

# Lecture 9: Unsupervised Learning and Clustering

INFO 1998: Introduction to Machine Learning



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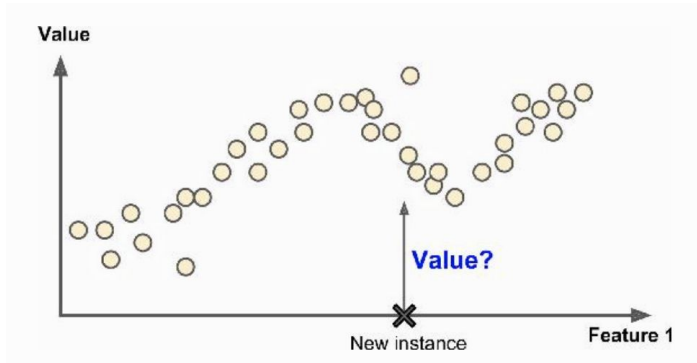
# Announcements

- Final project due date pushed back!
  - Nov 30th as of now
  - Go to OH for help/feedback before then!

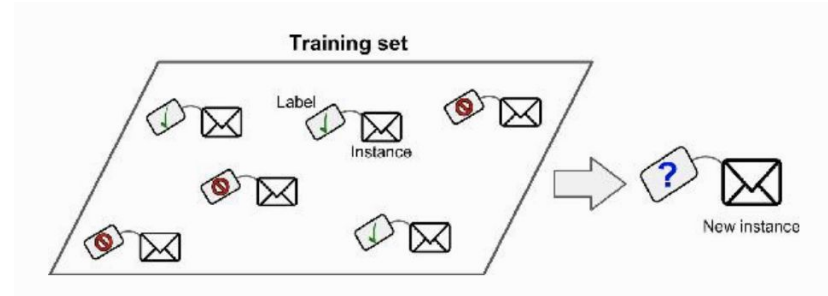


# Recap: Supervised Learning

- The training data you feed into your algorithm includes **desired solutions**
- Two types you've seen so far: **regressors and classifiers**
- In both cases, there are definitive “answers” to learn from



Example 1: Regressor  
**Predicts value**



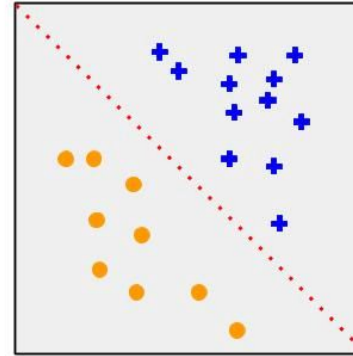
Example 2: Classifier  
**Predicts label**



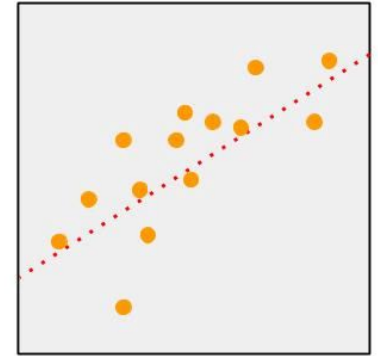
# Recap: Supervised Learning

Supervised learning algorithms we have covered so far:

- k-Nearest Neighbors
- Linear Regression
- Logistic Regression
- Perceptron / SVM
- Decision Trees / Random Forest



Classification



Regression

Which of these are classifiers? Which are regressors?

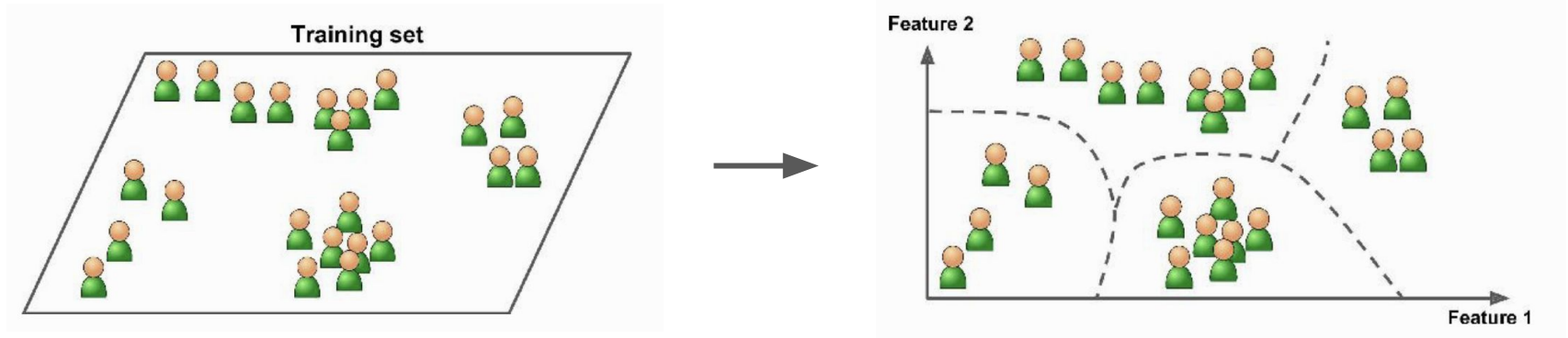


What are some **limitations** of supervised learning?



# Today: Unsupervised Learning

- In unsupervised learning, the training data is **unlabeled**
- Algorithm tries to learn by itself



An Example: Clustering



# Unsupervised Learning

Some types of unsupervised learning problems:

1

## Clustering

k-Means, Hierarchical Cluster Analysis (HCA), Gaussian Mixture Models (GMMs), etc.

2

## Dimensionality Reduction

Principal Component Analysis (PCA), Locally Linear Embedding (LLE)

3

## Association Rule Learning

Apriori, Eclat, Market Basket Analysis

...

*More*



# Unsupervised Learning

Some types of unsupervised learning problems:

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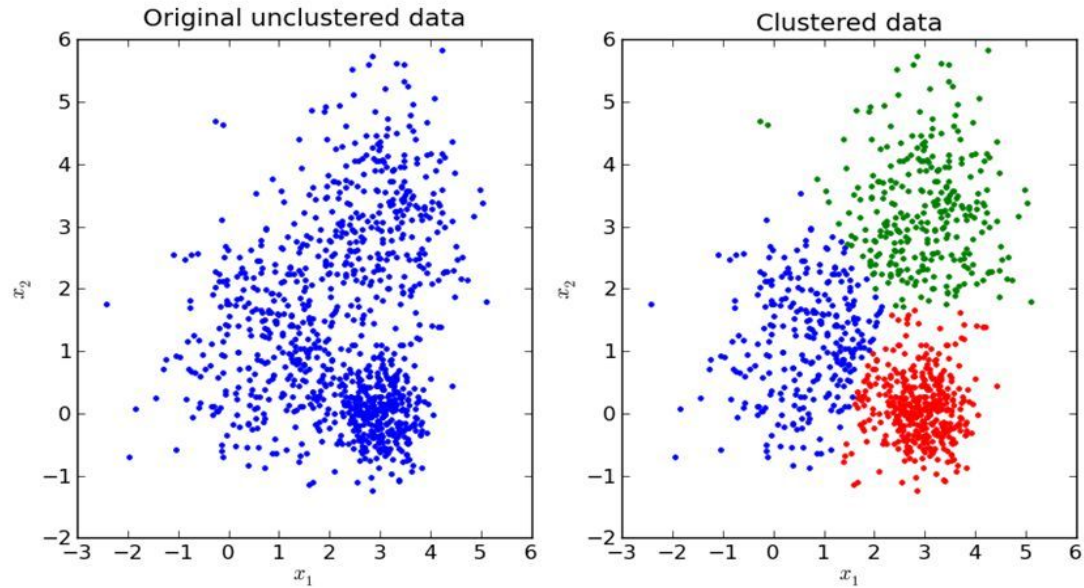
...

*More*





# Cluster Analysis



# Cluster Analysis

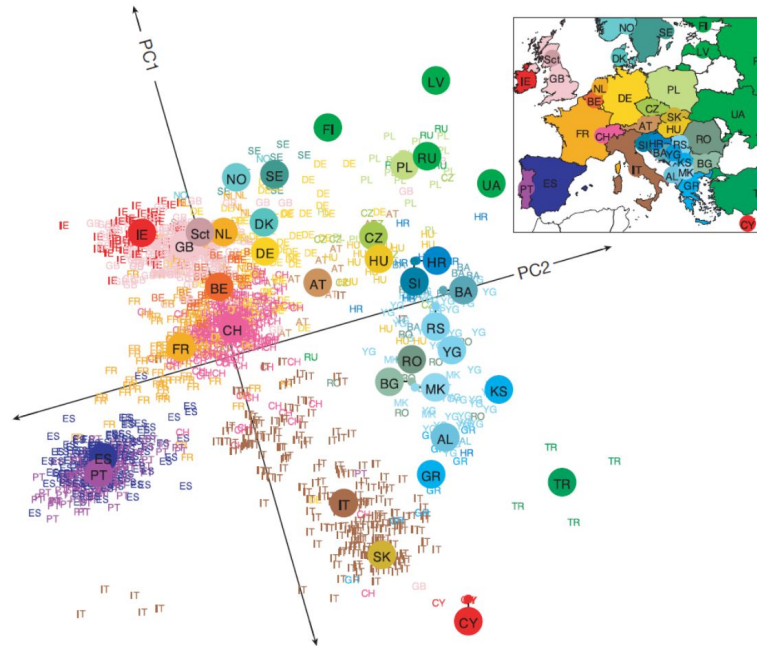
- **Loose definition:** Clusters have objects which are “similar in some way” (and “dissimilar to objects in other clusters)
- Clusters are **latent variables (variables that are unknown)**
- Understanding clusters can:
  - Yield underlying trends in data
  - Supply useful parameters for predictive analysis
  - Helpful exercise, take any arbitrary supervised task, pretend it’s unsupervised and work backwards. We can then see based on clustering what features/latent variables cause the trends or classifications



# Clustering Application

## Finding Population Structure in Genetic Data

From 1,387  
European  
samples



# Clustering Application

## Recommender Systems

Intuition: People who are “similar”, will like the same things



A Bunch of Cool Logos



# Running Example: Recommender Systems

## Use 1: Collaborative Filtering

- “People similar to you also liked X”
- Use other’s rating to suggest content

### Pros

If cluster behavior is clear,  
can yield good insights

### Cons

Computationally expensive  
Can lead to dominance of certain  
groups in predictions



# Running Example: Recommend MOVIES

	Amy	Jef	Mike	Chris	Ken
The Piano	—	—	+		+
Pulp Fiction	—	+	+	—	+
Clueless	+		—	+	—
Cliffhanger	—	—	+	—	+
Fargo	—	+	+	—	+



# Running Example: Recommender Systems

## Use 2: Content filtering

- “Content similar to what YOU are viewing”
- Use user’s watch history to suggest content

### Pros

Recommendations made by learner are intuitive

Scalable

### Cons

Limited in scope and applicability



## Another Example: Cambridge Analytica

- Uses Facebook profiles to build psychological profiles, then use traits for target advertising
- Ex. has personality test measuring openness, conscientiousness, extroversion, agreeableness and neuroticism -> different types of ads



Cambridge  
Analytica





How do we actually perform this  
**“cluster analysis”?**



## Defining 'Similarity'

- Remember from K Nearest Neighbors Discussion
- How do we calculate proximity of different data points?
- Euclidean distance:

$$E(x, y) = \sqrt{\sum_{i=0}^n (x_i - y_i)^2}$$

- Other distance measures:
  - Squared euclidean distance, manhattan distance



# Popular Clustering Algorithms

Hierarchical  
Cluster Analysis  
(HCA)

k-Means  
Clustering

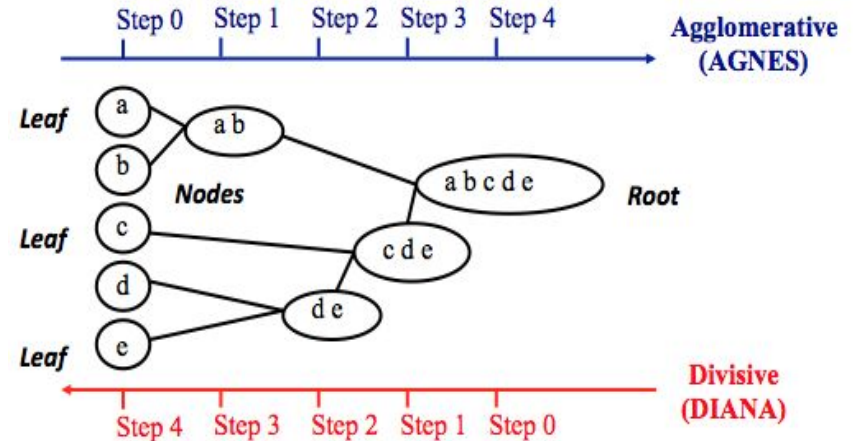
Gaussian  
Mixture Models  
(GMMs)



# Algorithm 1: Hierarchical Clustering

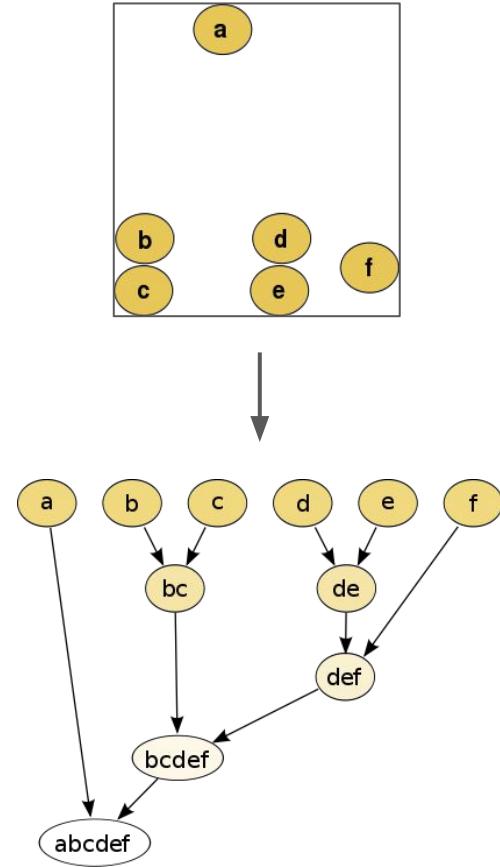
Two types:

- Agglomerative Clustering
  - Creates a tree of **increasingly large** clusters  
(*Bottom-up*)
- Divisive Hierarchical Clustering
  - Creates a tree of **increasingly small** clusters  
(*Top-down*)



# Agglomerative Clustering Algorithm

- Steps:
  - Start with each point in its own cluster
  - Unite adjacent clusters together
  - Repeat
- Creates a tree of **increasingly large** clusters

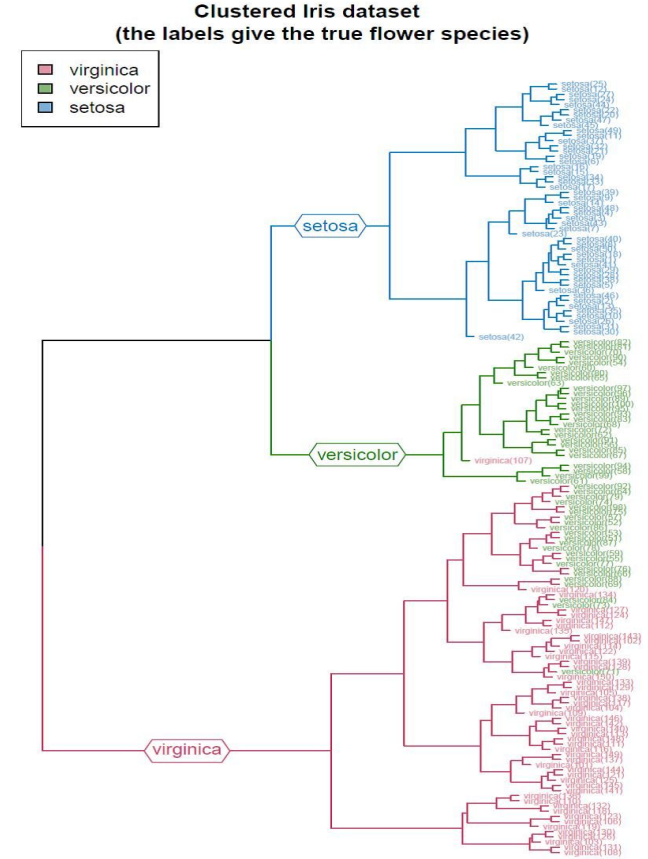


# Agglomerative Clustering Algorithm

*How do we visualize clustering?*

Using **dendrograms**

- Each width represents distance between clusters before joining
- Useful for estimating how many clusters you have



*The iris dataset that we all love*

# Demo 1



# Popular Clustering Algorithms

Hierarchical  
Cluster Analysis  
(HCA)

k-Means  
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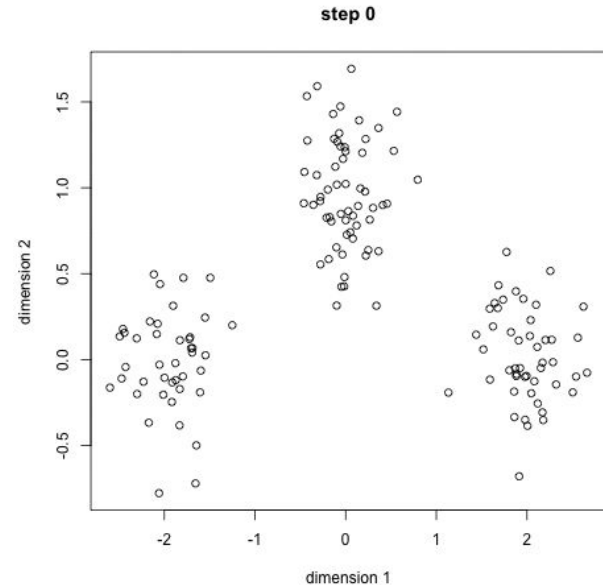




# Algorithm 2: k-Means Clustering

Input parameter:  $k$

- Starts with  $k$  random centroids
- Cluster points by calculating distance for each point from centroids
- Take average of clustered points
- Use as new centroids
- Repeat until convergence



Interactive Demo: <https://www.naftaliharris.com/blog/visualizing-k-means-clustering/>



## Algorithm 2: k-Means Clustering

- A **greedy** algorithm
- Disadvantages:
  - Initial means are randomly selected which can cause suboptimal partitions  
*Possible Solution:* Try a number of different starting points
  - Depends on the value of  $k$



# Demo 2



# Popular Clustering Algorithms

Hierarchical  
Cluster Analysis  
(HCA)

k-Means  
Clustering

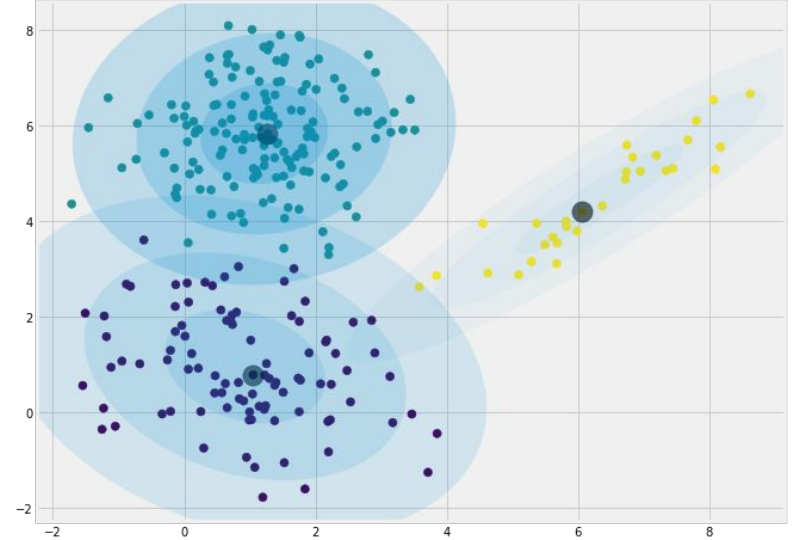
Gaussian  
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# Algorithm 3: Gaussian Mixture Models

Input parameter:  $k$

- Starts with  $k$  Gaussian distributions
- Train on data to find the appropriate means and covariances for each cluster
- Compute probability of each test point lying inside each distribution and predict the one with the highest probability.



# Demo 3



# Coming Up

- **Assignment 9:**
  - Due next Wednesday, Nov 16th, 7:30PM
- **Last Lecture:**
  - Real-world applications of ML
- **Final Project:**
  - Due next next next Wednesday, Nov 30th, 11:59PM



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