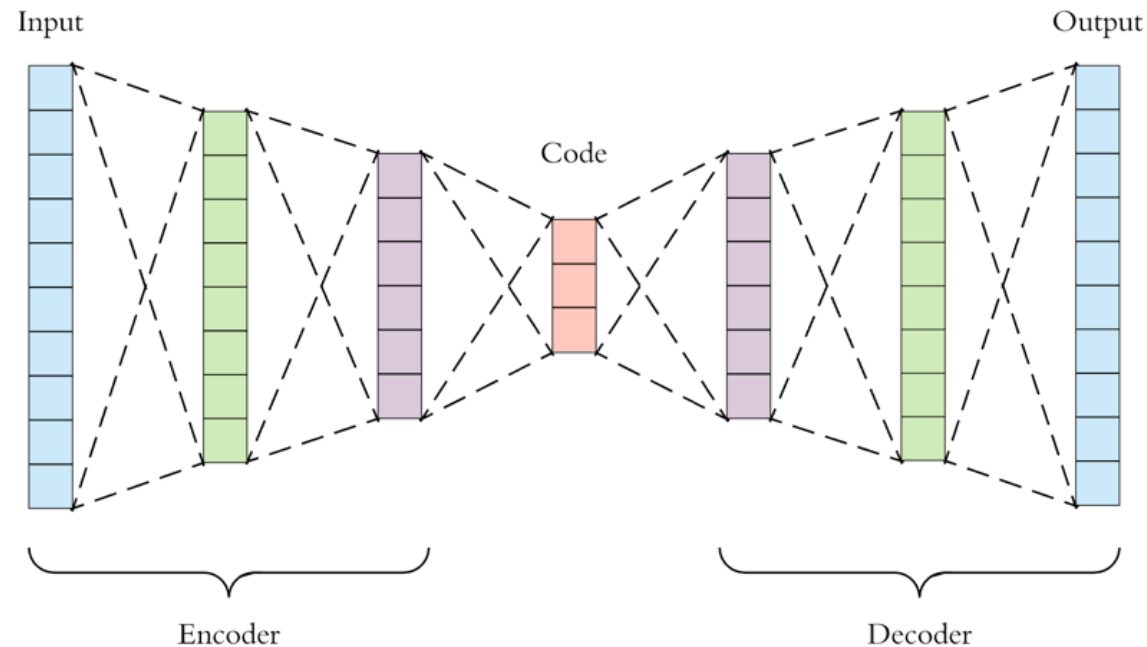
edges



pixels

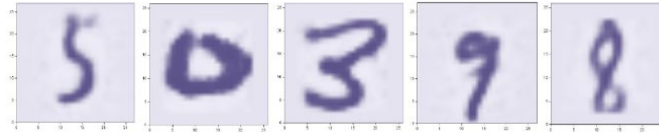
Deep learning based autoencoders

- Create a multi-layer neural network to encode the data into a smaller or simpler representation such that the original data can be reconstructed with high fidelity.

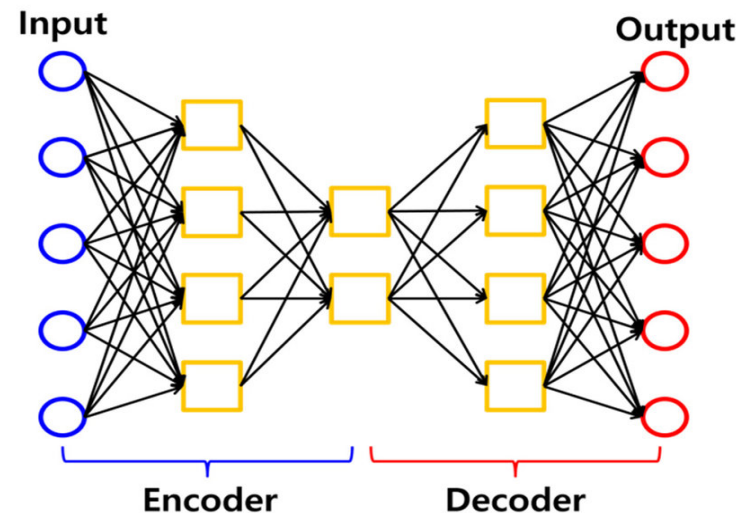


Autoencoder example

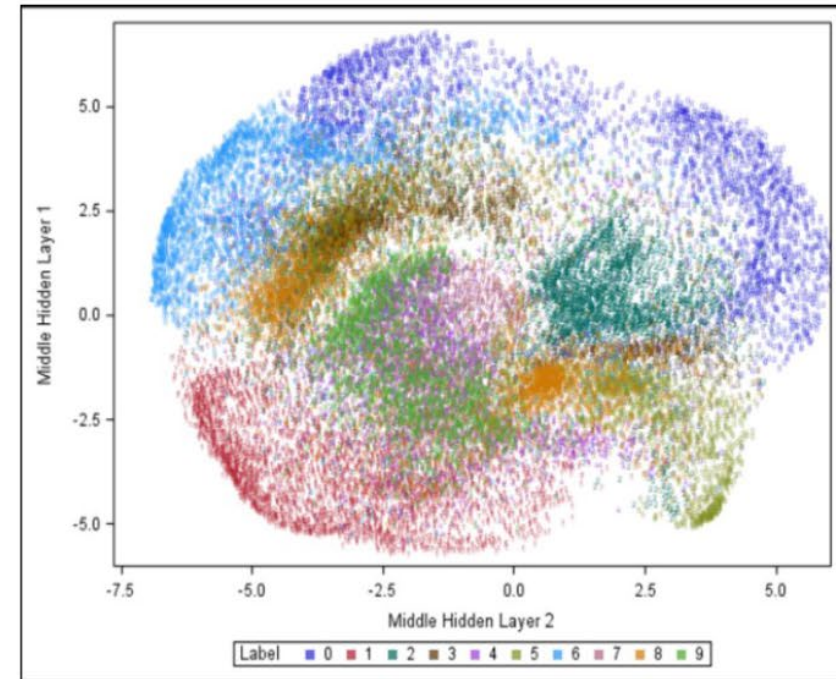
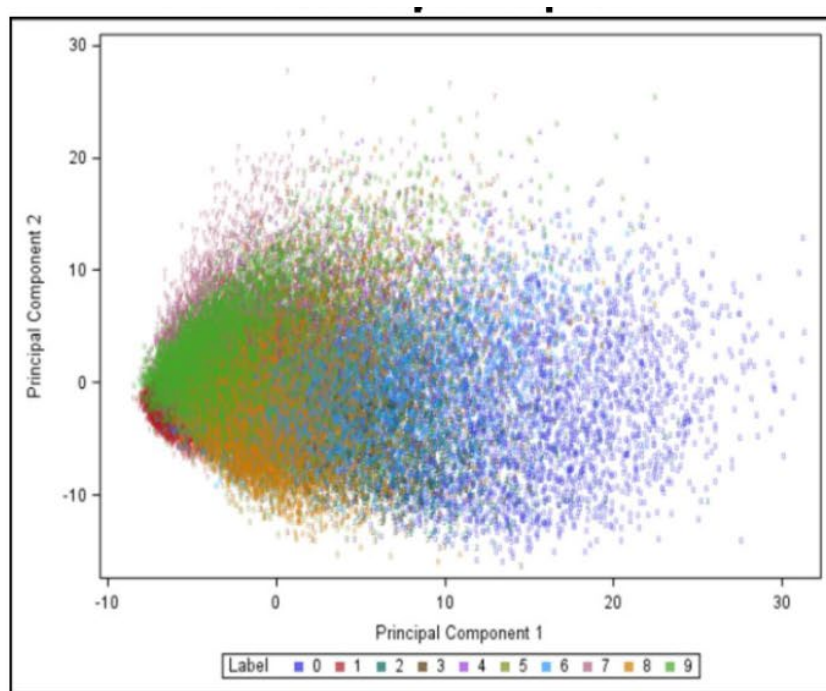
- Trained on MNIST data: a “classic” (widely used) ML research dataset that contains ~10000 images of handwritten digits, with labels from 0 through 9:



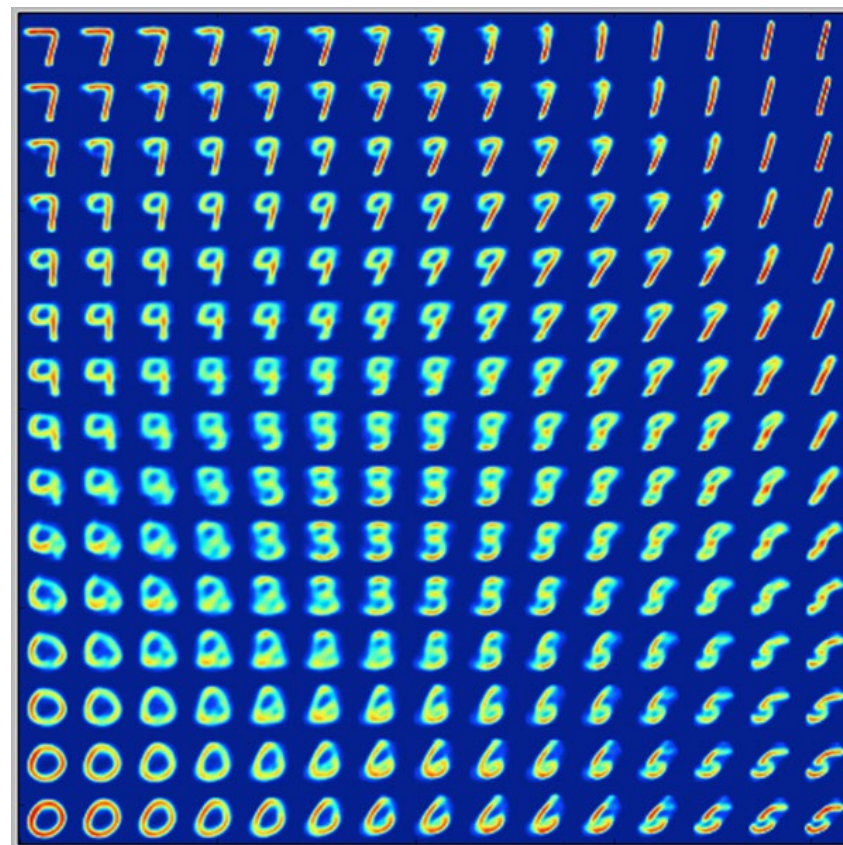
- Hour-glass architecture: 300x100x2x100x300 hidden units:



First two principal components vs. middle hidden layer



Computer-generated digits

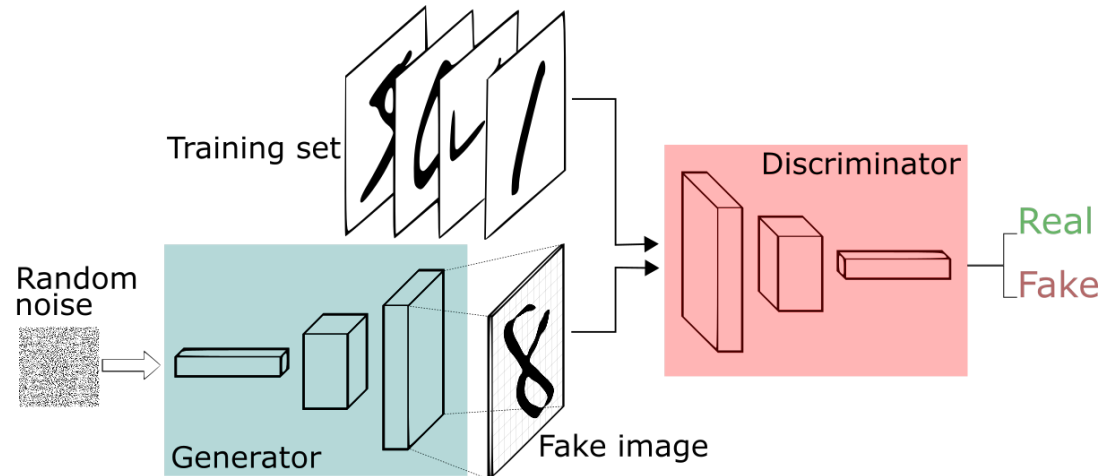


GANs

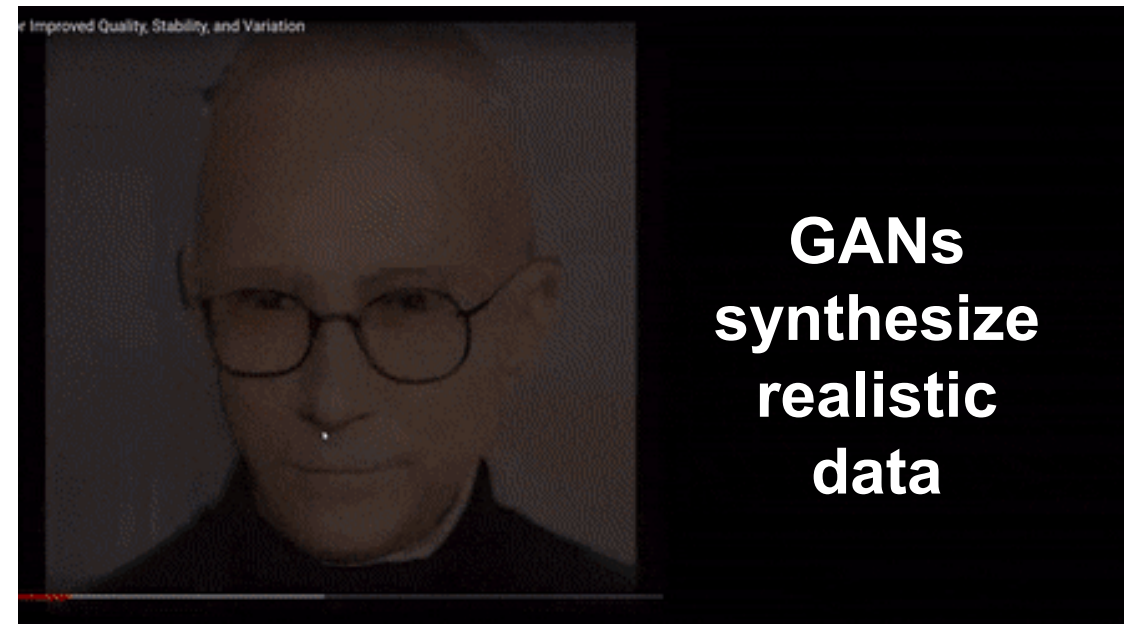
Generative Adversarial Networks

- One model generates examples
- Another model discriminates between those examples and a training set

Improved generation of realistic data



Example: artificial celebrity faces using GANs



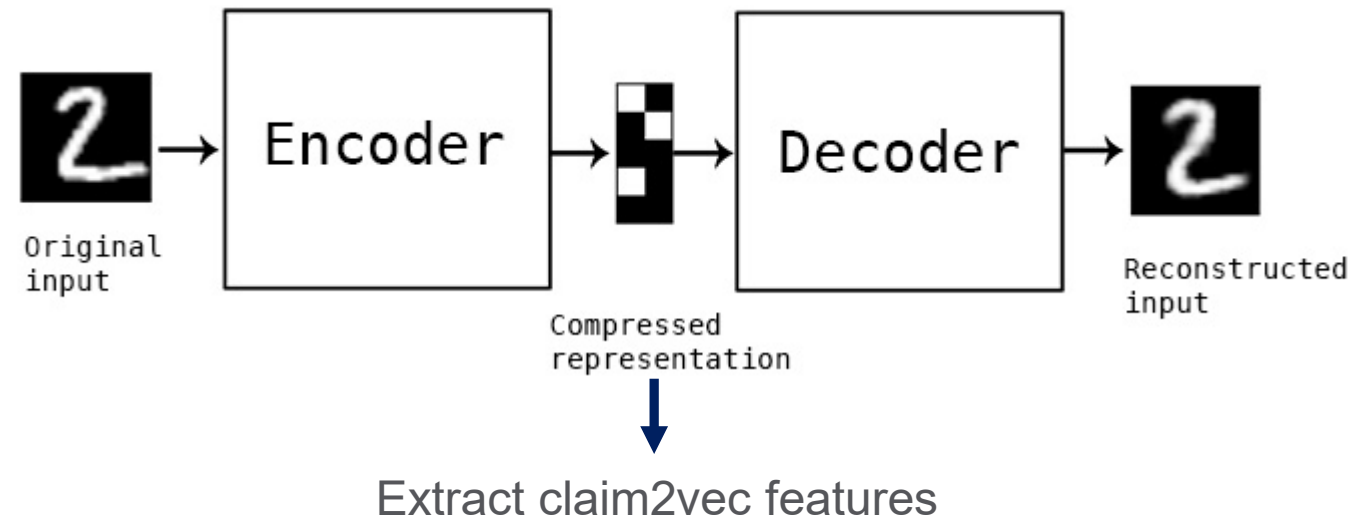
Deep learning in healthcare

Claim2vec: A new kind of feature

Medical codes are the essence of claims, but sparsity makes them difficult to use

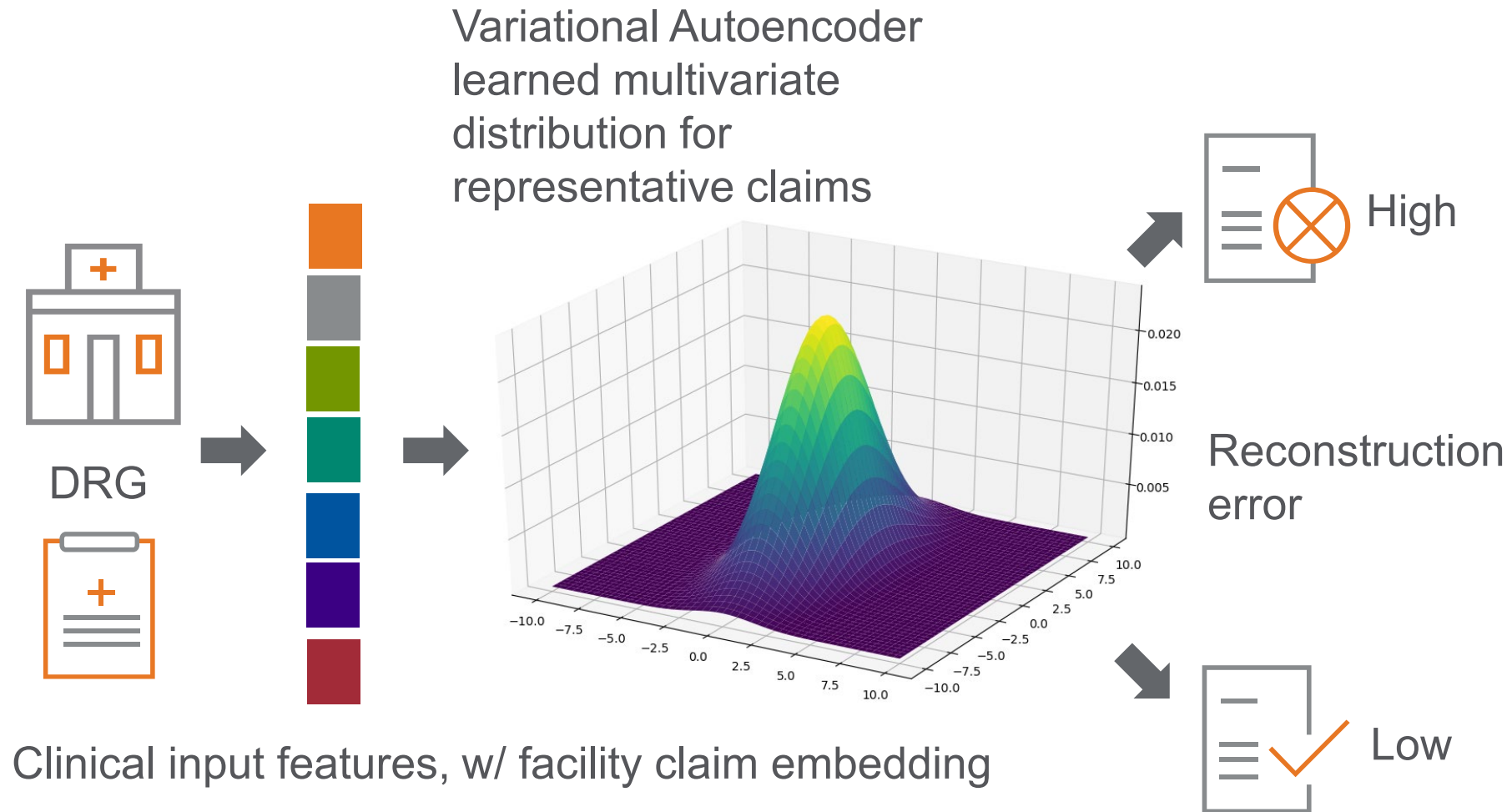
- There are tens of thousands of codes that appear within claims
- Each claim line uses only a few codes

We train encoder and decoder neural networks to reconstruct codes used in claims



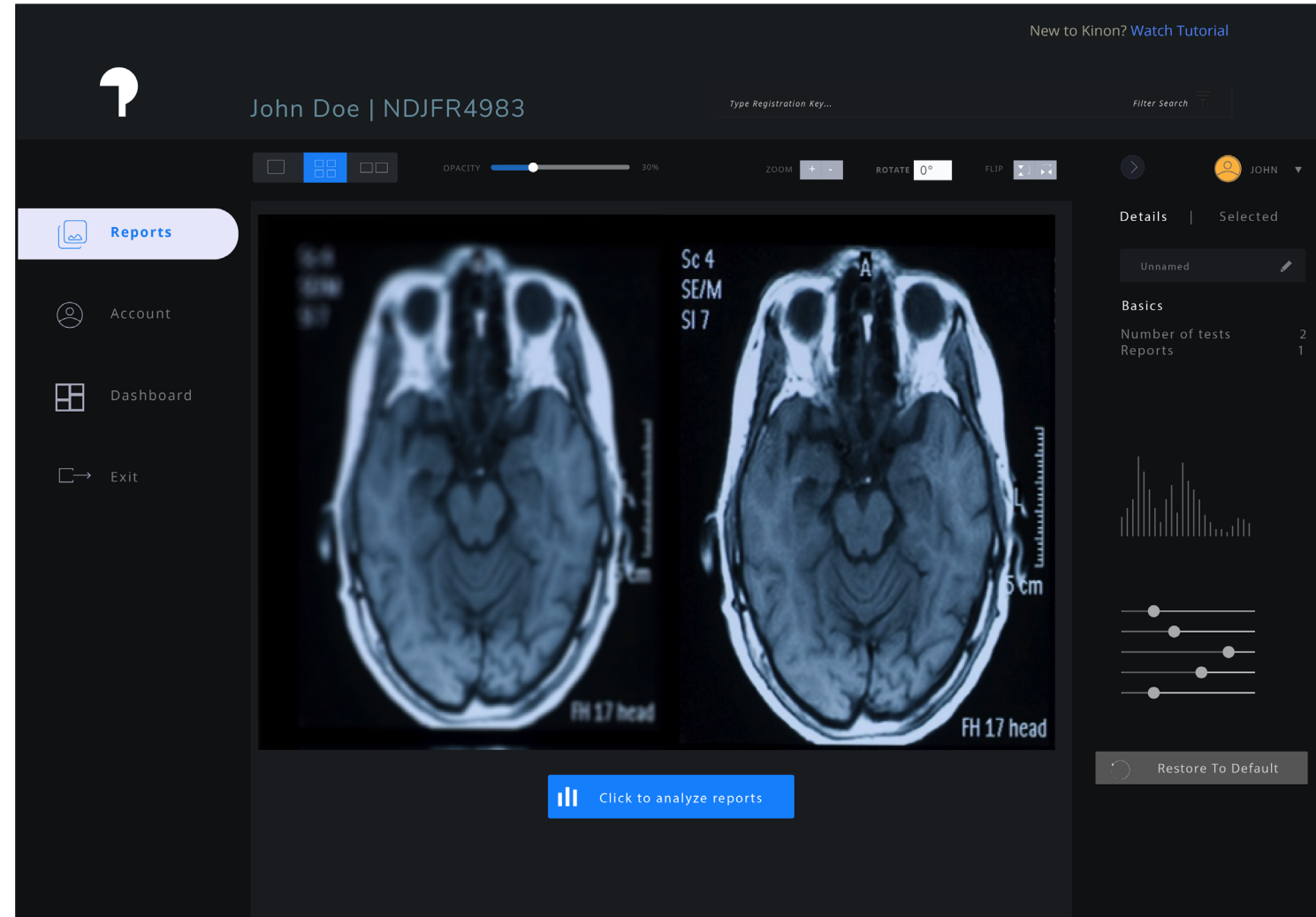
The compressed representation provides 100 dense claim2vec features for use in anomaly detection, and have increased our detection precision by 14%

fPSM: Facility predictive scoring model



GANs and medical imaging

- GANs that provide superior resolution to medical imaging.
- GANs are trained on several previously acquired high-resolution radiography images.
- The information from high-quality radiography imaging equipment can be leveraged even in areas with a relatively poor quality of the equipment.



Summary

Why is deep learning so successful?

- Lots of data (examples)
 - 300 million+ photos are uploaded on Facebook EVERY DAY
 - 2.5 quintillion (18 zeros!) bytes of data generated every day
- Computing power
 - GPUs, TPUs, custom processors for specialty Deep Nets
 - able to build big and flexible models to translate and store examples
- Very flexible models
 - can handle numeric, nominal, categorical, image, video and sound data
 - able to build large and flexible models

From deep learning to deeply effective healthcare

