### **INFO 1998: Introduction to Machine Learning**



### **Announcements**

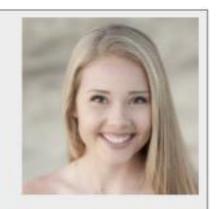
- Final project due next week
- Extra credit opportunity: Zoom Data Talk on Monday, 5PM



## Cornell Data Talk - Apple

Join to hear about journeys in Data Science from...

**Jenna Kressin** ~ AR Software Engineer at Apple and Cornell Data Science Alum '21!



April 25th, 5 PM on Zoom: shorturl.at/gsAN7



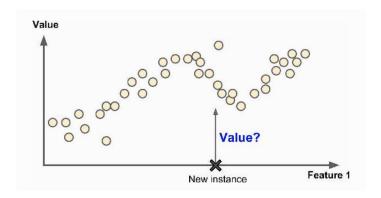
### Lecture 9: Clustering and Unsupervised Learning

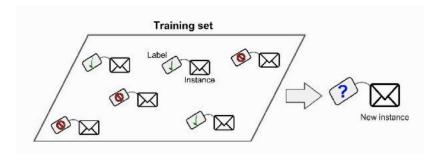
**INFO 1998: Introduction to Machine Learning** 



### **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** 

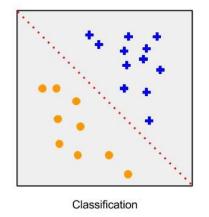


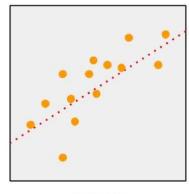


### **Recap: Supervised Learning**

### Supervised learning algorithms we have covered so far:

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





Regression



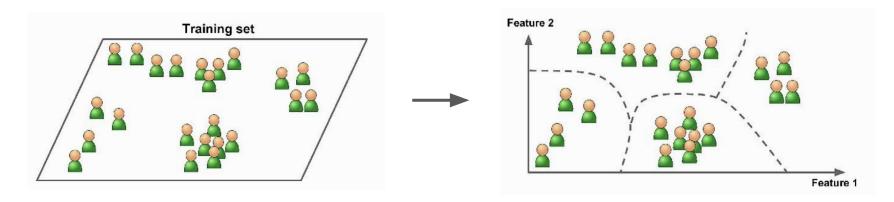
## What are some limitations of supervised learning?





## **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:

- Clustering
  k-Means, Hierarchical Cluster Analysis (HCA), Gaussian Mixture Models (GMMs), etc.
- Dimensionality Reduction
  Principal Component Analysis (PCA), Locally Linear Embedding (LLE)
- Association Rule Learning
  Apriori, Eclat, Market Basket Analysis
- ... More





### **Unsupervised Learning**

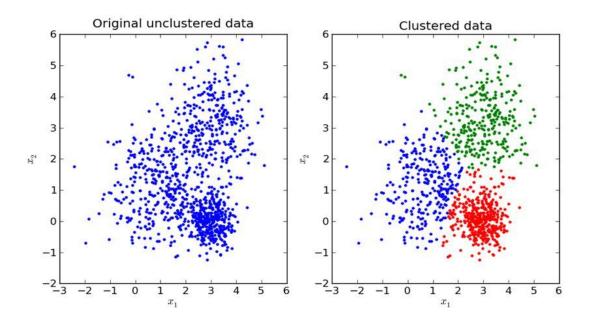
Some types of unsupervised learning problems:

- 1 Clustering
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- Dimensionality Reduction
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- Association Rule Learning
  Apriori, Eclat, Market Basket Analysis
- ... 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**

### **Recommender Systems**

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









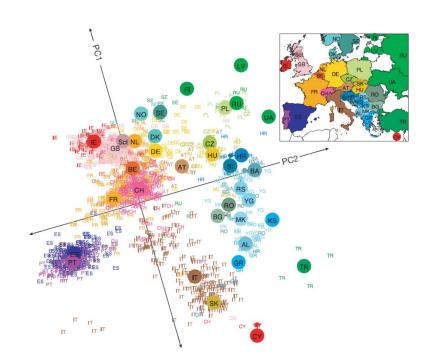




## **Clustering Application**

### **Finding Population Structure in Genetic Data**

From 1,387 European samples







### **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







# How do we actually perform this "cluster analysis"?





### **Popular Clustering Algorithms**

Hierarchical Cluster Analysis (HCA)

k-Means Clustering Gaussian Mixture Models (GMMs)





### **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

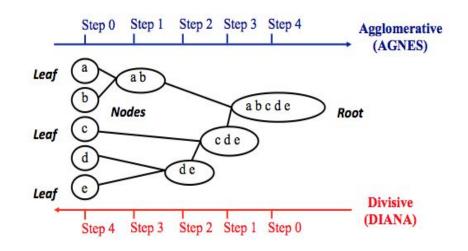




### **Algorithm 1: Hierarchical Clustering**

### 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)

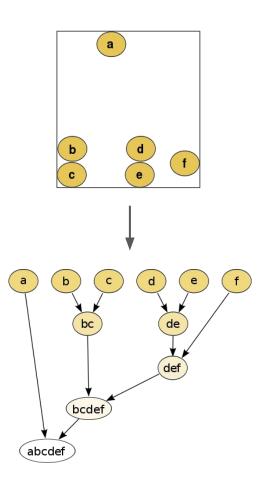






### **Agglomerative Clustering Algorithm**

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



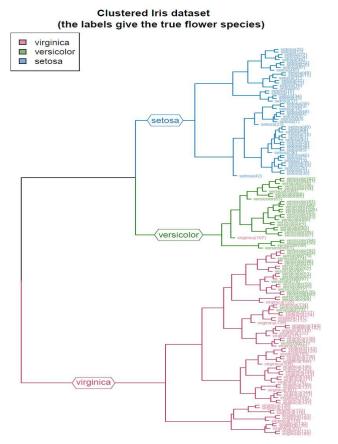




## **Agglomerative Clustering Algorithm**

How do we visualize clustering? Using dendrograms

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









## Demo 1





### **Popular Clustering Algorithms**

Hierarchical Cluster Analysis (HCA)

k-Means Clustering Gaussian Mixture Models (GMMs)

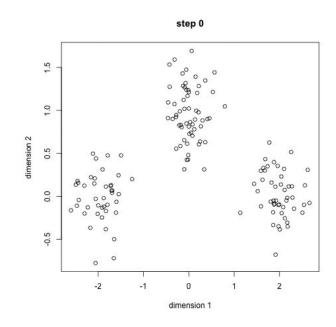




### **Algorithm 2: k-Means Clustering**

### 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







### **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 Mixture Models (GMMs)

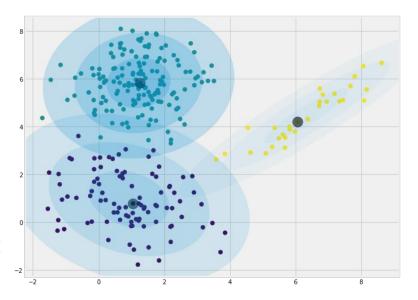




### **Algorithm 3: Gaussian Mixture Models**

### 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





### **Final Project Last Minute Tips**

- Talk to TA's for final project
- Feature engineering worth looking into turning categorical into continuous/discrete





### **Coming Up**

- Assignment 9:
  - <u>Due</u> next Wednesday, April 27th, 5:30PM
- Last Lecture:
  - Real-world applications of ML
- Final Project:
  - ALSO due next Wednesday, April 27th, 11:59PM

