INTRO TO DATA SCIENCE CLUSTER ANALYSIS

AGENDA 2

- I. CLUSTER ANALYSIS
- II. THE K-MEANS ALGORITHM
- III. CHOOSING K
- IV. EXAMPLE

I. CLUSTER ANALYSIS

	continuous	categorical
supervised	???	???
unsupervised	???	???

LOGISTIC REGRESSION

supervised
unsupervisedregression
dimension reductionclassification
clustering

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CLUSTER ANALYSIS

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In general, greater similarity between points leads to better clustering.

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CLUSTER ANALYSIS 11

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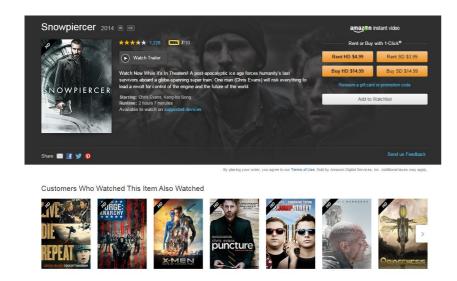
A: To enhance our understanding of a dataset by dividing the data into groups.

Clustering provides a layer of abstraction from individual data points.

The goal is to extract and enhance the natural structure of the data

Clustering can be useful in a wide variety of domains, including genetics, consumer internet and business.

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Health Spotlight	Trending on Google+: Foreign jihadists flocking to Iraq and Syria on control of the Google of the Go	Adjust Sources Adjust the frequency of any news source New York Times +

CLUSTER ANALYSIS 17

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There are many kinds of classification procedures. For our class, we will be focusing on K-means clustering, which is one of the most popular clustering algorithms.

K-means is an iterative method that partitions a data set into k clusters.

II. K-MEANS CLUSTERING

K-MEANS CLUSTERING

Q: How does the algorithm work?

- 2) for each point:
 - find distance to each centroid
 - assign point to nearest centroid

- 3) recalculate centroid positions
- 4) repeat steps 2-3 until stopping criteria met

STEP 1 — CHOOSING INITIAL CENTROIDS

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 - perform alternative clustering task, use resulting centroids as initial k-means centroids
 - start with global centroid, choose point at max distance, repeat (but might select outlier)

STEP 2 – ASSESS SIMILARITY

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In the case of k-means clustering, the similarity metric is the **Euclidian distance**:

$$d(x_1, x_2) = \sqrt{\sum_{i=1}^{N} (x_{1i} - x_{2i})^2}$$

STEP 3 — RECOMPUTING THE CENTER

Q: How do we recompute the positions of the centers at each iteration of the algorithm?

A: By calculating the centroid (i.e., the geometric center)

STEP 4 – CONVERGENCE

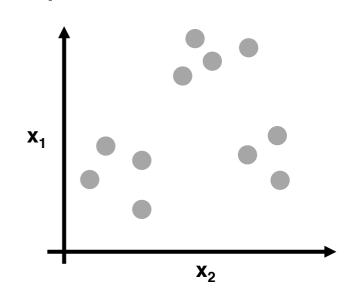
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Stopping criteria can be based on the centroids (eg, if positions change by no more than ε) or on the points (eg, if no more than x% change clusters between iterations).

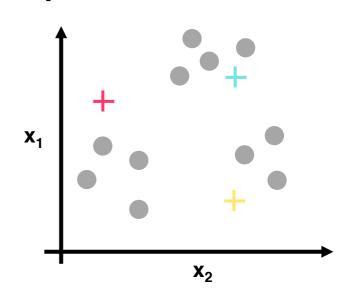
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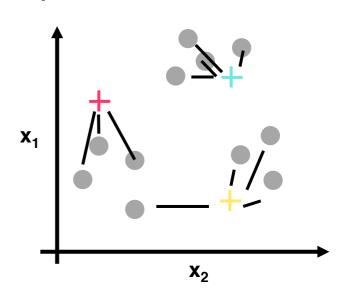
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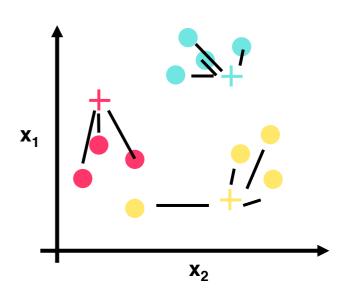
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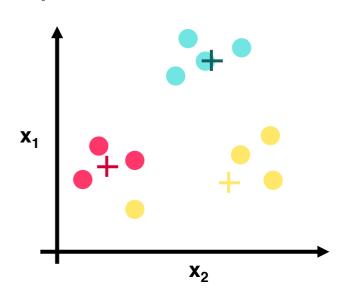
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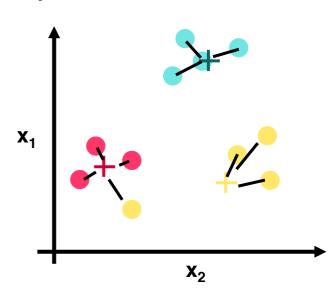
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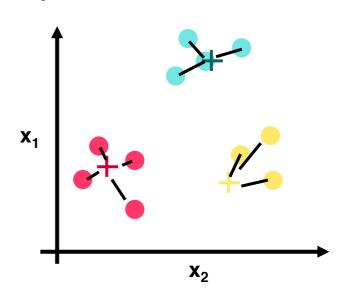
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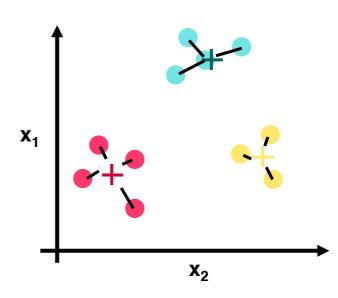
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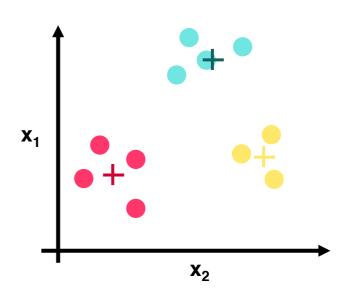
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III. CLUSTER VALIDATION

In general, k-means will converge to a solution and return a partition of k clusters, even if no natural clusters exist in the data.

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We will look at two validation metrics useful for partitional clustering, cohesion and separation.

Cohesion measures clustering effectiveness within a cluster.

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Separation measures clustering effectiveness between clusters.

$$\hat{S}(C_i, C_j) = d(c_i, c_j)$$

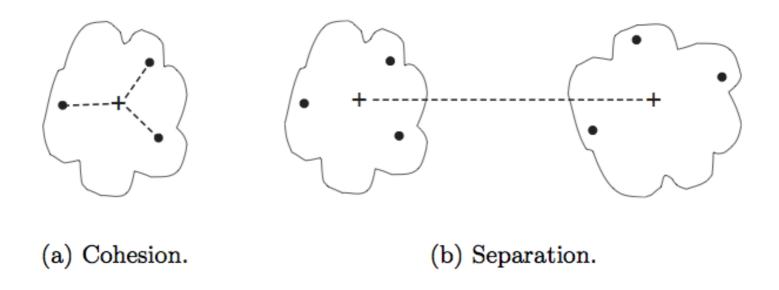


Figure 8.28. Prototype-based view of cluster cohesion and separation.

One useful measure than combines the ideas of cohesion and separation is the silhouette coefficient. For point x_i , this is given by:

$$SC_i = \frac{b_i - a_i}{max(a_i, b_i)}$$

such that:

 a_i = average in-cluster distance to x_i b_{ij} = average between-cluster distance to x_i b_i = $min_i(b_{ii})$ The silhouette coefficient can take values between -1 and 1.

In general, we want separation to be high and cohesion to be low. This corresponds to a value of SC close to +1.

A negative silhouette coefficient means the cluster radius is larger than the space between clusters, and thus clusters overlap. The silhouette coefficient for the cluster C_i is given by the average silhouette coefficient across all points in C_i :

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This gives a summary measure of the overall clustering quality.

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Q: How would you do this?

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Q: How would you do this?

A: By computing the SSE or SC for different values of k.

Ultimately, cluster validation and clustering in general are suggestive techniques that rely on human interpretation to be meaningful.

Strengths:

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Weaknesses:

However, K-means is highly scale dependent, and is not suitable for data with widely varying shapes and densities.

EX: K-MEANS CLUSTERING