Predictive Modeling Book Chapter 12: Unsupervised Learning

CAS Annual Meeting November, 2014
Louise Francis, FCAS, MAAA
Francis Analytics and Actuarial Data Mining, Inc
www.data-mines.com

Objectives

- Introduce chapter on unsupervised learning to actuaries
- Provide some insight into statistics underlying unsupervised learning
- Provide examples relevant to actuaries
- Indicate what resources are available

ICA 2014 CIA
WASHINGTON DC

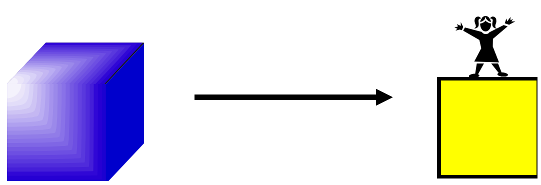
Major Kinds of Modeling

- Supervised learning
  - Most common situation
  - A dependent variable
    - Frequency
    - Loss ratio
    - Fraud/no fraud
  - Some methods
    - Regression
    - CART
    - Some neural networks

- Unsupervised learning
  - No dependent variable
  - Group like records together
    - A group of claims with similar characteristics might be more likely to be fraudulent
    - Ex: Territory assignment, Text Mining
  - Some methods
    - Association rules
    - K-means clustering
    - Kohonen neural networks

Dimension Reduction

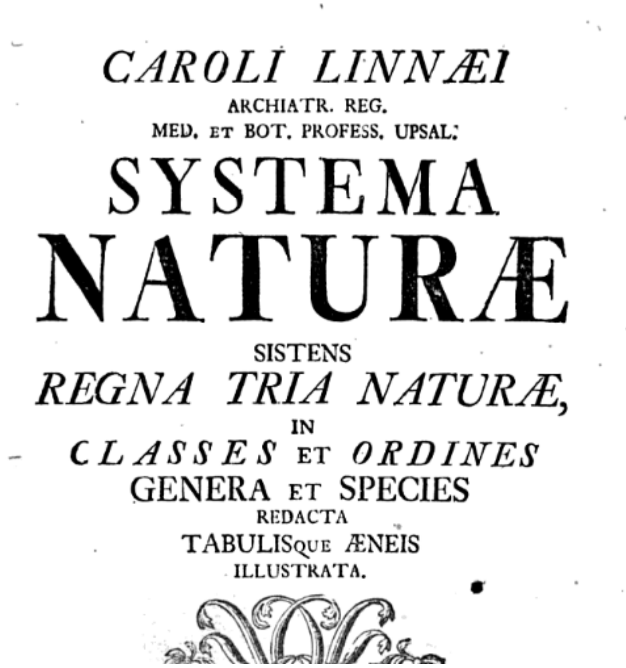
OCCURRENCE LIMIT	CSL	InitialindemnityReserve	InitialExpenseReserve	INITIALRESERVE
1,000,000	-	1,000	1,000	2,000
-	1,000,000	150,000	35,000	185,000
-	500,000	7,500	-	7,500
-	1,000,000	5,000	-	5,000
-	1,000,000	10,000	10,000	20,000
1,000,000	-	17,500	3,500	21,000
-	1,000,000	65,000	-	65,000
-	1,000,000	75,000	25,000	100,000
500,000	-	5,600	-	5,600
1,000,000	-	15,500	-	15,500



ICA 2014 CIA WASHINGTON DC

Unsupervised Learning – a historical example

- Carl von Linaeus – Classification of plants and Animals



CAROLI LINNÆI
ARCHIATR. REG.
MED. ET BOT. PROFESS. UPSAL.
SYSTEMA
NATURÆ
SISTENS
REGNA TRIA NATURÆ,
IN
CLASSES ET ORDINES
GENERA ET SPECIES
REDACTA
TABULISQUE ÆNEIS
ILLUSTRATA.

Classical Unsupervised Learning in P&C Insurance

- From Shaver “Revision of Rates Applicable to a Class of Property Insurance”, PCAS, 1957

ing the resulting factor to each rate involved in the particular classification. If, for example, the experience indicates a 5% increase for Class 029, construction-protection code 1 (Dwellings—Buildings only —frame protected,) it would be necessary to apply the 5% increase to the rates for the following Class 029 combinations:

Class of Bldg.	*Town Class*	*No. of Fam.*	*Occ. Class*	*Const.-Prot.*	*Rate*
Frame approved roof	1 to 4	1 to 2	029	1	.12
Frame approved roof	1 to 4	3 to 4	029	1	.14
Frame approved roof	5 and 6	1 to 2	029	1	.13
Frame approved roof	5 and 6	3 to 4	029	1	.15
Frame approved roof	7 and 8	1 to 2	029	1	.15
Frame approved roof	7 and 8	3 to 4	029	1	.17
Frame unapproved roof	1 to 4	1 to 2	029	1	.16
Frame unapproved roof	1 to 4	3 to 4	029	1	.18

ICA 2014 CIA
WASHINGTON DC

Data

- Inflation data from the BLS
- CAARP (California Auto Assigned Risk) data – Actual and Simulated
  - The original data contain exposure information (car counts, premium) and claim and loss information (Bodily Injury (BI) counts, BI ultimate losses, Property Damage (PD) claim counts, PD ultimate losses)
- Texas Closed Claim Data. Download from:
  - http://www.tdi.texas.gov/reports/report4.html
  - Data collected annually on closed liability claims that exceed a threshold (i.e., 10,000).
    - from a number of different casualty lines, such as general liability, professional liability, etc.
    - includes information on the characteristics of the claim such as report lag, injury type and cause of loss, as well as data on various financial values such as economic loss, legal expense and primary insurer's indemnity.

Simulated Automobile PIP Fraud Data

ICA 2014 CIA WASHINGTON DC

Software

- R Programming Language was used
  - Clustering, principal components and Factor Analysis libraries used
- All procedures can also be done in commonly available software such as SAS, SPSS, Statistica
- Simulated data programmed in R
- RStudio editor used
  - Code is available

Variable Reduction

- Classical Approaches
  - – Principal Components
  - – Factor Analysis

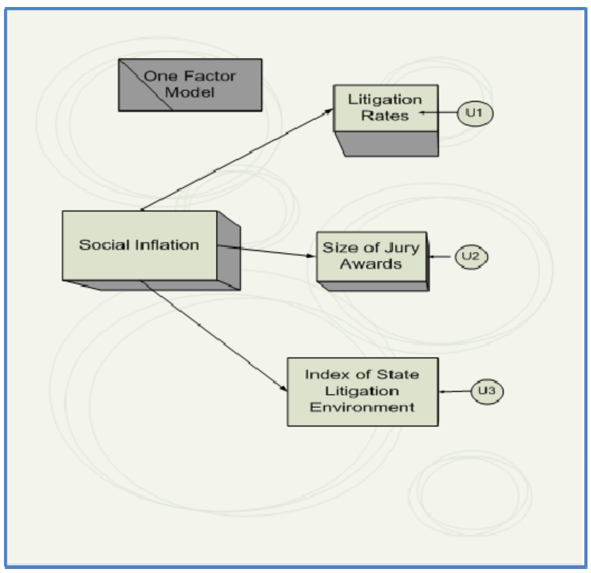
- Newer Approaches
  - – PRIDITS
  - – MDS and SVD
  - – Some kinds of neural networks

Factor analysis Model

- Views random variable as a combination of an unobserved factor and a unique random component
- Correlation matrices are important
  - Highly correlated variables have same underlying factor

$x_i = b_i F + u_i,\ x = \text{variable}, b = \text{loading}, F = \text{factor}, u = \text{unique component}$

Illustration: P&C Trends

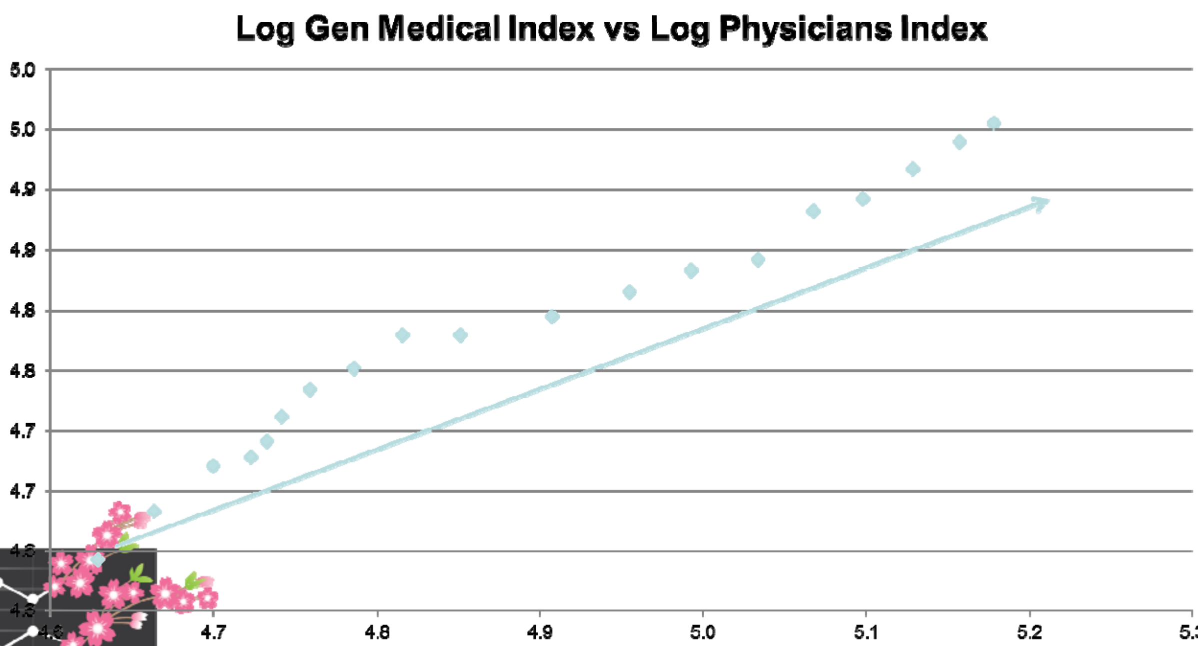


Principal Components Analysis

- No assumption about underlying causal factor
- Instead it posits that a set of (typically correlated) variables can be decomposed into components
- The "pattern" underlying the variables can then be reconstructed from a suitable weighting of the components

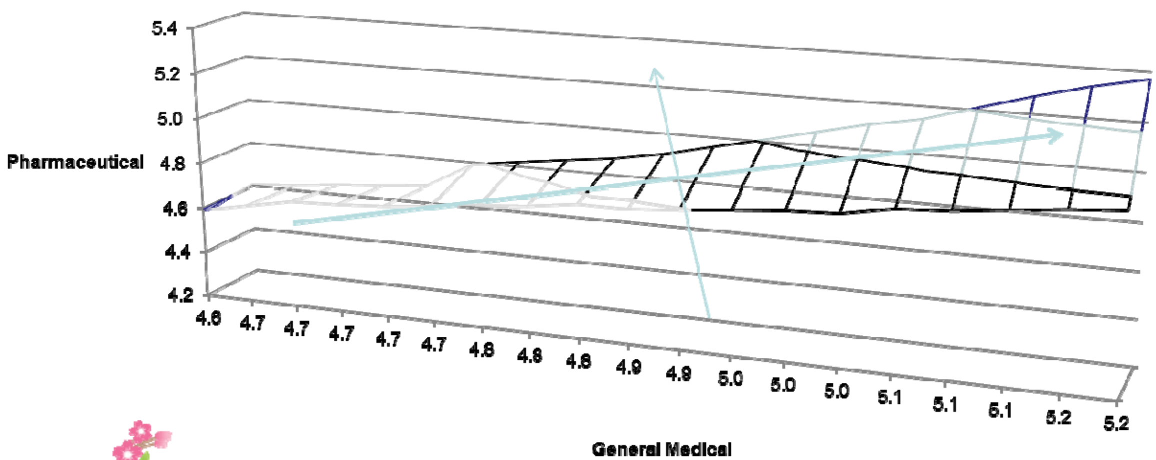
ICA 2014 CIA
WASHINGTON DC

Illustration: Medical CPI vs 2 Components of Medical Cost



ICA 2014 CIA
WASHINGTON DC

Another Example: 3 Medical Components



ICA 2014 CIA
WASHINGTON DC

Principal Components Uses Correlation or Covariance Matrix to Fit Components

	GenMedical	*Physicians*	*Pharma*	*HealthInsurance*	*CPI*	*Compensation*	*WC Severity*
GenMedical	1.000						
Physicians	0.980	1.000					
Pharma	0.988	0.986	1.000				
HealthInsurance	0.994	0.968	0.984	1.000			
CPI	0.990	0.993	0.990	0.985	1.000		
Compensation	0.972	0.988	0.980	0.973	0.993	1.000	
WC Severity	0.952	0.958	0.977	0.962	0.963	0.966	1.000

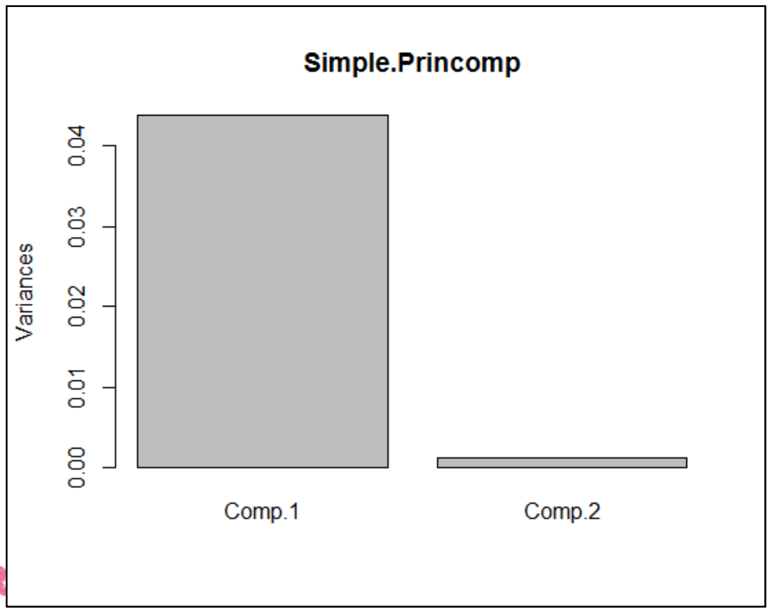
$$\Sigma = C^T \lambda C, \lambda = \text{eigenvalues}, C = \text{eigenvectors}$$

Using R to Find Principal Components

- MedIndices2<-data.frame(Indices$LnGeneralMed,Indices$LnPhysicians)
- Simple.Princomp<-princomp(MedIndices2,scores=TRUE)
  - princomp procedure gives us the “loadings” on each of the components.
  - The loadings help us understand the relationship of the original variables to the principal components.
  - Note that both variables are negatively related to the principal component.
- > Simple.Princomp$loadings
- Loadings:
- Comp.1 Comp.2
- Indices.LnGeneralMed -**0.880** **0.475**
- Indices.LnPhysicians **-0.475** **-0.880**

ICA 2014 CIA WASHINGTON DC

Eigenvalues of Principal Components



Similarity/Dissimilarity Matrices

- Two popular dissimilarity measures are Euclidian distance and Manhattan distance

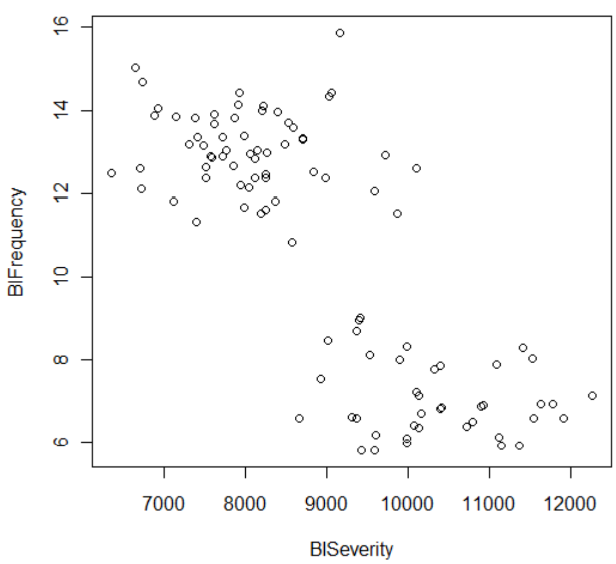
$$d_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2}$$

$$d_{ij} = \sum_{k=1}^{p} \left| x_{ik} - x_{jk} \right|$$

ICA 2014 CIA
WASHINGTON DC

Clustering Using Dissimilarity:

Try to group like zip codes together



K-Means Clustering

- iterative procedure is used to assign each record in the data to one of the k clusters
- iteration begins with the initial centers or mediods for k groups.
- often they are randomly selected from records
- uses a dissimilarity measure to assign records to a group and to iterate to a final grouping.

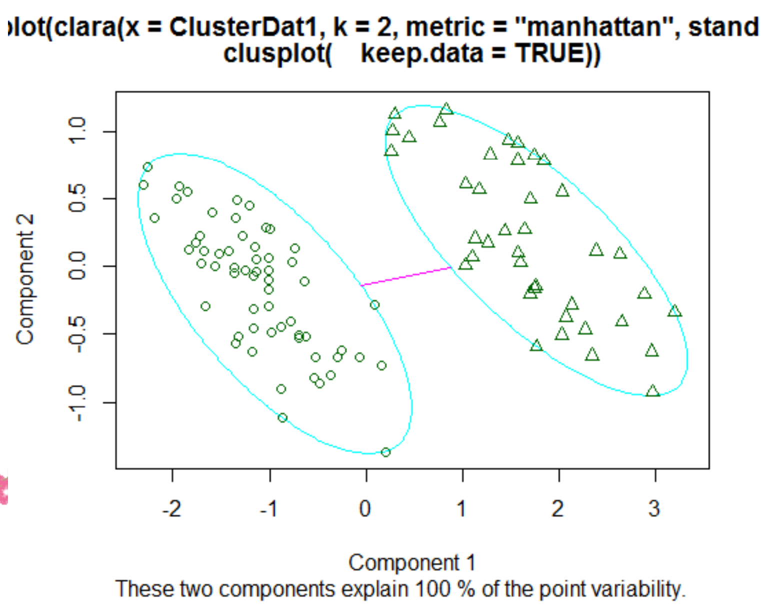
Automobile Example

- Group based on BI frequency, BI severity
- >BICluster1<-pam(ClusterDat1,2,metric="euclidean")
- >BICluster1<-clara(ClusterDat1,2,metric="euclidean")
- Data can be standardized

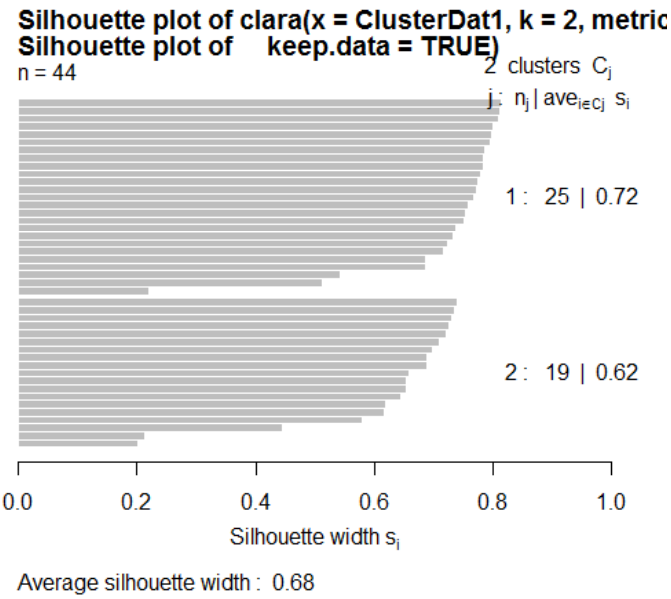
```
> BICluster1
Call:    clara(x = ClusterDat1, k = 2, metric = "euclidean")
Medoids:
     BIFrequency BISeverity
[1,]    11.39769   8202.802
[2,]    13.28089  10749.593
Objective function:     577.0351
Clustering vector:      int [1:100] 1 1 2 1 1 1 1 1 1 1 1 2 1 2 2 2 1 1
Cluster sizes:          63 37
```

Plot the Components

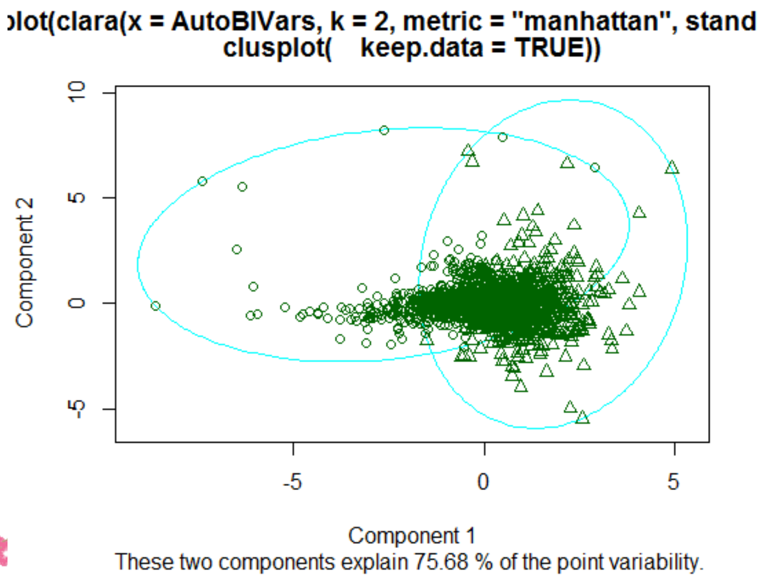
- plot(BICluster2)



Silhouette Plot



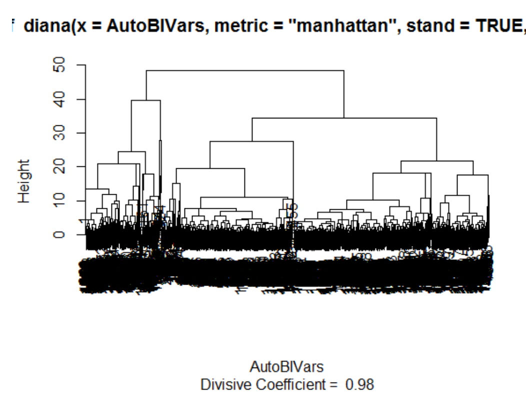
Clustering Real Data



Hierarchical Clustering

- Sequentially partitions the data
- Does not create a specific number of clusters
- Results presented in a graphic that looks like an inverted tree
- Divisive or

agglomerative



Common Insurance Applications of Unsupervised Learning

- Cluster based:
  - Find best territorial grouping
  - Find outlier records
  - Text mining
- Factor/Principal Components based
  - Fraud Analysis
  - Text mining
  - Reduce dimensionality of dataset to be used in predictive modeling
  - Understanding drivers of inflation/trend as in Masterson's indices

ICA 2014 CIA WASHINGTON DC

Coming Attractions

- In volume 2 of the predictive modeling book there will be a chapter on advanced unsupervised learning
- The chapter will cover the following methods
  - the PRIDIT method
  - Random forest clustering
- other