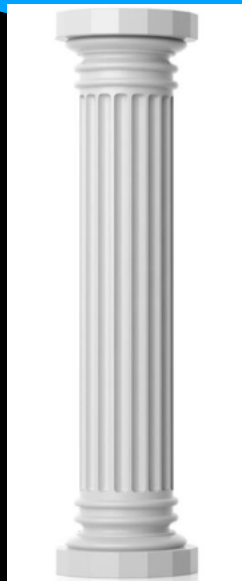


Unsupervised Learning Motivation

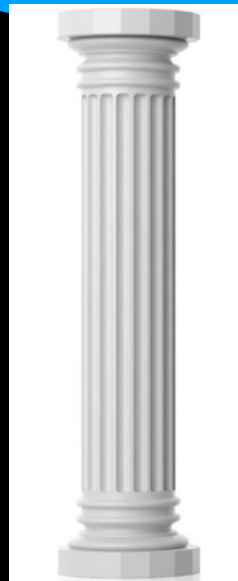
Earl Wong

Learning

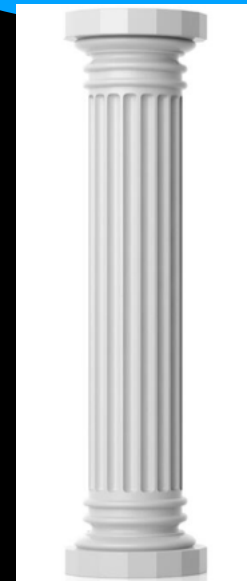
Supervised Learning



Unsupervised Learning



**Reinforcement
Learning**

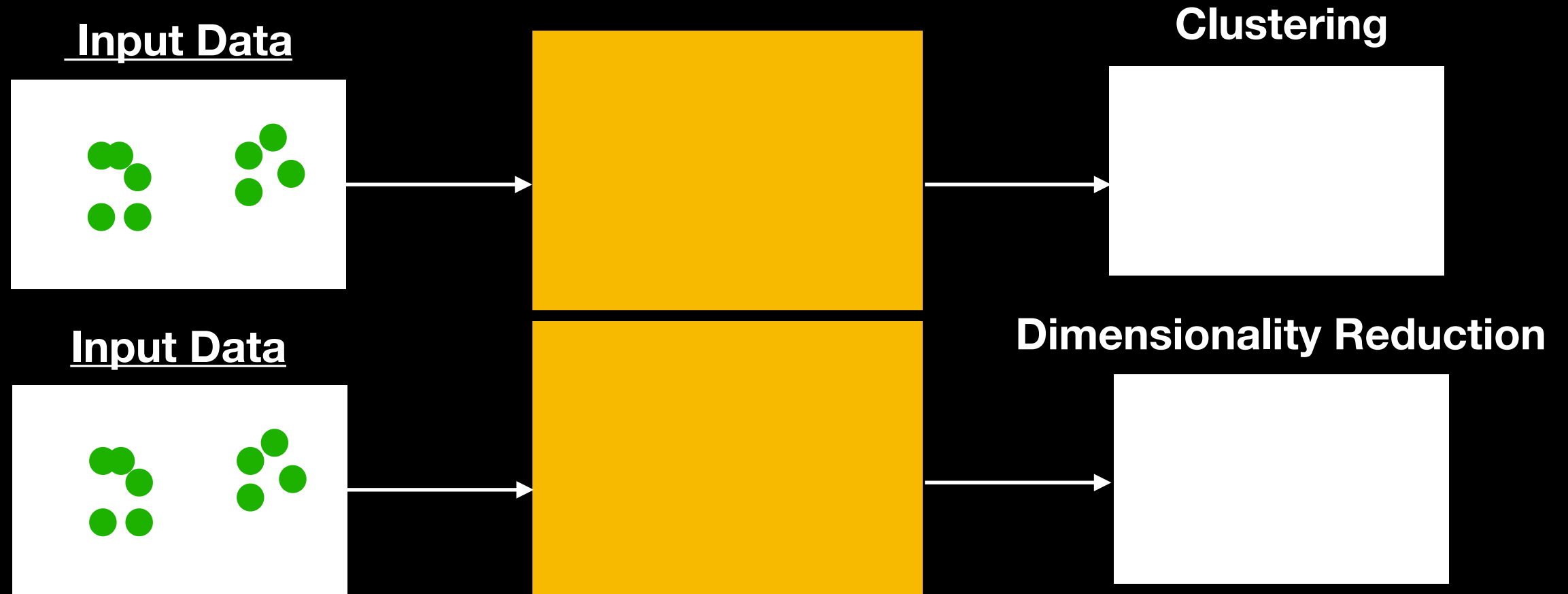


Learning

Learn from the data itself
There are no labels.
[Input Data, Label]

Unsupervised Learning

We learn the underlying
hidden structure in the data.



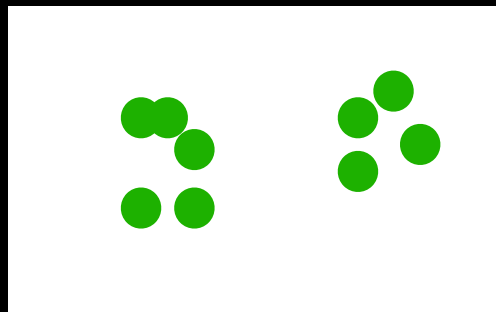
Learning

Learning From the data itself
There are no labels:
[Input Data, Label]

Unsupervised Learning

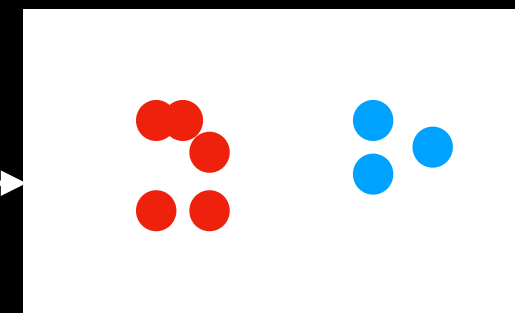
We learn the underlying
hidden structure in the data.

Input Data

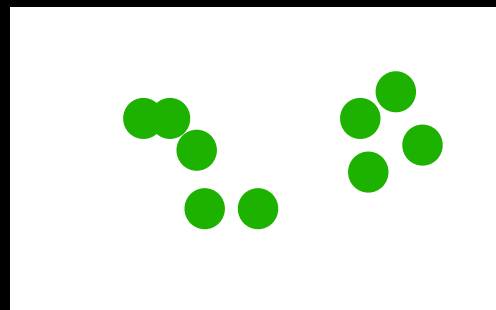


K Means
Clustering
(K = 2)

Clustering

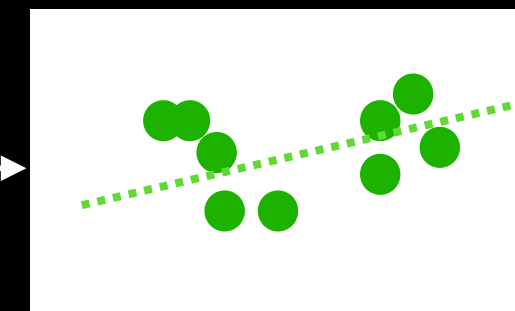


Input Data



Principle
Component
Analysis
(PCA)

Dimensionality Reduction



Motivation

- We want to learn from unlabeled data.
- Why?
 - 1) Unlabeled data is plentiful and occurs naturally in nature.
 - 2) Annotation is expensive and time consuming.
- As shown on the previous slide, classical unsupervised learning techniques (such as clustering and dimensionality reduction) learn hidden structure in the data.

Motivation

- In general, there is a wealth of information contained in unlabeled data.
- Goal: Finding meaningful ways to extract this information / convert the information into meaningful representations for downstream tasks like image recognition, object detection, etc.

Two Possible Methods

- Learn a model from the data.
- For example, maximum likelihood estimation can be used to learn the parameters of a statistical model, using samples drawn from that model.
- Learn meaningful representations from the data.
- For example, instead of learning representations of a deep neural network from labeled data, the representations are learned in an encoder-decoder framework, using unlabeled data.

Next: A Deeper Dive

- Explicit Models (AutoRegressive, Flow)
- Approximate Models (Variational AutoEncoder)
- Implicit Models (Generative Adversarial Networks)
- State of the Art Representation Learning using Unlabeled Data

References

- Some Methods for Classification and Analysis of Multi Variate Observations, J. MacQueen, Proceedings Fifth Berkeley Symposium on Mathematical Statistics and Probability 1967
- On Lines and Planes of Closest Fit to Systems of Points in Space, Pearson, London, Edinburgh and Dublin Philosophical Magazine, 1901
- Visualizing Data using t-SNE, Maaten and Hinton, JMLR 2008