

Implementing Dimensionality Reduction Using Restricted Boltzmann Machines in scikit-learn



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Overview

Introducing Restricted Boltzmann Machines (RBMs)

Using RBMs for dimensionality reduction

RBMs as pre-processing step during classification

Neural Networks in scikit-learn

Supervised

Unsupervised

Neural Networks in scikit-learn

**Multi-layer Perceptrons
(MLP)**

**Restricted Boltzmann
Machines (RBM)**

Neural Networks in scikit-learn

Multi-layer Perceptrons
(MLP)

Restricted Boltzmann
Machines (RBM)

Perform dimensionality
reduction in an **unsupervised**
manner by trying to
reconstruct the input

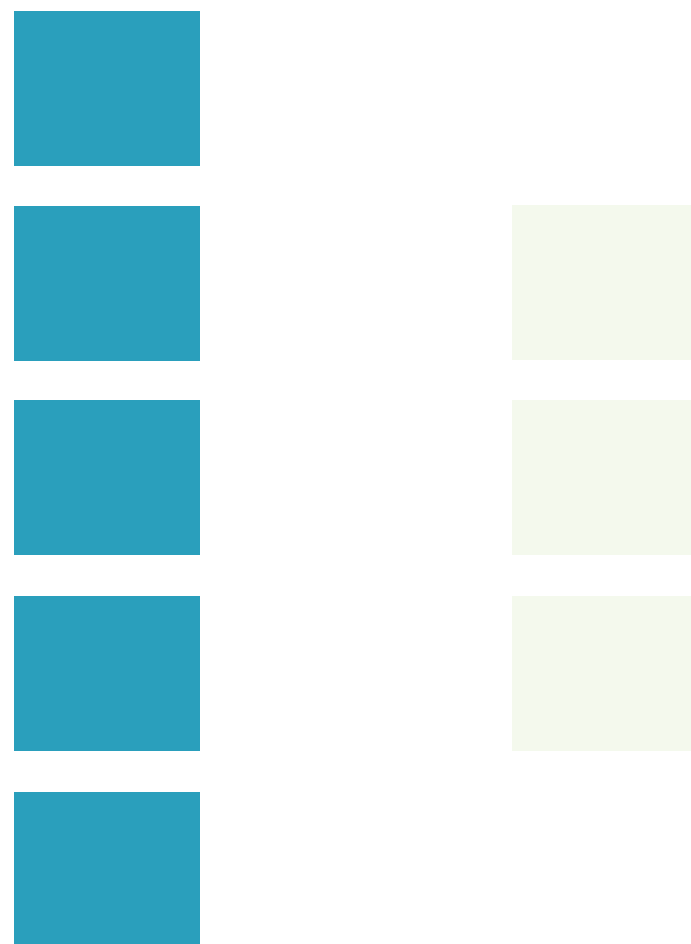
Restricted Boltzmann Machines (RBMs) for Dimensionality Reduction

Restricted Boltzmann Machines



Two layers of a neural network

Restricted Boltzmann Machines



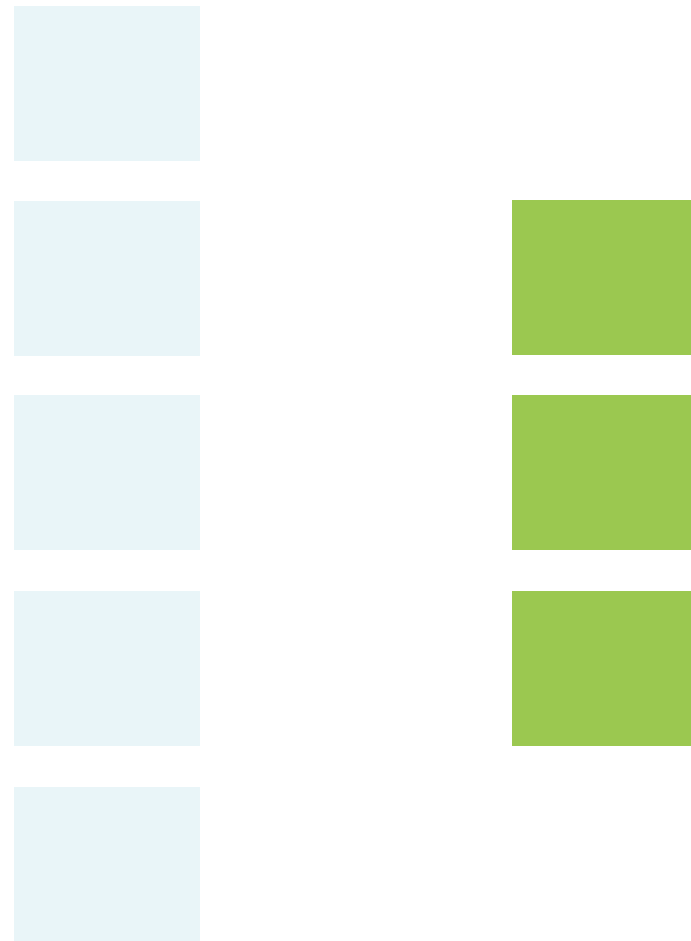
Visible layer

Restricted Boltzmann Machines



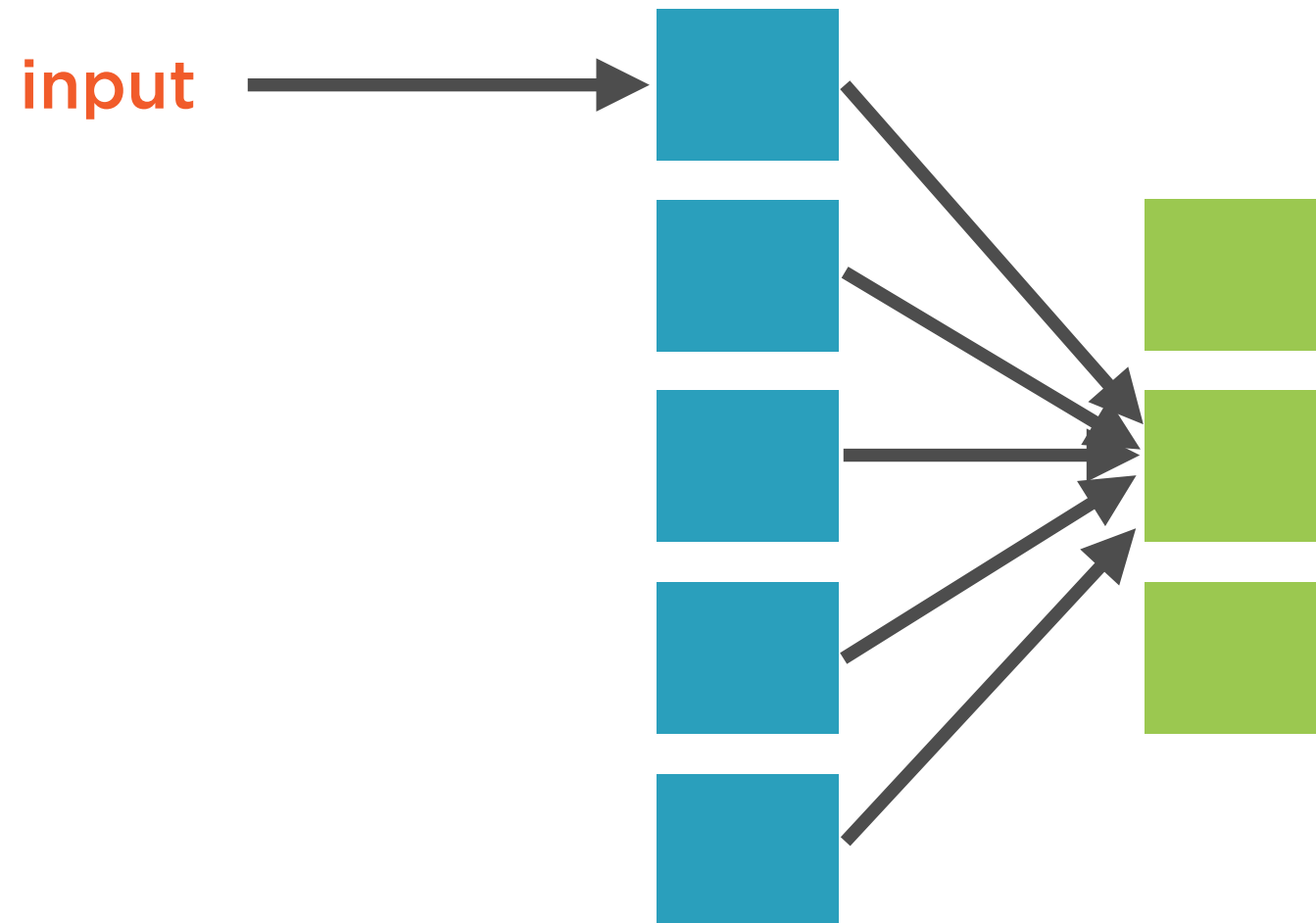
Hidden layer

Restricted Boltzmann Machines



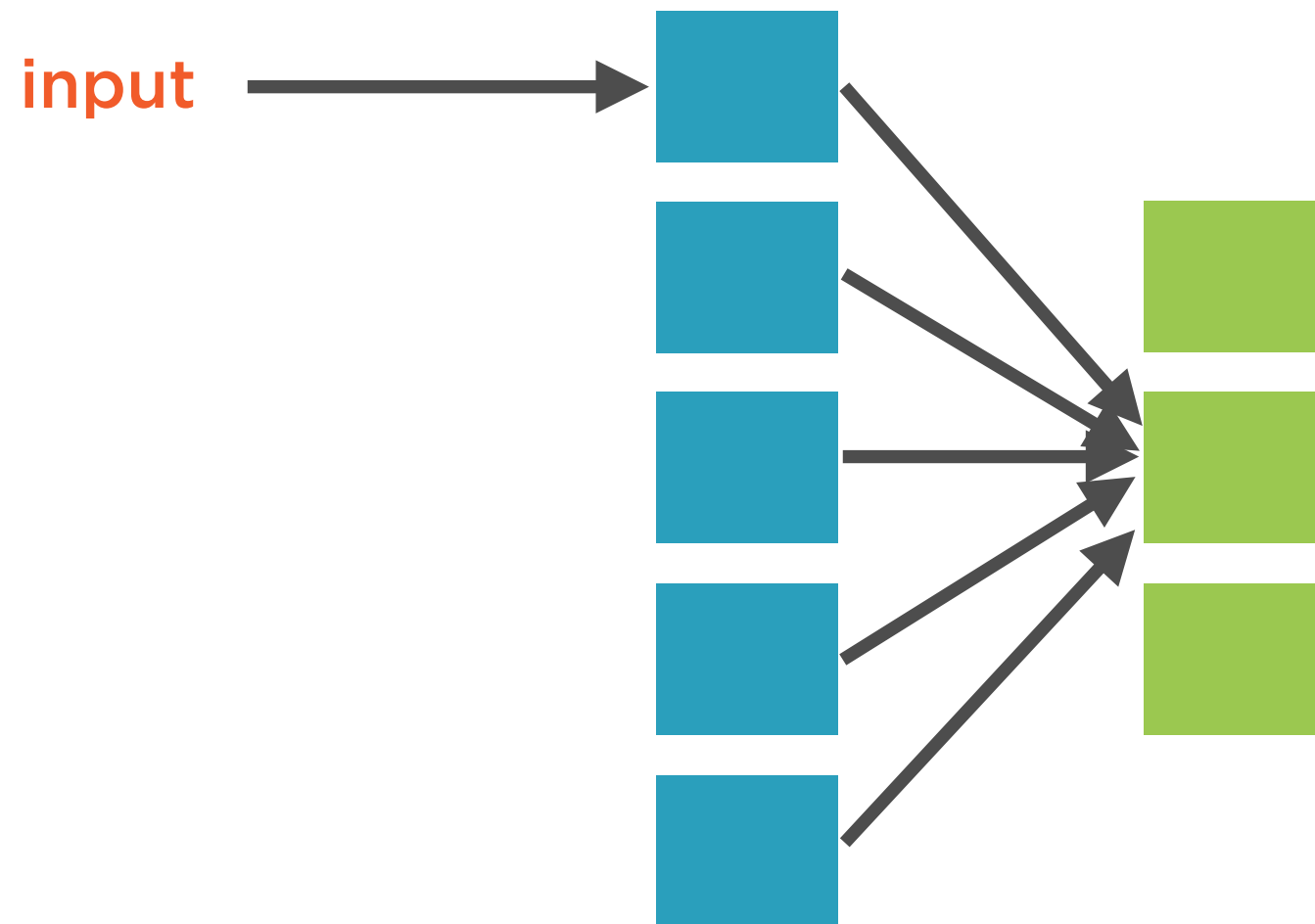
Smaller than the visible layer into which inputs are fed, produces **lower dimensionality** outputs

Restricted Boltzmann Machines



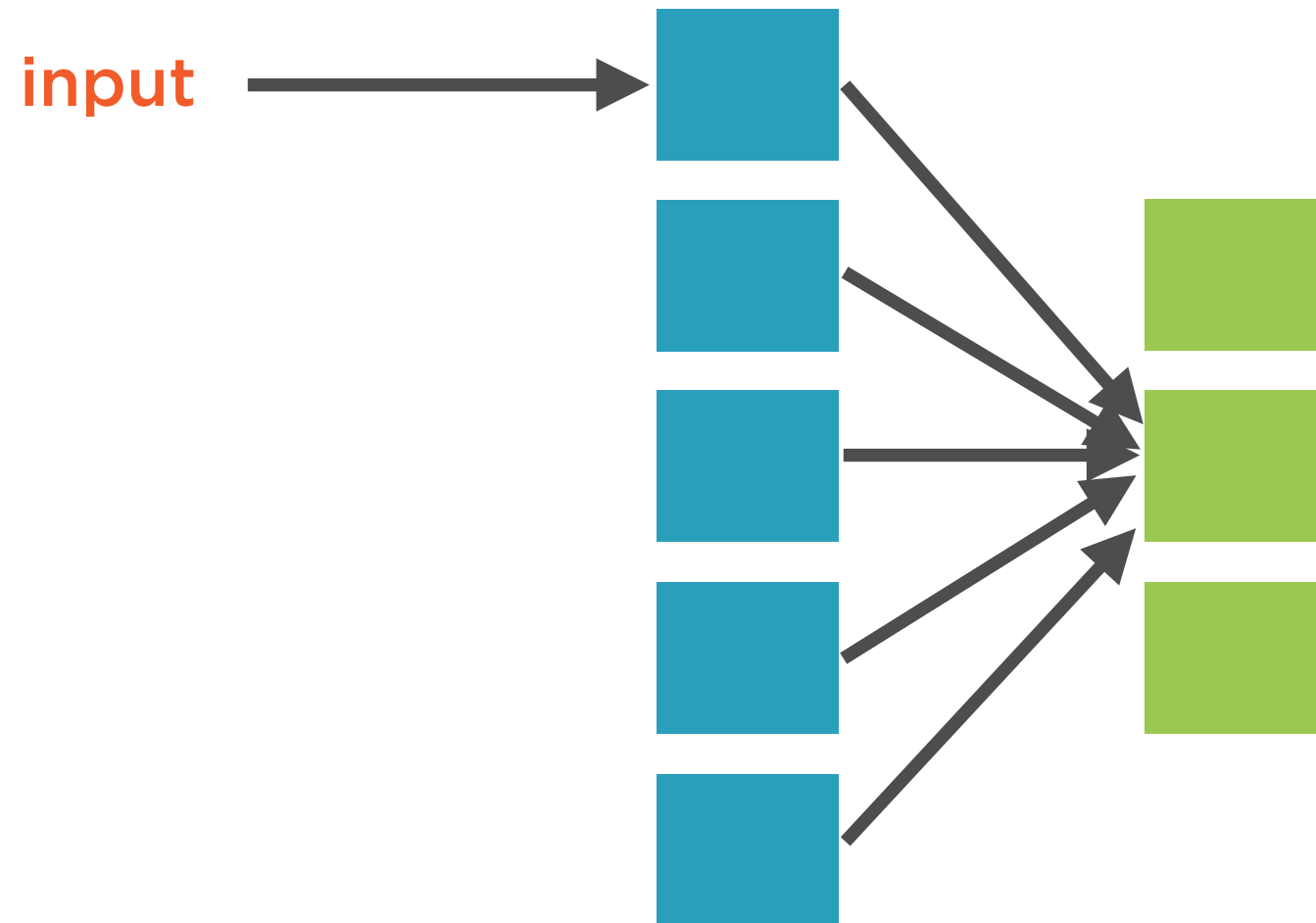
**Every neuron is connected only to
neurons in other layers**

Restricted Boltzmann Machines



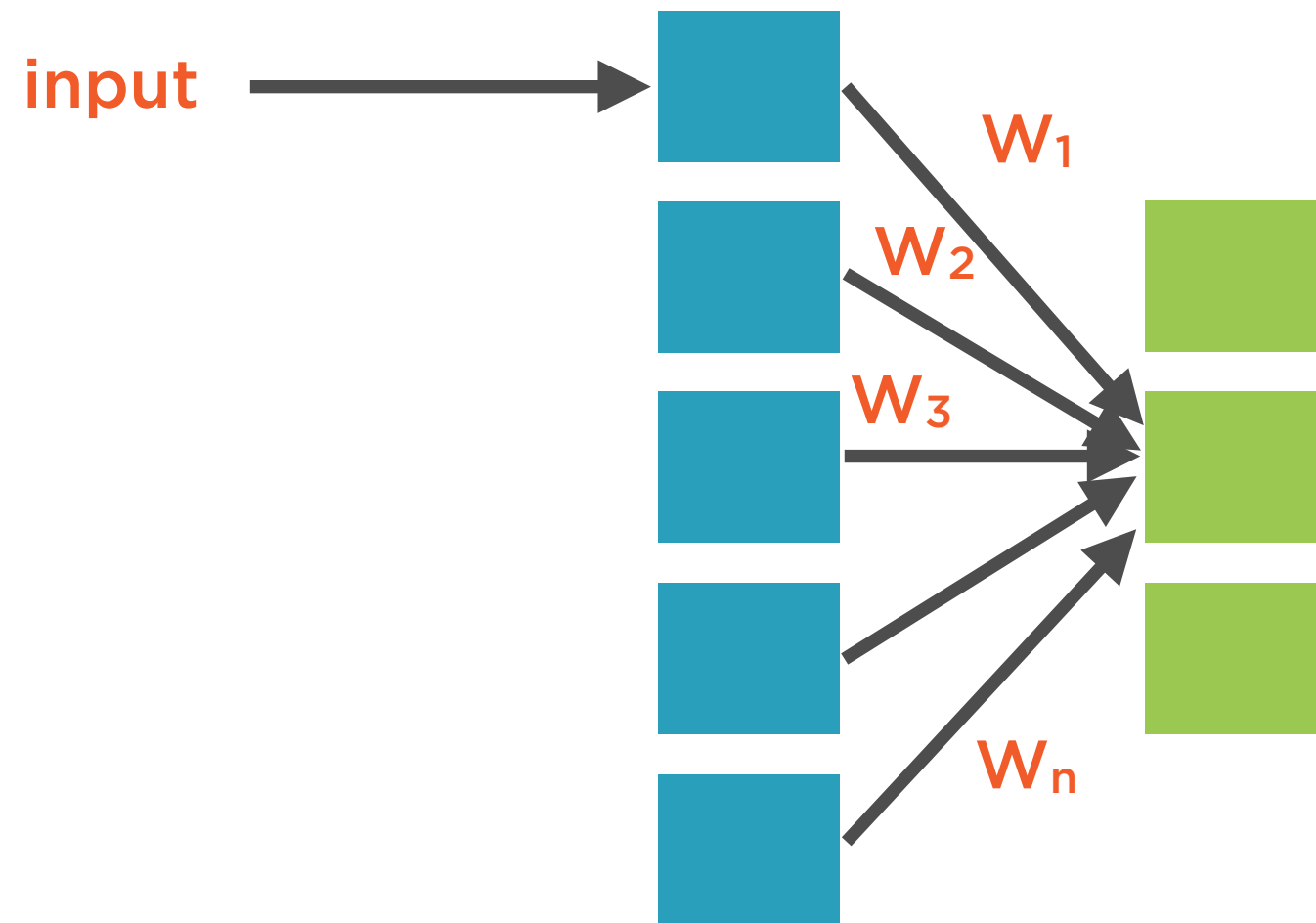
There is no intra-layer communication -
this is the **restriction**

Restricted Boltzmann Machines



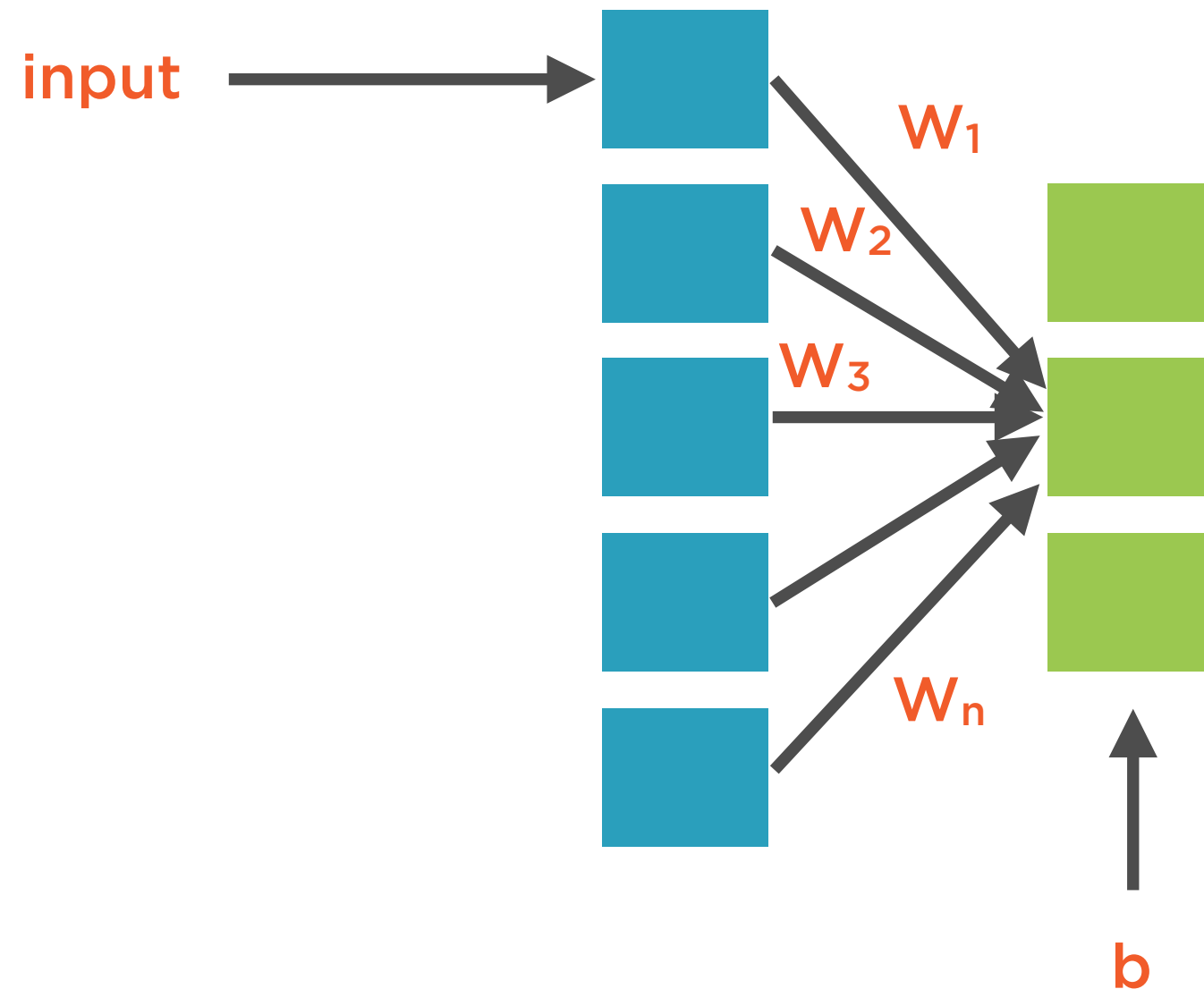
Each node processes the input and makes stochastic decisions about whether to transmit the input or not

Restricted Boltzmann Machines



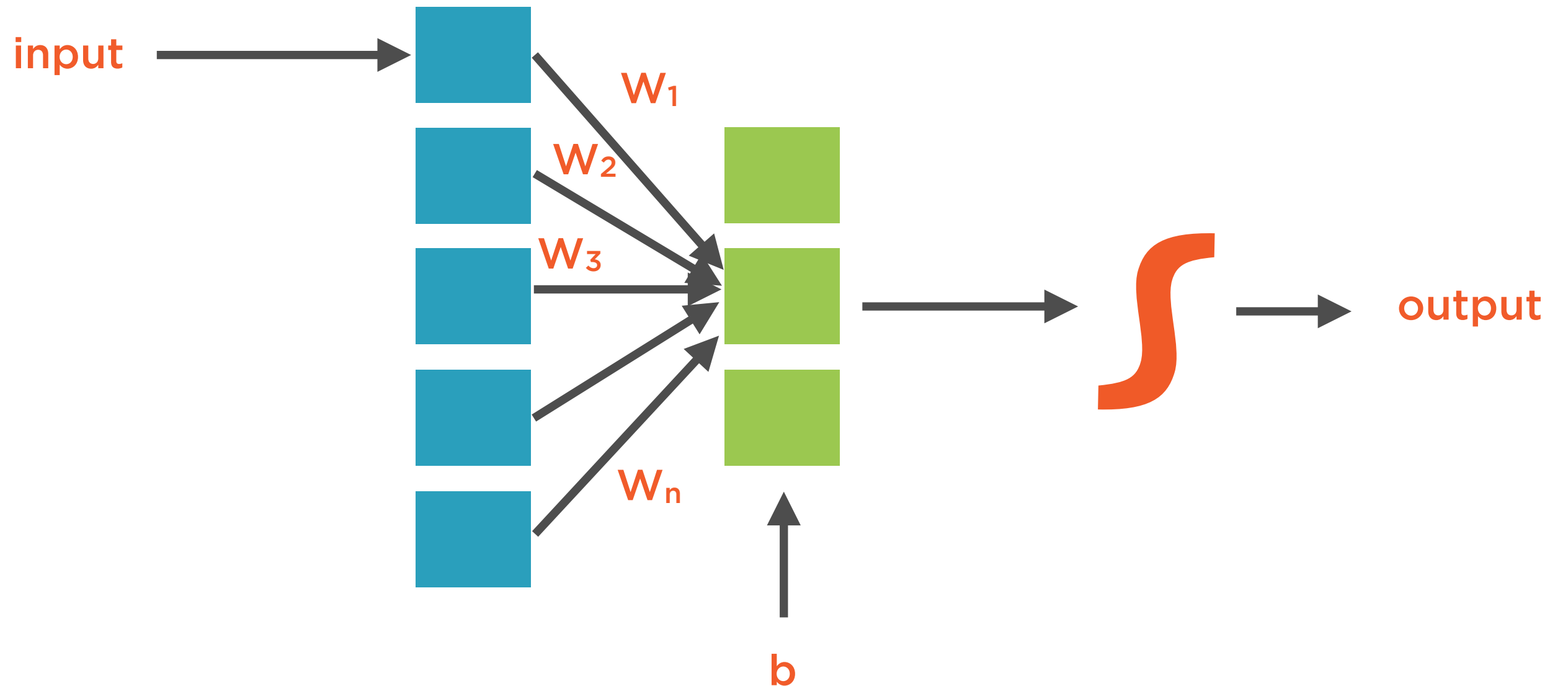
All interconnections are associated with weights

Restricted Boltzmann Machines



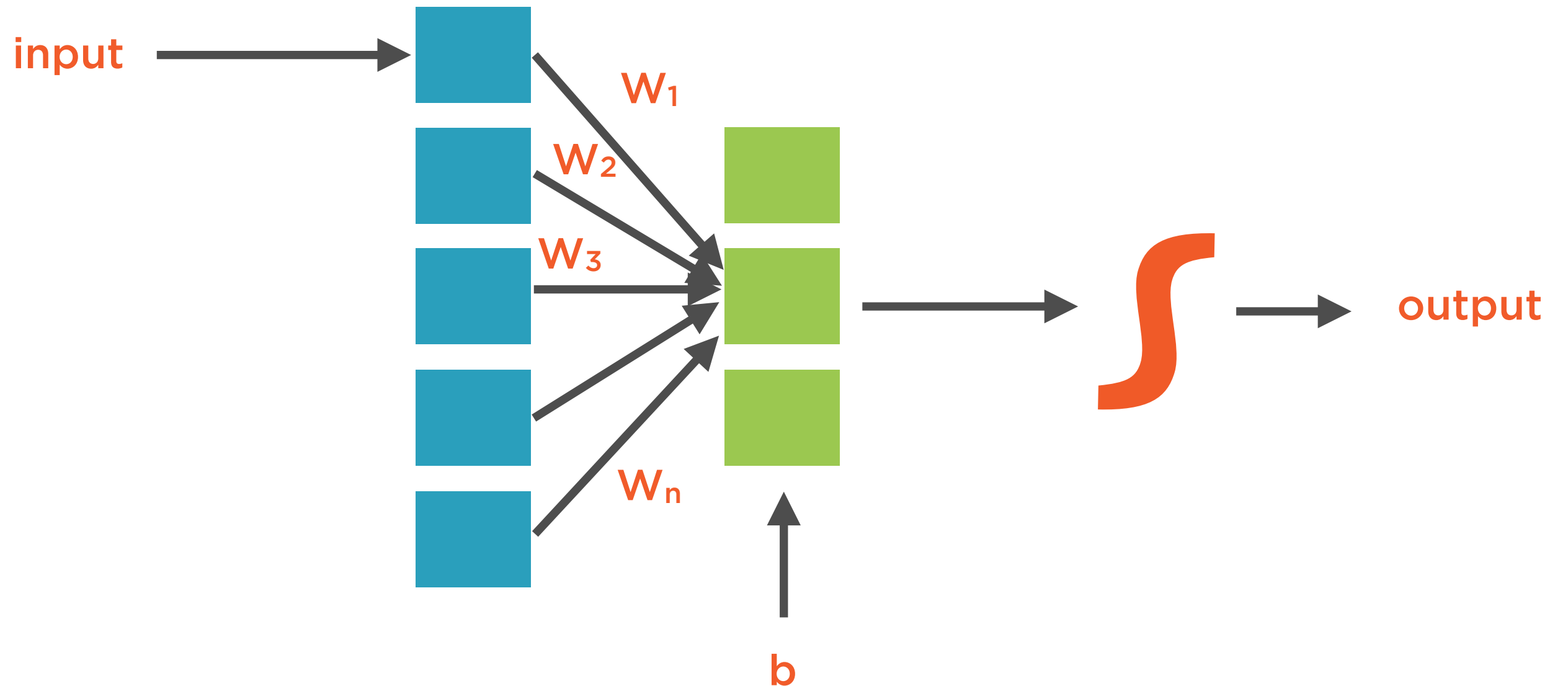
A bias is added to the weighted input

Restricted Boltzmann Machines



The final output is passed through an activation function

Restricted Boltzmann Machines

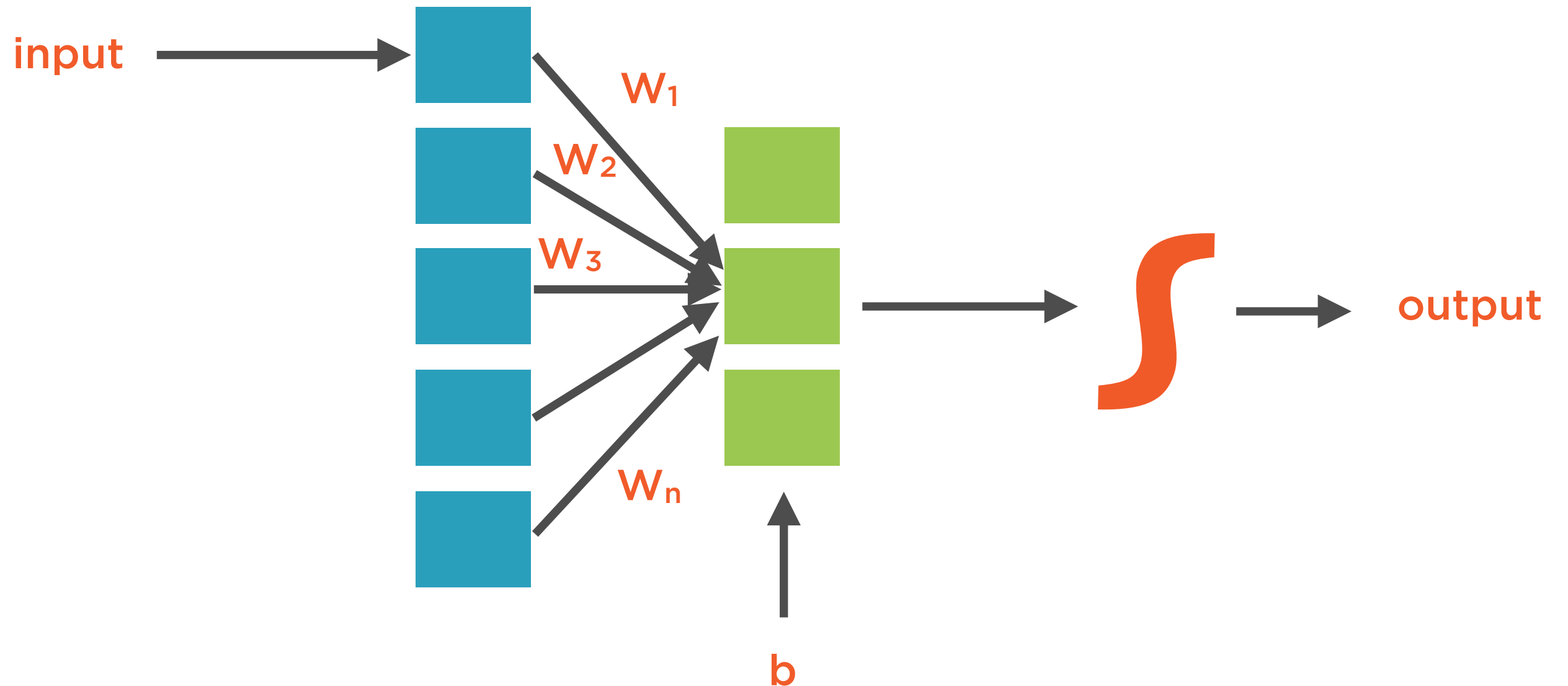


All inputs from all visible nodes are fed to hidden nodes -
this is a **symmetric bipartite graph**

Bipartite Graph

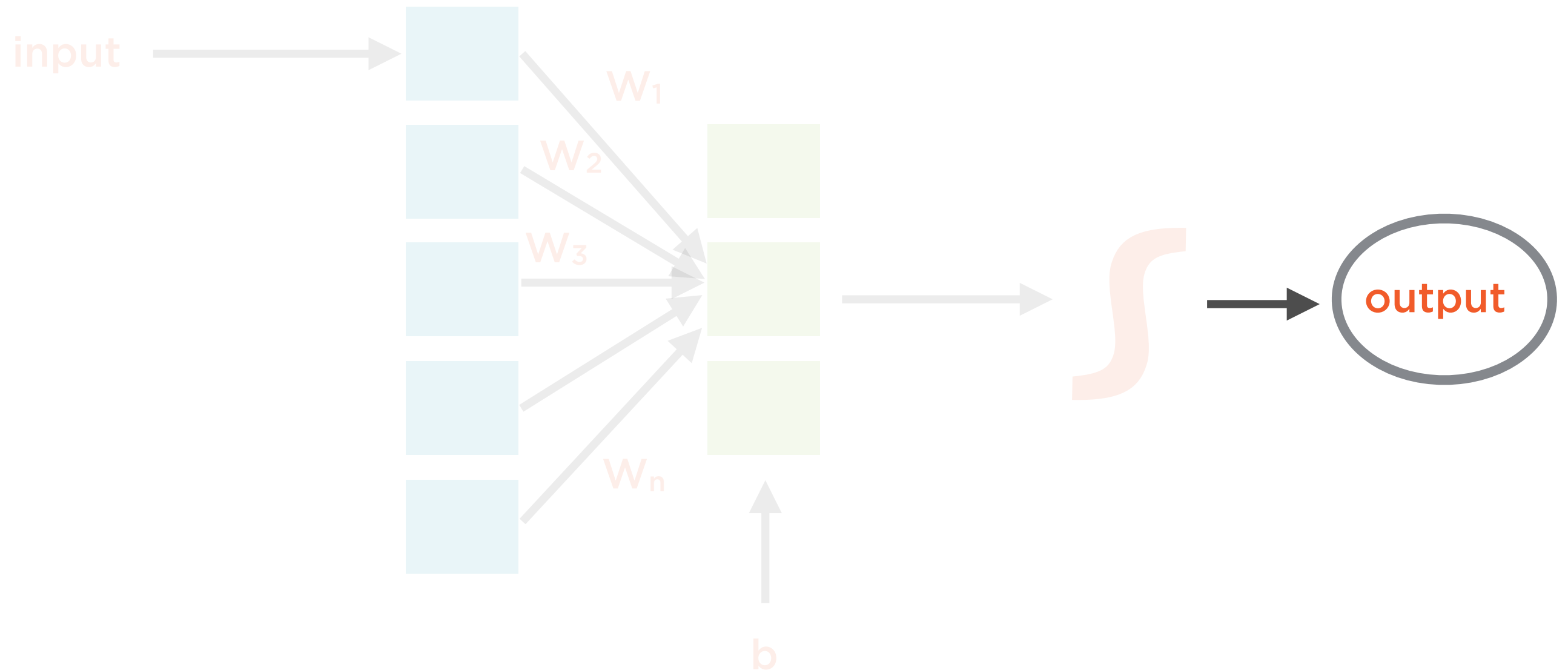
Graph whose vertices can be divided into two disjoint and independent sets U and V such that each edge connects a vertex in U to a vertex in V .

Restricted Boltzmann Machines



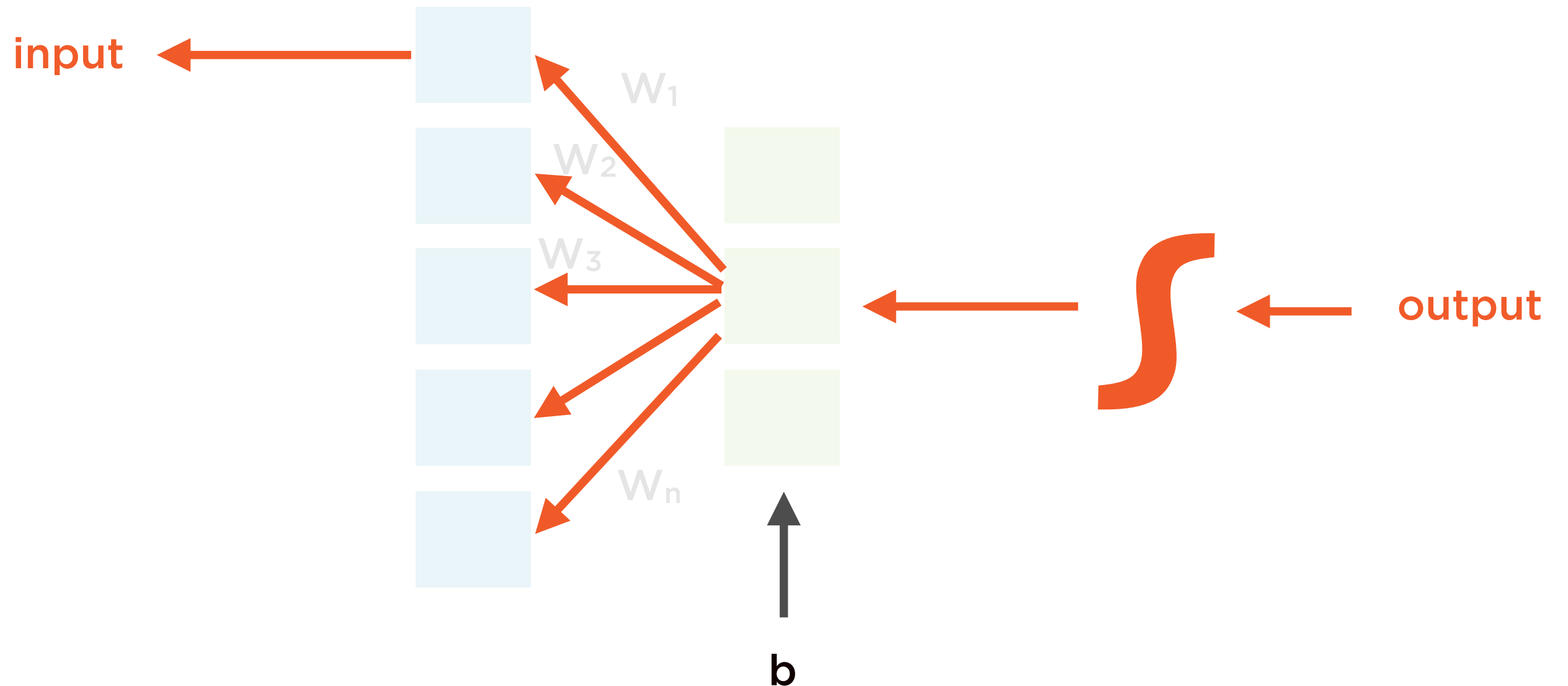
RBMs learn latent factors by reconstructing data by themselves in an unsupervised manner

Restricted Boltzmann Machines



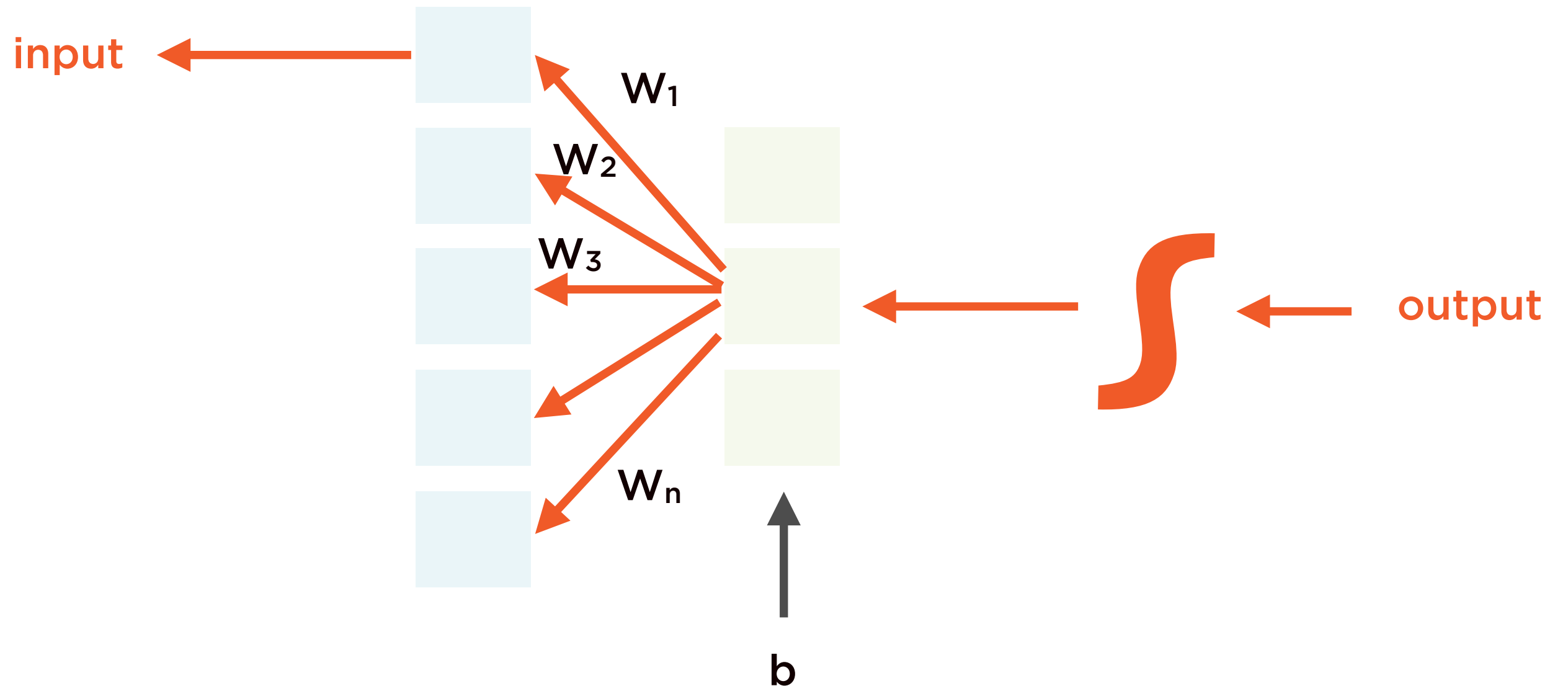
The output generated by the forward pass is sent back into the RBM

Restricted Boltzmann Machines



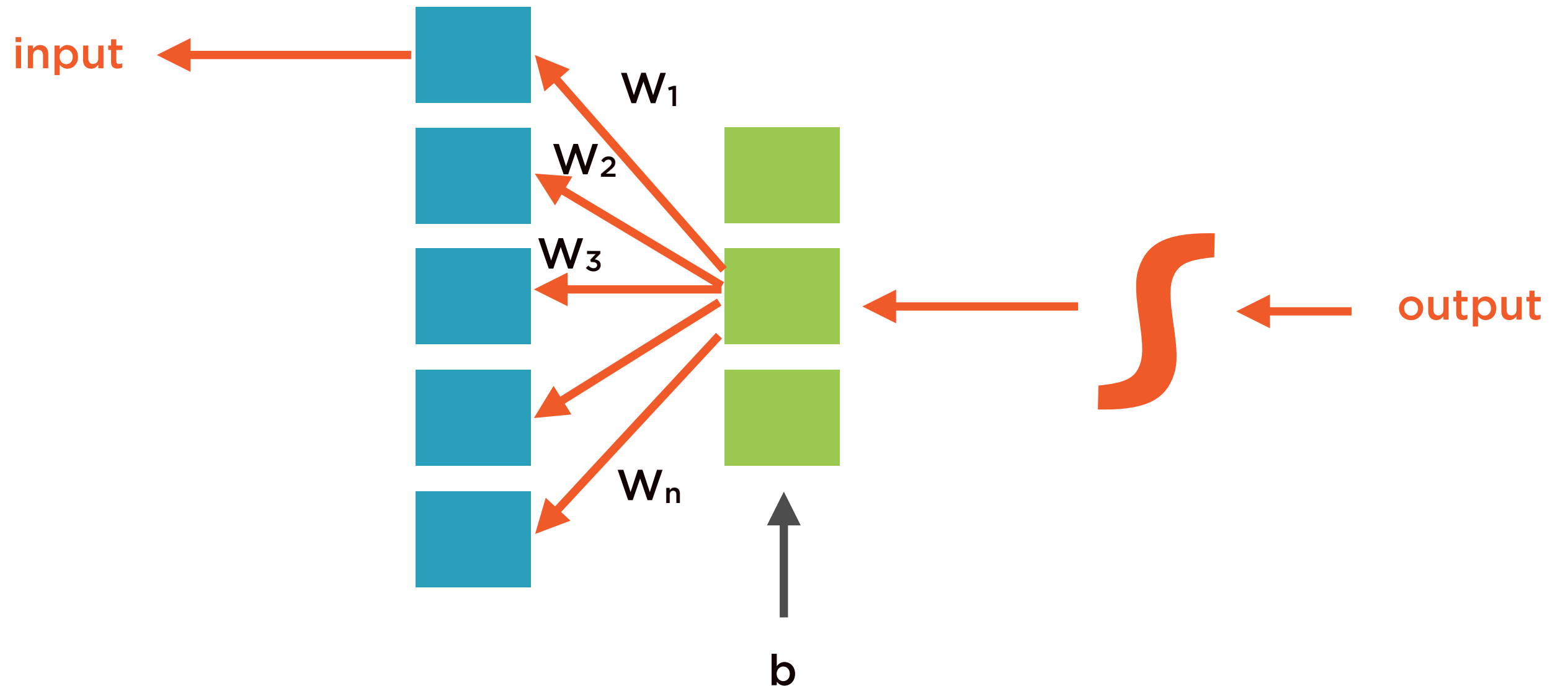
The backward pass tries to reconstruct the input

Restricted Boltzmann Machines



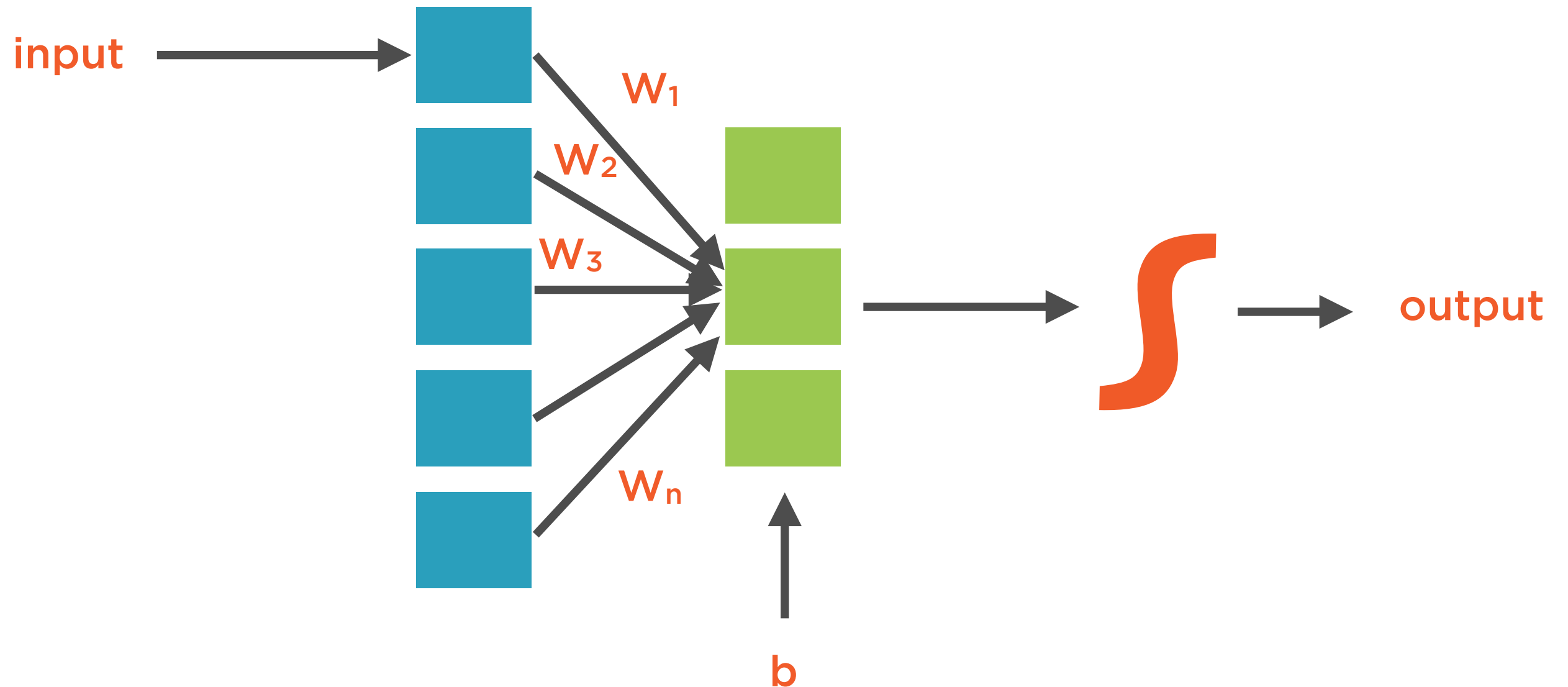
The weights of the RBM are adjusted to improve the reconstruction of the input

Restricted Boltzmann Machines



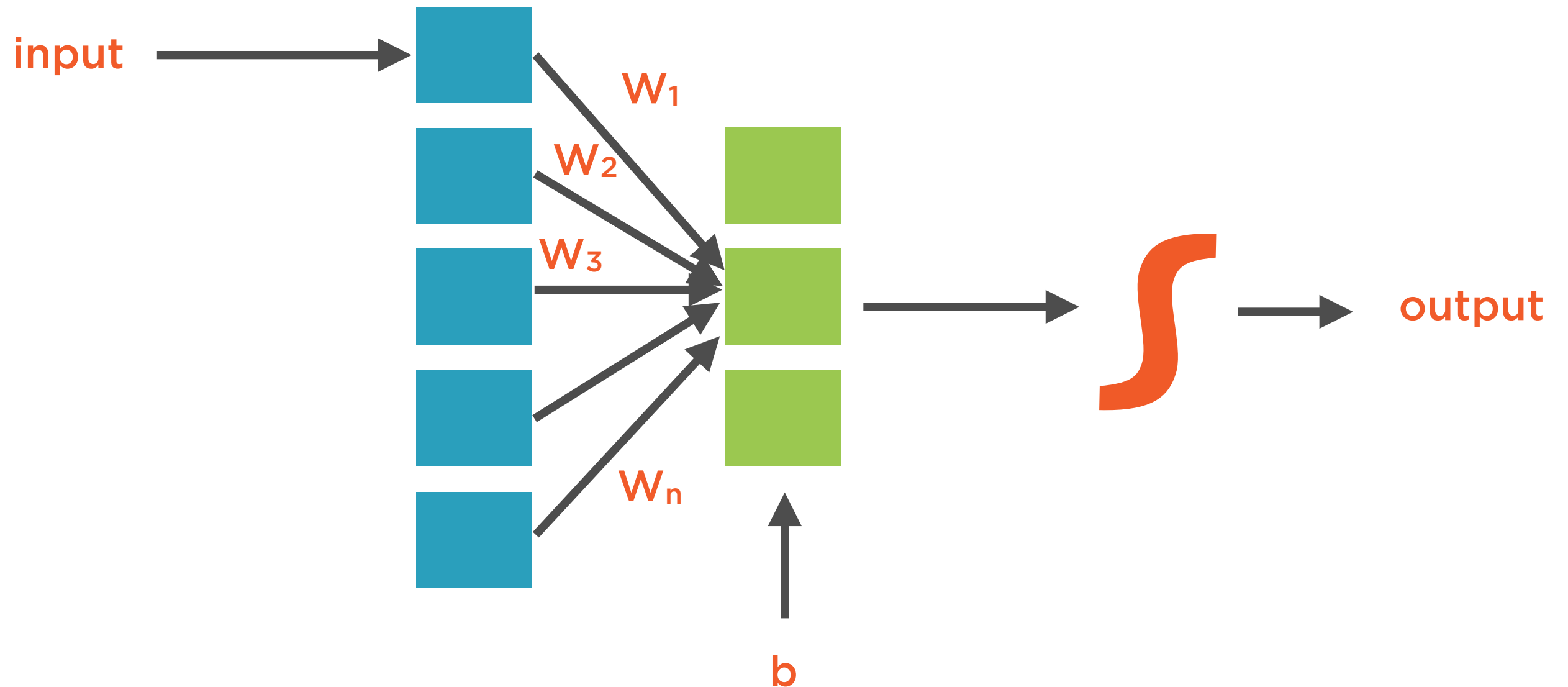
Multiple forward and backward passes improve the reconstruction of the input

Restricted Boltzmann Machines



The final lower dimensionality hidden output represents latent features in the input

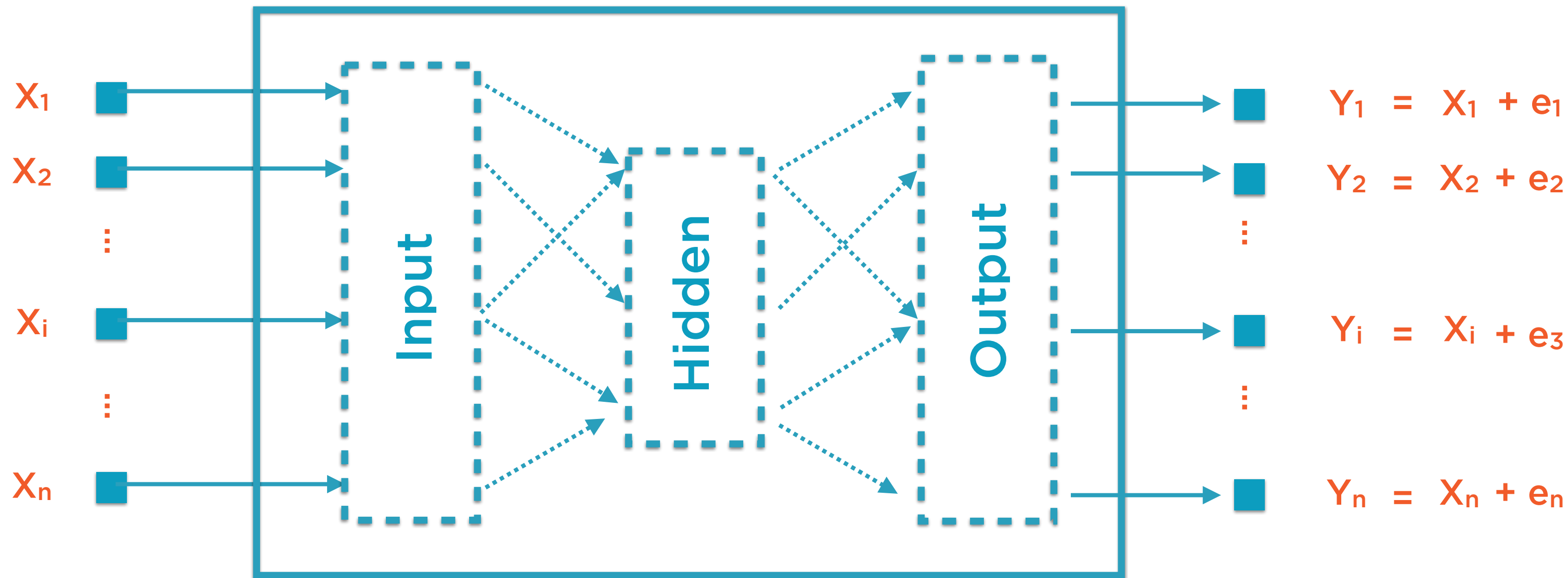
Restricted Boltzmann Machines



This dimensionality reduction is often used as a pre-processing step in building ML models

RBM's are an older concept
and have been replaced by
newer models such as
autoencoders

Autoencoder



Hidden layer learns latent factors which the output uses to reconstruct the input

Restricted Boltzmann Machines (RBMs) - a Brief History

Evolution of RBMs

Hopfield Networks (1974)

Early form of RNN - had memory

Quite inefficient - huge networks needed

Restricted Boltzmann Machines (1986)

Became quite popular in the mid-2000s

Impose constraints on Boltzmann machines to ease training

Boltzmann Machines (1985)

“Stochastic Hopfield net with hidden units”

Not possible to train efficiently

Deep Belief Nets (2009)

Compose (stack) RBM or autoencoder layers

Generative - like GANs. e.g. caption generation

Evolution of RBMs

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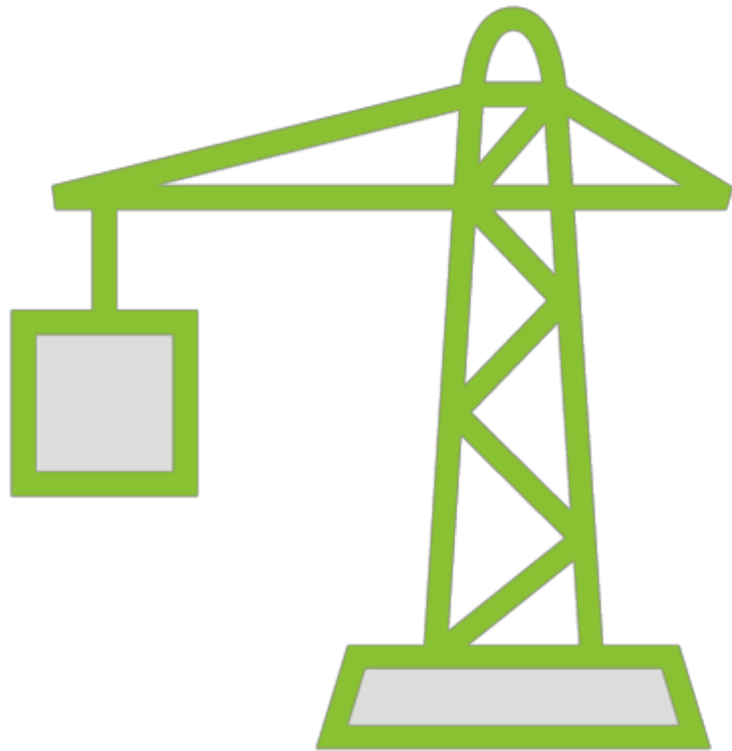
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Deep Belief Nets (2009)

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Generative - like GANs. e.g. caption generation

Boltzmann Machines



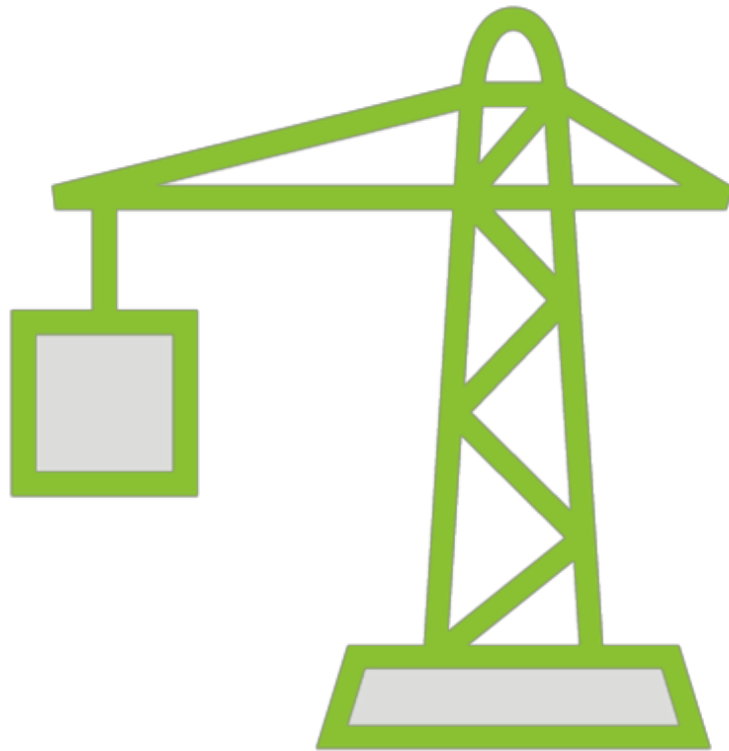
Fully connected neural networks

Visible and hidden layers

Use special type of neuron

Stochastic Neuron

Boltzmann Machines



Output is probabilistic rather than deterministic

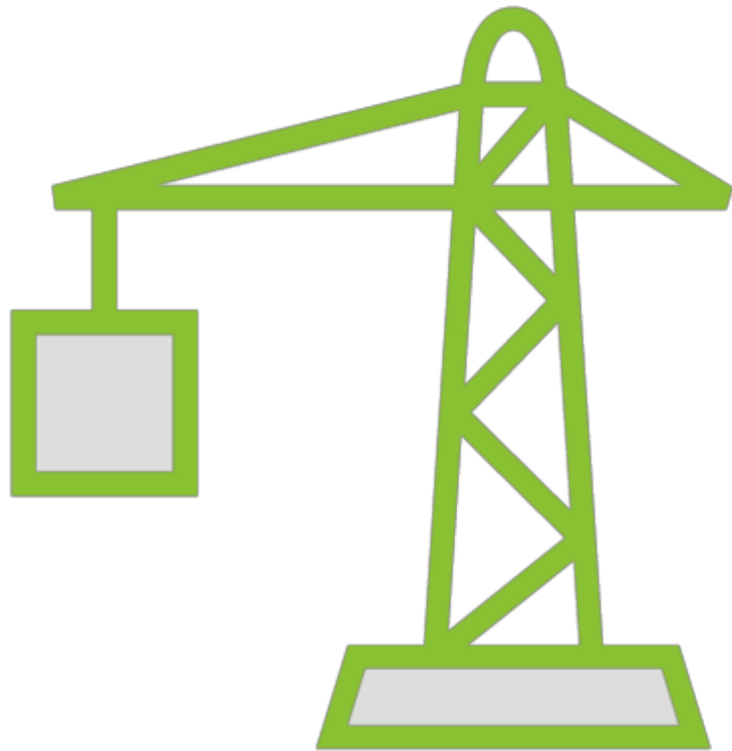
Neurons output 1 or 0 with specific probabilities

Rely on Boltzmann probability distribution

Hence the name

Used to model the
distribution of the input at
the output to help
reconstruct the input

Boltzmann Machines



Very hard to train efficiently

Tweaks proposed to enable practical use

Impose restrictions on architecture of Boltzmann machine

Evolution of RBMs

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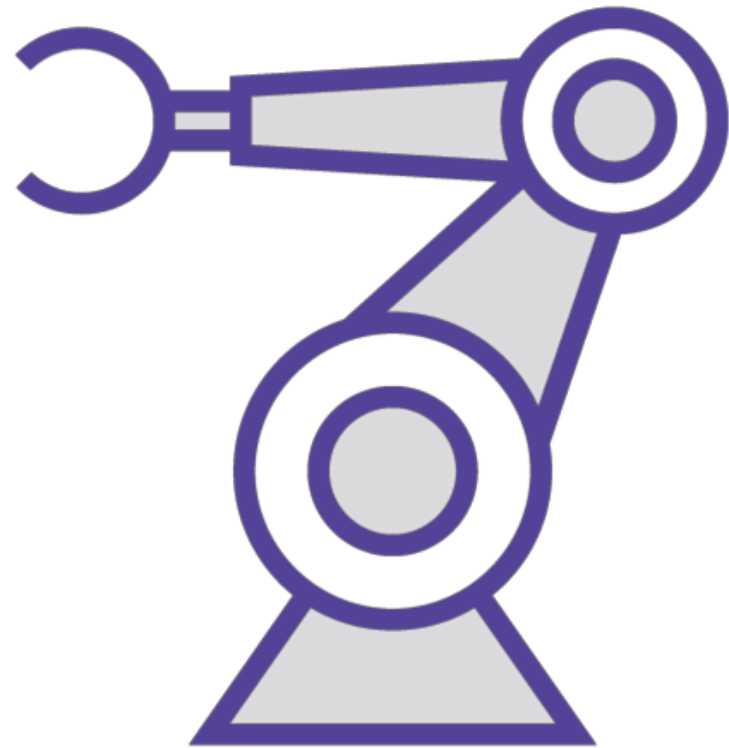
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Deep Belief Nets (2009)

Compose (stack) RBM or autoencoder layers

Generative - like GANs. e.g. caption generation

Restricted Boltzmann Machines



No connections allowed

- between two visible neurons
- between two hidden neurons

Only connections allowed

- between visible and hidden neurons

Network forms Bipartite Graph

Contrastive Divergence Algorithm

Efficient training used for training RBMs

Similar to backpropagation, but differs in some important aspects

- Gibbs Sampling: Monte Carlo-based technique to generate sample sequence
- Employ likelihood approximation called **pseudolikelihood**

Demo

**Performing dimensionality reduction
using Restricted Boltzmann Machines**

**Using lower dimensionality data to
train a classifier model**

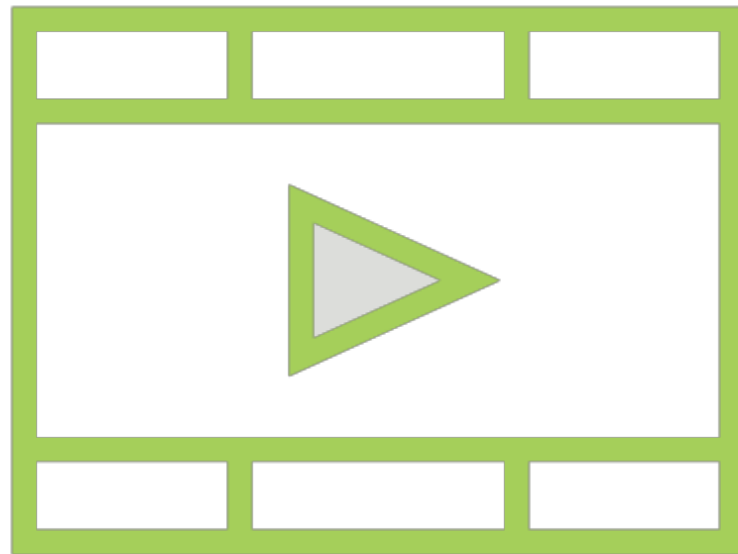
Summary

Introducing Restricted Boltzmann Machines (RBMs)

Using RBMs for dimensionality reduction

RBMs as pre-processing step during classification

Related Courses



**Building Clustering Models with
scikit-learn**

**Employing Ensemble Methods with
scikit-learn**