

# Introduction and overview

Stats 503

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# Learning from Data

- **Fact:** The amount of data and information collected and stored is constantly increasing, due to advances in data collection, computerization of many aspects of life and breakthroughs in storage technology.
- **Consequence:** Statistical problems have increased both in size and complexity.
- **The data analyst's job:** make sense of all these data! Identify patterns and trends, uncover "interesting" relationships among the variables and/or the observations, predict future behavior.

- Technology helps

- ▶ Faster computers  $\Rightarrow$  more flexible and thus more powerful techniques  $\Rightarrow$  fewer modeling assumptions
- ▶ New graphic capabilities (a picture is worth a thousand words...)

- But not always: Faster computers do not solve all problems

- ▶ Some problems are inherently computationally intractable
- ▶ “Easy” black-box data analysis can lead to a lot of misuse and misunderstanding
- ▶ Flexible models can overfit (too much of a good thing)
- ▶ Understanding underlying assumptions and interpreting conclusions correctly remains as important as ever

# What is “multivariate analysis”?

- The name historically refers to a particular set of techniques
- **Multivariate data:**  $X = \{X_1, \dots, X_p\}$ , the variables  $X_1, \dots, X_p$  can be quantitative, ordinal, categorical, or a mix of all of the above.
- This is in contrast to **univariate data**, where there is only one variable  $X$
- **Response:** an additional variable  $Y$  (scalar- or vector-valued) that depends on  $X$ .
- When a response is present, it is usually of interest to **understand the relationship** between  $Y$  and  $X$  and/or **predict**  $Y$  from  $X$ .

# Supervised vs unsupervised learning

**Unsupervised learning:** only  $X$  is observed

- Goal: understand/summarize/visualize the relationships between the variables in  $X$
- Examples: principal components analysis, clustering

**Supervised learning:**  $X$  and  $Y$  are observed

- Goal: understand/summarize/visualize the relationships between  $X$  and  $Y$ , learn to **predict**  $Y$  from  $X$
- Examples: regression (continuous  $Y$ ), classification (categorical  $Y$ ), ANOVA (categorical  $X$ , continuous  $Y$ )

# This course covers

- Unsupervised techniques
  - ▶ Principal components analysis
  - ▶ Dimension reduction
  - ▶ Clustering
- Supervised techniques
  - ▶ Model-based classification (discriminant analysis, logistic regression)
  - ▶ Model-free classification (trees, support vector machines, ensemble methods)
- Categorical data analysis (briefly)
- Visualization as appropriate

# Some important issues we'll talk about

- Underlying probability models and statistical inference – where possible
- The role of the multivariate normal distribution
- Computational inference: bootstrap, permutation tests
- Algorithmic considerations, where possible: do the methods scale to “Big Data”?
- Interpretation: what the analysis does and does not tell us

## Example: U.S. cities crime data

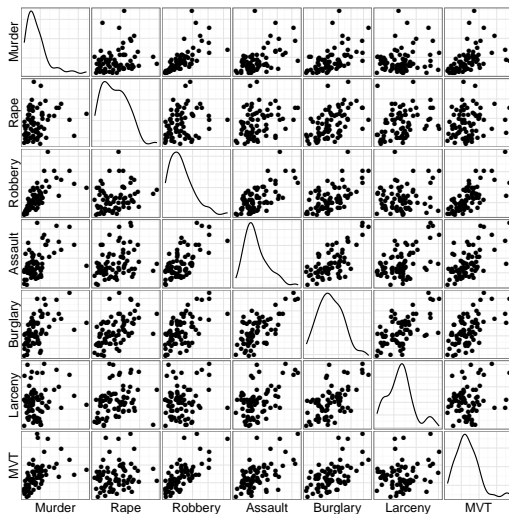
The data give crime rates per 100,000 people for 73 large U.S. cities.  
The variables are:

- 1 Murder
- 2 Rape
- 3 Robbery
- 4 Assault
- 5 Burglary
- 6 Larceny
- 7 Motor Vehicle Thefts (MVT)

Goal: summarize, visualize – **unsupervised analysis**



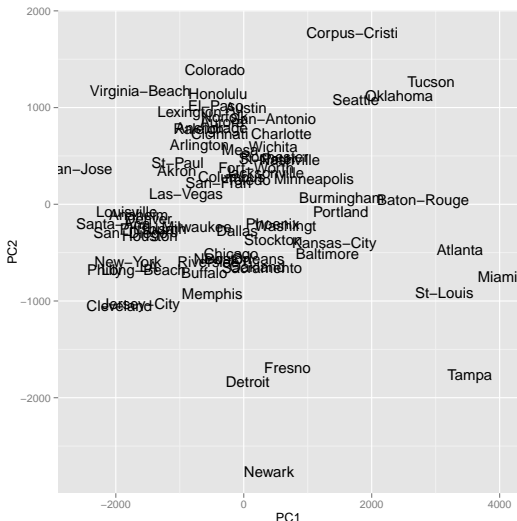
# Scatterplot matrix of U.S. cities crime data



Scatterplots of many variables can be hard to read.

## A 2-d representation of U.S. cities crime data

Can combine the variables and produce a safety "index": a principal components analysis plot



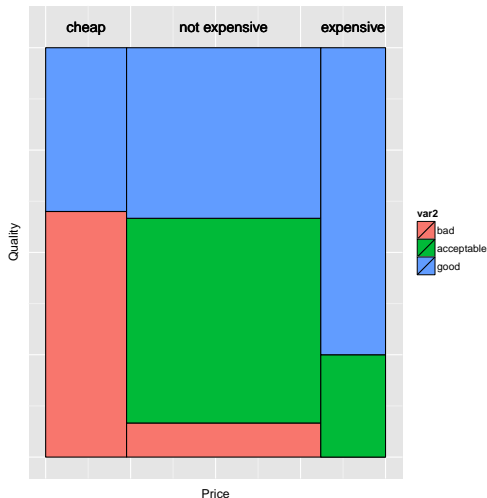
## Example: sleeping bags (categorical data)

- The variables are price, fiber and quality for 21 sleeping bags
- All variables are categorical; cannot do a scatterplot.
- Goal: understand something about the relationship between price and quality of available sleeping bags – **unsupervised analysis**

	cheap	not expensive	expensive	down fibers	synthetic fibers	good	acceptable	bad
Brand	Price			Fiber		Quality		
One Kilo Bag	1	0	0	0	1	1	0	0
Sund	1	0	0	0	1	0	0	1
Kompakt Basic	1	0	0	0	1	1	0	0
Finmark Tour	1	0	0	0	1	0	0	1
Interlight Lyx	1	0	0	0	1	0	0	1
Kompakt	0	1	0	0	1	0	1	0
Touch the Cloud	0	1	0	0	1	0	1	0
Cat's Meow	0	1	0	0	1	1	0	0
Igloo Super	0	1	0	0	1	0	0	1
Donna	0	1	0	0	1	0	1	0
Tyin	0	1	0	0	1	0	1	0
Travellers Dream	0	1	0	1	0	1	0	0
Yeti Light	0	1	0	1	0	1	0	0
Climber	0	1	0	1	0	0	1	0
Viking	0	1	0	1	0	1	0	0
Eiger	0	0	1	1	0	0	1	0
Climber light	0	1	0	1	0	1	0	0
Cobra	0	0	1	1	0	1	0	0
Cobra Comfort	0	1	0	1	0	0	1	0
Foxfire	0	0	1	1	0	1	0	0
Mont Blanc	0	0	1	1	0	1	0	0

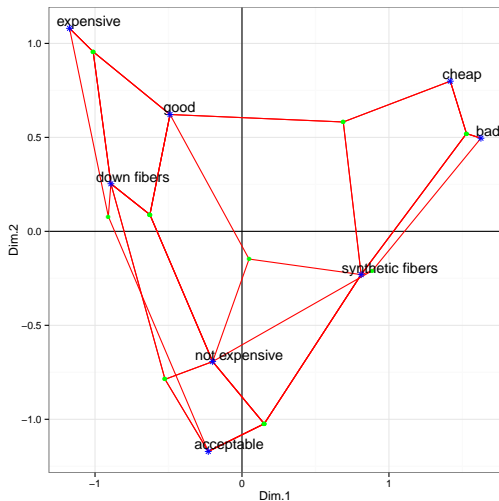
# How do we visualize the sleeping bag data?

A panel plot for price and quality variables



# How do we visualize the sleeping bag data?

A plot from multiple correspondence analysis

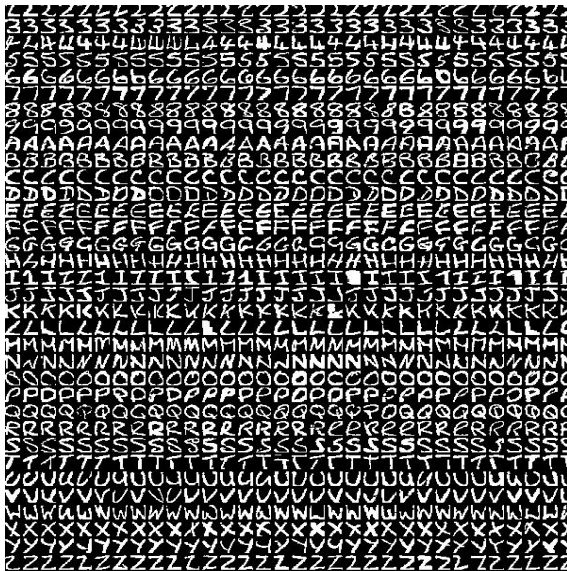


green points represent the sleeping bags

## Some findings off the sleeping bags picture

- there are good, expensive, down-filled sleeping bags
- there are bad, cheap, synthetic-filled sleeping bags
- there are some expensive ones of acceptable quality and some cheap ones of good quality
- there are no bad expensive sleeping bags
- all expensive bags are filled with down

# Example: optical character recognition





## Example: handwritten letters and digits dataset

- Data: images of single handwritten letters and digits
- Each image is  $20 \times 16$  pixels, with pixel intensities from 0 to 255. This vector of 320 quantitative variables is  $X$  (features).
- Response/outcome: the identity of each image  $\{A, B, \dots, Z, 0, 1, \dots, 9\}$ . This categorical variable with 36 levels is  $Y$ .
- Goal: build an algorithm (classifier, learner) to predict the identity  $Y$  from pixel values  $X$  using a **training dataset** of labelled images – **supervised analysis**
- A good algorithm should predict well not only on training data, but also on **test data** (pairs of  $X$  and  $Y$  that have not been used to build/train the algorithm).

## Example: DNA expression data

- DNA is the basic material that makes up human chromosomes.
- DNA microarrays and other gene chips are new technologies measuring quantitative expression of thousands of genes simultaneously from a single sample of cells.
- Here is a tiny sample of DNA expression data: 3 genes (variables) and 4 samples (observations).

21652	3.2025	1.6547	3.2779	1.0060
25725	0.0681	0.0710	0.1160	0.1906
22260	0.1243	0.0520	0.1014	0.1035

- The full dataset has approximately 7000 genes (rows) and around 100 samples (columns), where the samples correspond to different cancer tumors.

# What can one learn from expression data?

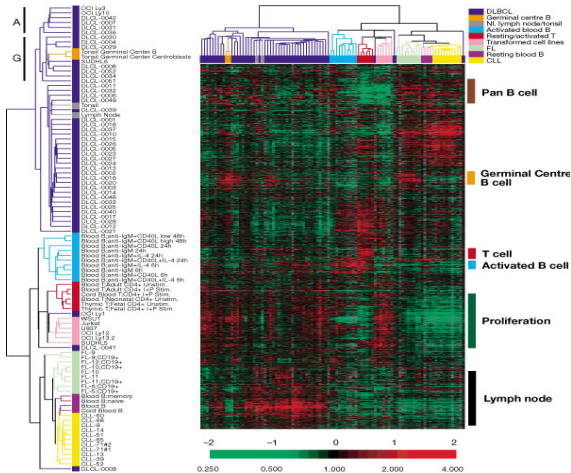
## Typical unsupervised questions (Hastie et al., 2001):

- Which samples are most similar to each other, in terms of their expression profiles across genes? (clustering)
- Which genes are most similar to each other, in terms of their expression profiles across samples? (clustering)
- Do "interesting" patterns exist between subsets of genes and samples (e.g. very high/low expression levels)?

## Typical supervised questions:

- Can type of tumor be predicted from gene expression levels?
- Which genes are most predictive for which tumors?

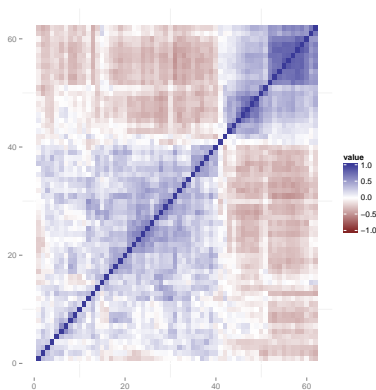
# Heat map of DNA microarray data after clustering



Picture taken from Alizadeh et. al (2000), *Nature*

## Another visualization example: the correlation matrix

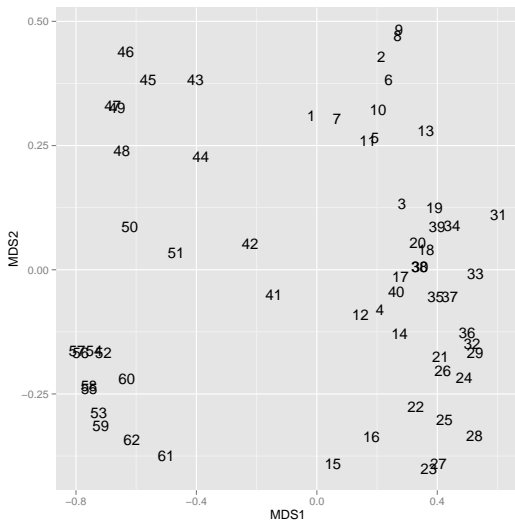
- $62 \times 62$  correlation matrix of 62 lymphoma samples, computed from gene expression measurements of 4000+ genes, from the previous example of Alizadeh et. al (2000).
- How are these lymphoma samples related to each other?
- Too many numbers to examine – visualize this matrix via a heatmap:



# Distance-based representation

- How do we see groups in the tumors more clearly?
- Another look: plot samples as points in the plane, keeping their distances as close as possible to those implied by correlations (small distance = high correlation)

# A correlation distance-based map of the tumors



# Good quotes to keep in mind

*Essentially, all models are wrong, but some are useful.*

– George Box (Box and Draper, 1987).

*There is no true interpretation of anything; interpretation is a vehicle in the service of human comprehension. The value of interpretation is in enabling others to fruitfully think about an idea.*

– Andreas Buja (quote taken from Hastie et al., 2001))



# Practice

- Join up with one or two neighbors
- Brainstorm as a group and come up with an example of multivariate data that you'd be interested in analyzing
- Formulate one specific question about your example and decide whether it is a supervised or an unsupervised question