Attempts to Axiomatize Clustering

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NIPS Workshop December 2005

Workshop Goals

Assuming we agree that theory is needed,

We wish to create a basis for a research community:

- Define/detect concrete open problems.
- Foster common language/ terminology/ classification-ofresearch-directions, among us.
- Stimulate/ brain-storm.
- Increase awareness of what others are/were doing.

The Theory-Practice Gap

Clustering is one of the most widely used tool for exploratory data analysis.

Social Sciences Biology Astronomy Computer Science

All apply clustering to gain a first understanding of the structure of large data sets.

Yet, there exist distressingly little theoretical understanding of clustering The Inherent Obstacle

Clustering is not well defined.

There is a wide variety of different clustering tasks, with different (often implicit) measures of quality.

Common Solutions

• Consider a restricted set of distributions:

Mixtures of Gaussians [Dasgupta '99], [Vempala,, '03], [Kannan et al '04], [Achlitopas, McSherry '05].

- Add structure:
- "Relevant Information"
 - Information Bottleneck approach [Tishby, Pereira, Bialek '99]
- Postulate an Objective Utility/Loss Functions
 - K means
 - Correlation Clustering [Blum, Bansal Chawla]
 - Normalized Cuts [Meila and Shi]
- Information Theoretic Objective Functions:
 - Bregman Divergences [Banerjee, Dhilon, Gosh, Merugu]
 - Rate-distortion [Slonim, Atwal, Tkacik, Bialek]
 - Description length [Cilibrasi-Vitanyi, Myllymaki]

Common Solutions (2)

Fitting Generative Models

- Mixture of Gaussians
- SuperParaMagnetic Clustering [Blatt, Weiseman, Domany]
- Density Traversal Clustering [Storkey and Griffith]

• Focus on specific algorithmic paradigms

- Agglomerative techniques (e.g., single linkage) [Hartigan, Stuetzle]
- Projections based clustering (random/spectral) [Ng, Jordan, Weiss]
- Spectral-based representations [Belkin, Niyogi]
- Unsupervised SVM's [Xu and Schuurmans]

Many more

Formalizing the broad notion of clustering – Why?

- Different clustering techniques often lead to qualitatively different results. Which should be used when? (Model selection).
- Evaluating the quality of clustering methods *currently this is embarrassingly ad hoc.*
- Distinguishing significant structure from random fata morgana.
- Providing performance guarantees for sample-based clustering algorithms.
- Much more ...

Some attempts to Axiomatizing Clustering

- Jardine and Sibson (1971),
- Hartigan (1975),
- Jane and Dubes (1981)
- Puzicha-Hofmann-Buhmann (2000)
- Kleinberg (2002)

The Basic Setting

- For a finite domain set S, a dissimilarity function (DF) is a symmetric mapping
 d:SxS → R⁺ such that
 d(x,y)=0 iff x=y.
- A *clustering function* takes a dissimilarity function on **S** and returns a partition of **S**.

We wish to define the properties that distinguish clustering functions (from any other functions that output domain partitions).

Kleinberg's Axioms

- Scale Invariance
 F(λd)=F(d) for all d and all non-negative λ.
- Richness
 For any finite domain S,
 {F(d): d is a DF over S}={P:P a partition of S}

Consistency

If *d*' equals *d* except for shrinking distances within clusters of *F(d)* or stretching between-cluster distances (w.r.t. *F(d)*), then *F(d)=F(d')*.

Kleinberg's Impossibility result

There exist no clustering function



A Different Perspective-Axioms as a tool for classifying clustering paradigms

• The goal is to generate a variety of axioms (or properties) over a fixed framework, so that different clustering approaches could be classified by the different subsets of axioms they satisfy.

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	"Axioms"			"Properties"		
	Scale Invariance	Richness	Local Consistency	Full Consistency		
Single Linkage	-	+	+	+		
Center Based	+	+	+	-		
Spectral	+	+	+	-		
MDL	+	+	-			
Rate Distortion	+	+	-			



- We would like to have a list of *simple properties* so that major clustering methods are distinguishable from each other using these properties.
- We would like the *axioms* to be such that *all* methods satisfy *all* of them, and *nothing* that is clearly not a clustering satisfies all of them.

(this is probably too much to hope for).

• In the remainder of this talk, I would like to discuss some candidate "axioms" and "properties" to get a taste of what this theory-development program may involve.

Types of Axioms/Properties

Richness requirements

E.g., relaxations of Kelinberg's richness, e.g., **{F(d): d** is a DF over **S}={P:P** a partition of **S** into **k** sets**}**

 Invariance/Robustness/Stability requirements.
 E.g., Scale-Invariance, Consistency, robustness to perturbations of *d* ("smoothness" of *F*) or stability w.r.t. sampling of *S*.

Relaxations of Consistency

Local Consistency –

Let C_1, \ldots, C_k be the clusters of F(d). For every $\lambda_0 \ge 1$ and positive $\lambda_1, \ldots, \lambda_k \le 1$, if d' is defined by:

$$d'(a,b) = \begin{cases} \lambda_i d(a,b) \text{ if } a \text{ and } b \text{ are in } C_i \\ \lambda_0 d(a,b) \text{ if } a,b \text{ are not in the same } F(d)\text{-cluster,} \end{cases}$$

then F(d)=F(d').

Is there any known clustering method for which it fails?

(What about Rate Distortion? ..)

Some more structure

- For partitions P₁, P₂ of {1, ...m} say that P₁ refines P₂ if every cluster of P₁ is contained in some cluster of P₂.
- A collection C={P_i} is a chain if, for any P, Q, in C, one of them refines the other.
- A collection of partitions is an **antichain**, if no partition there refines another.
- Kleiberg's impossibility result can be rephrased as *"If F is Scale Invariant and Consistent then its range is an antichain".*

Relaxations of Consistency

Refinement Consistency

Same as Consistency (shrink in-cluster, strech betweenclusters) but we relax the Consistency requirement "F(d)=F(d')" to "one of F(d), F(d') is a refinement of the other".

Note: A natural version of Single Linkage ("join x,y, iff d(x,y) < λ[max{d(s,t): s,t in X}]") satisfies this + Scale Invariance+ Richness.
 So Kleinberg's impossibility result breaks down.

Should this be an "axiom"? Is there any common clustering function that fails that?

More on 'Refinement Consistency'

- *"Minimize Sum of In-Cluster Distances"* satisfies it (as well as *Richness* and *Scale Invariance*).
- Center-Based clustering fails to satisfy Refinement
 Consistency
- This is quite surprising, since they look very much alike.

$$\sum_{i=1}^{k} \sum_{x,y \in C_{i}} d^{2}(x,y) = 2\sum_{i=1}^{k} |C_{i}| \sum_{x \in C_{i}} d^{2}(x,c_{i})$$

(Where *d* is Euclidean distance, and c_i the center of mass of C_i)

Hierarchical Clustering

 Hierarchical clustering takes, on top of *d*, a "coarseness" parameter *t*.

For any fixed *t*, *F(t,d)* is a clustering function.

- We require, for every **d**:
 - $C_d = \{F(t,d): 0 \le t \le Max\}$ a chain.
 - $F(0,d) = \{\{x\}: x \in S\} \text{ and } F(Max,d) = \{S\}.$

Hierarchical versions of axioms

- Scale Invariance: For any d, and λ>0,
 {F(t,d): t} = {F(t, λd):t} (as sets of partitions).
- *Richness:* For any finite domain *S*,
 {{F(t,d):t}: d is a DF over *S}={C:C* a chain of partitions of *S* (with the needed Min and Max partitions)}.
- Consistency: If, for some t, d' is an F(t,d) -consistent transformation of d, then, for some t', F(t,d)=F(t',d')

Characterizing Single Linkage

- Ordinal Clustering axiom
 If, for all w,x,y,z,
 d(w,x)<d(y,z) iff d'(w,x)<d'(yz)</p>
 then {F(t,d): t} = {F(t,d'):t} (as sets of partitions).
 (note that this implies Scale Invariance)
- Hierarchical *Richness* + *Consistency* + *Ordinal Clustering* characterize Single Linkage clustering.

Stability/Robustness axioms

- Relaxing *Invariance* to "*Robustness*"
 Namely, "Small changes in *d* should result in small changes of *f(d)*".
- Statistical setting and *Stability* axioms.
- Axioms as tools for Model Selection.

Sample Based Clustering

- There is some large, possibly infinite, domain set X.
- An unknown probability distribution *P* over *X* generates an i. i.d sample, *S* <u></u>*C X*.
- Upon viewing such a sample, a learner wishes to deduce a clustering, as a simple, yet meaningful, description of the distribution.

Stability - basic idea

- Cluster independent samples of the data.
- Compare the resulting clusterings.
- Meaningful clusterings should not change much from one independent sample to another.
- Rational: To help quantify whether algorithmgenerated clusterings reflect properties of the underlying data distribution, rather than being just an artifact of sample randomness.

Other types of clustering

- Culotta and McCallum's "Clusterwise Similarity"
- *Edge-Detection* (advantage to smooth contours)
- Texture clustering

-The professors example.



Conclusions and open questions

- There is a place for developing an axiomatic framework for clustering.
- The existing negative results do not rule out the possibility of useful axiomatization.
- We should also develop a system of "clustering properties" for a taxonomy of clustering methods.
- There are many possible routes to take and hidden subtleties in this project.