

# Applied Analytics and Predictive Modeling

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Lecture-3

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# Today's agenda

- Data Preprocessing
- Dimensionality Reduction
- Including class exercises
- Case study-1

# Overview

# What is data?

- Collection of **data objects** and their **attributes**
- According to Tan et al.,
- An **attribute** is a property or characteristic of an object
  - Also known as variable, field, characteristic, dimension, or feature
- A collection of attributes describe an **object**
  - Also known as tuple, record, point, case, sample, etc.

**Attributes**

<i>Tid</i>	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

**Objects**

# More views of data

- Data may have parts
- The different parts of data may have relationships
- More generally, data may have structure
- Data can be incomplete

# Attribute values

- Attribute values are numbers or symbols assigned to an attribute for a particular object
- Distinction between attributes and attribute values
  - Same attribute can be mapped to different attribute values
    - Example: Height can be measured in feet or meters
  - Different attributes can be mapped to the same set of values
    - Example: Attribute values for ID and age are integers
    - But properties of attribute values can be different

# Types of Attributes

- **Nominal**
  - Examples: ID numbers, zip codes, eye color
- **Ordinal**
  - Examples: Rankings (expertise level on a scale of 1-10), grades, height {tall, medium, short}
- **Interval**
  - Examples: Calendar dates, temperature in Celsius or Fahrenheit
- **Ratio**
  - Examples: Temperature in Kelvin, length, time, counts

# Discrete and Continuous attributes

- Discrete Attribute:
  - Has only a finite or countably infinite set of values
  - Examples: zip codes, counts, or the set of words in a collection of documents
  - Often represented as integer variables.
  - Note: binary attributes are a special case of discrete attributes
- Continuous Attribute:
  - Has real numbers as attribute values
  - Examples: temperature, height, or weight.
  - Practically, real values can only be measured and represented using a finite number of digits.
  - Continuous attributes are typically represented as floating-point variables.



# Types of datasets

- Record
  - Data Matrix
  - Document Data
  - Transaction Data
- Graph
  - World Wide Web
  - Molecular Structures
- Ordered
  - Spatial Data
  - Temporal Data
  - Sequential Data
  - Genetic Sequence Data

# Important characteristics of data

- Dimensionality (number of attributes)
  - High dimensional data brings a number of challenges
- Sparsity
  - Only presence counts
- Resolution
  - Patterns depend on the scale
- Size
  - Type of analysis may depend on size of data

# Record data

- Data that consists of a collection of records, each of which consists of a fixed set of attributes

<i>Tid</i>	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
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10	No	Single	90K	Yes

# Document data

- Each document becomes a 'term' vector
  - Each term is a component (attribute) of the vector
  - The value of each component is the number of times the corresponding term occurs in the document.

	team	coach	play	ball	score	game	win	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

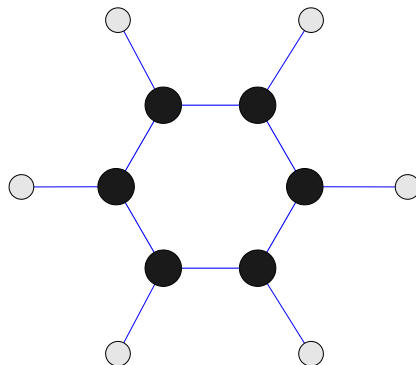
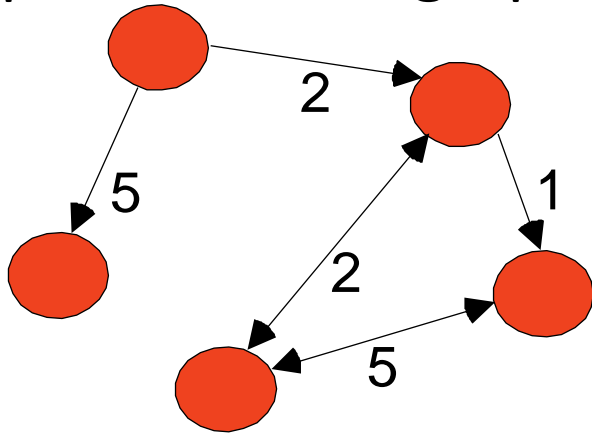
# Transaction data

- A special type of record data, where
  - Each record (transaction) involves a set of items.
  - For example, consider a grocery store. The set of products purchased by a customer during one shopping trip constitute a transaction, while the individual products that were purchased are the items.

<i><b>TID</b></i>	<i><b>Items</b></i>
<b>1</b>	<b>Bread, Coke, Milk</b>
<b>2</b>	<b>Beer, Bread</b>
<b>3</b>	<b>Beer, Coke, Diaper, Milk</b>
<b>4</b>	<b>Beer, Bread, Diaper, Milk</b>
<b>5</b>	<b>Coke, Diaper, Milk</b>

# Graph Data

- Examples: Generic graph, a molecule, and webpages



Benzene Molecule: C<sub>6</sub>H<sub>6</sub>

## Useful Links:

- [Bibliography](#)
- Other Useful Web sites
  - [ACM SIGKDD](#)
  - [KDnuggets](#)
  - [The Data Mine](#)

## Knowledge Discovery and Data Mining Bibliography

(Gets updated frequently, so visit often!)

- [Books](#)
- [General Data Mining](#)

## Book References in Data Mining and Knowledge Discovery

Usama Fayyad, Gregory Piatetsky-Shapiro, Padhraic Smyth, and Ramasamy uthurasamy, "Advances in Knowledge Discovery and Data Mining", AAAI Press/the MIT Press, 1996.

J. Ross Quinlan, "C4.5: Programs for Machine Learning", Morgan Kaufmann Publishers, 1993.  
Michael Berry and Gordon Linoff, "Data Mining Techniques (For Marketing, Sales, and Customer Support)", John Wiley & Sons, 1997.

## General Data Mining

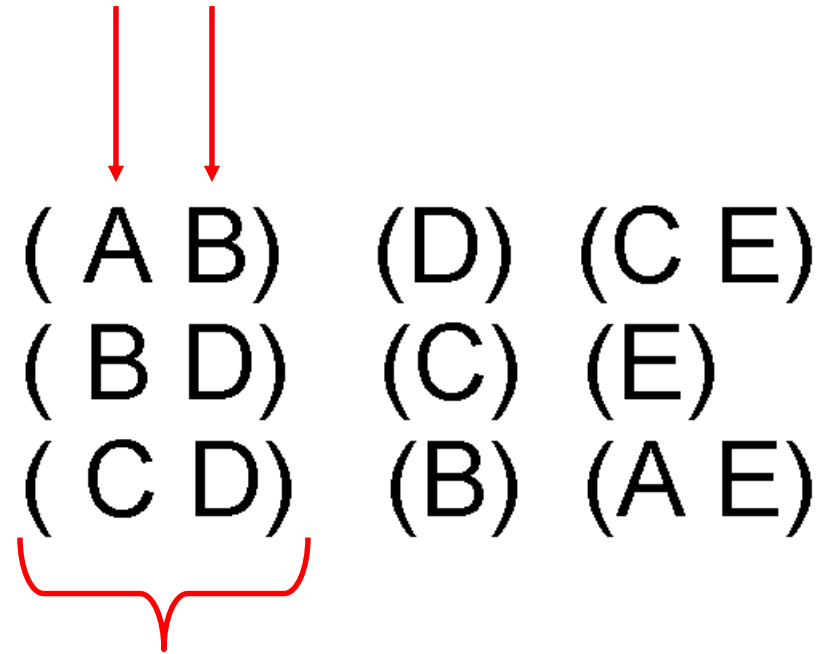
Usama Fayyad, "Mining Databases: Towards Algorithms for Knowledge Discovery", Bulletin of the IEEE Computer Society Technical Committee on data Engineering, vol. 21, no. 1, March 1998.

Christopher Matheus, Philip Chan, and Gregory Piatetsky-Shapiro, "Systems for knowledge Discovery in databases", IEEE Transactions on Knowledge and Data Engineering, 5(6):903-913, December 1993.

# Ordered Data

- Sequences of transactions

**Items/Events**



**An element of  
the sequence**

# Ordered Data

- Genomic sequence data

**GGTTCCGCCTTCAGCCCCGCGCC  
CGCAGGGCCCCGCCCCGCGCCGTC  
GAGAAGGGCCCCGCCTGGCGGGCG  
GGGGGAGGCGGGGCCGCCCGAGC  
CCAACCGAGTCCGACCAGGTGCC  
CCCTCTGCTCGGCCTAGACCTGA  
GCTCATTAGGCGGCAGCGGACAG  
GCCAAGTAGAACACGCGAAGCGC  
TGGGCTGCCTGCTGCGACCAGGG**

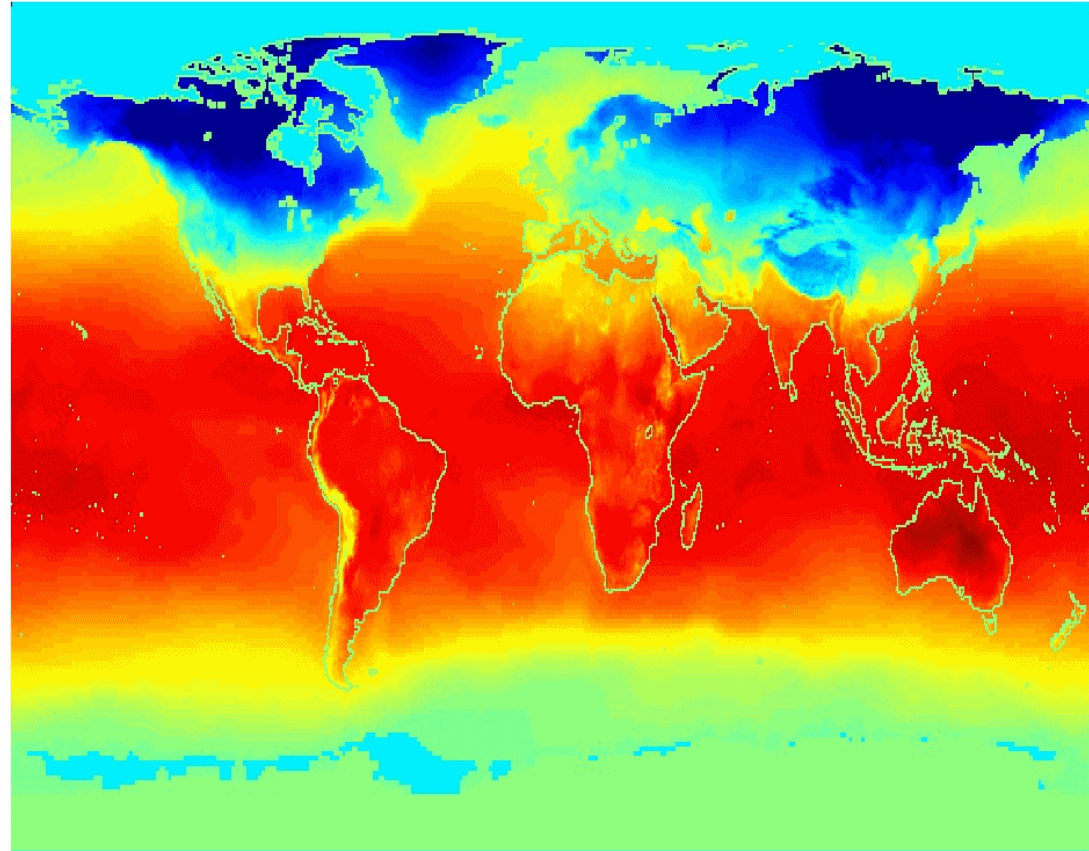


# Ordered Data

- Spatio-temporal data

**Average Monthly  
Temperature of  
land and ocean**

Jan



# Examples

- ID numbers
  - Nominal, ordinal, or interval?
- Number of cylinders in an automobile engine
  - Nominal, ordinal, or ratio?
- Biased Scale
  - Interval or Ratio

# Data Preprocessing

- Aggregation
- Sampling
- Dimensionality Reduction
- Feature subset selection
- Feature creation
- Discretization and Binarization
- Attribute Transformation

# Aggregation

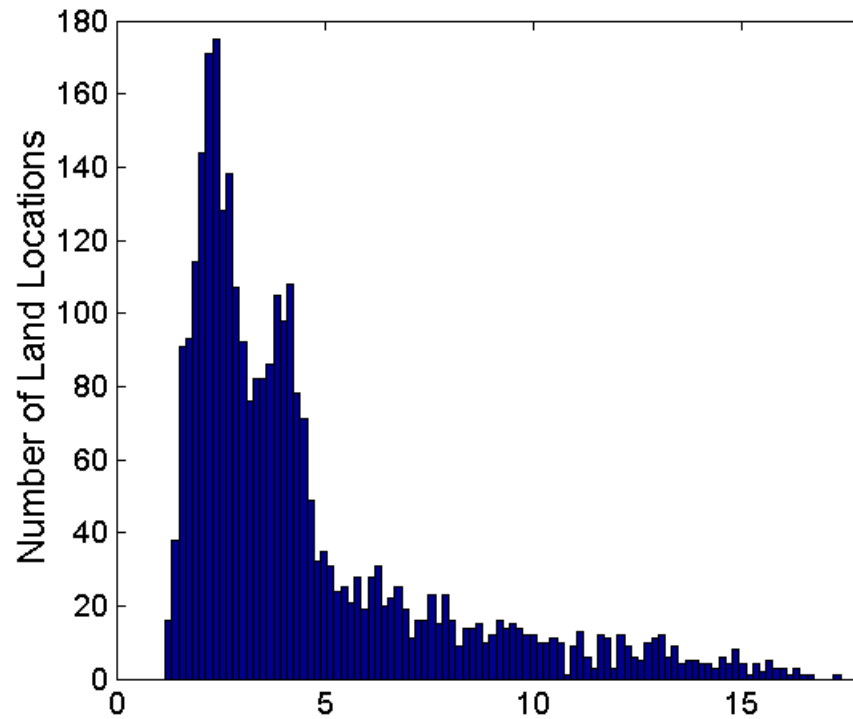
- Combining two or more attributes (or objects) into a single attribute (or object)
- Purpose
  - Data reduction
    - Reduce the number of attributes or objects
  - Change of scale
    - Cities aggregated into regions, states, countries, etc.
    - Days aggregated into weeks, months, or years
  - More “stable” data
    - Aggregated data tends to have less variability

# Example: Precipitation in Australia

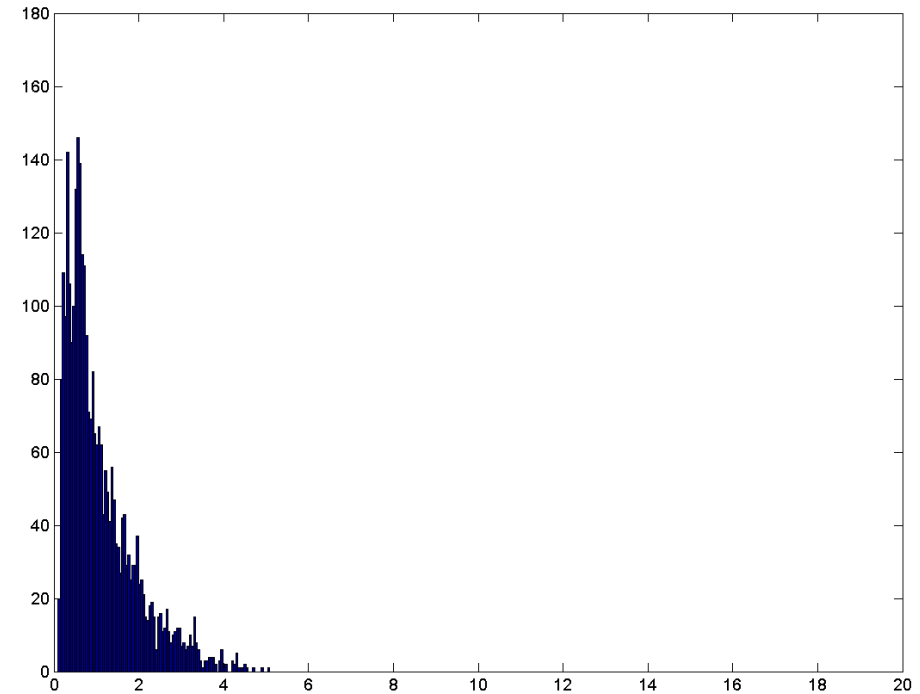
- This example is based on precipitation in Australia from the period 1982 to 1993.
- The next slide shows
  - A histogram for the standard deviation of average monthly precipitation for 3,030  $0.5^\circ$  by  $0.5^\circ$  grid cells in Australia, and
  - A histogram for the standard deviation of the average yearly precipitation for the same locations.
- The average yearly precipitation has less variability than the average monthly precipitation.
- All precipitation measurements (and their standard deviations) are in centimeters.

# Example: Precipitation in Australia..

- Variation of precipitation in Australia



**Standard Deviation of Average  
Monthly Precipitation**



**Standard Deviation of  
Average Yearly Precipitation**

# Sampling

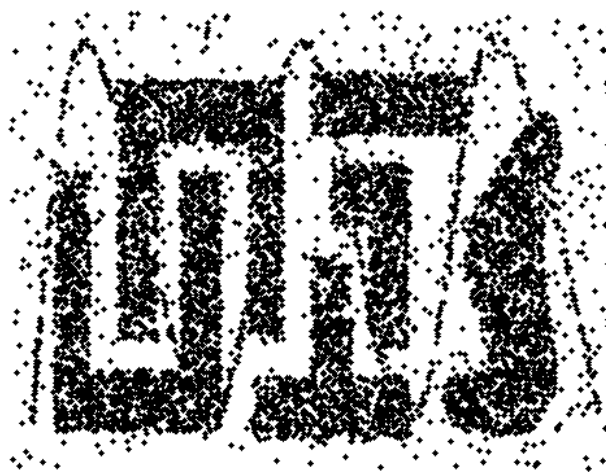
- Sampling is the main technique employed for data reduction.
  - It is often used for both the preliminary investigation of the data and the final data analysis.
- Statisticians often sample because **obtaining** the entire set of data of interest is too expensive or time consuming.
- Sampling is typically used in data mining because **processing** the entire set of data of interest is too expensive or time consuming.

# Sampling

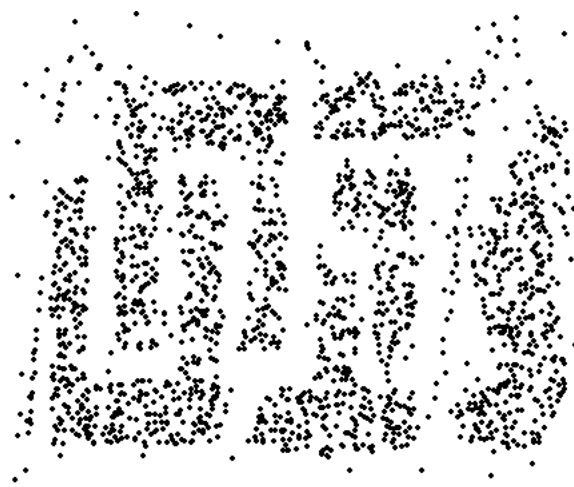
- The key principle for effective sampling is the following:
  - Using a sample will work almost as well as using the entire data set, if the sample is **representative**
  - A sample is **representative** if it has approximately the same properties (of interest) as the original set of data



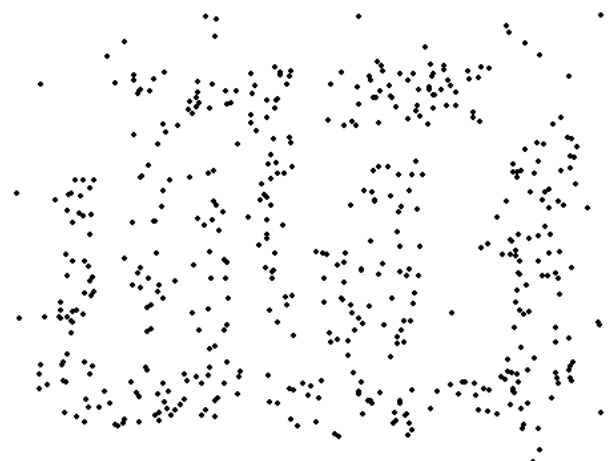
# Sample size



8000 points



2000 Points



500 Points

# Types of Sampling

- Simple Random Sampling
  - There is an equal probability of selecting any particular item
  - Sampling without replacement
    - As each item is selected, it is removed from the population
  - Sampling with replacement
    - Objects are not removed from the population as they are selected for the sample.
    - In sampling with replacement, the same object can be picked up more than once
- Stratified sampling
  - Split the data into several partitions; then draw random samples from each partition

# Curse of dimensionality

When dimensionality increases, data becomes increasingly sparse in the space that it occupies

# Dimensionality Reduction

- Purpose:
  - Avoid curse of dimensionality
  - Reduce amount of time and memory required by data mining algorithms
  - Allow data to be more easily visualized
  - May help to eliminate irrelevant features or reduce noise
- Techniques
  - Principal Components Analysis (PCA)
  - Singular Value Decomposition
  - Others: supervised and non-linear techniques

# Feature subset Selection

- Another way to reduce dimensionality of data
- Redundant features
  - Duplicate much or all of the information contained in one or more other attributes
  - Example: purchase price of a product and the amount of sales tax paid
- Irrelevant features
  - Contain no information that is useful for the data mining task at hand
  - Example: students' ID is often irrelevant to the task of predicting students' GPA
- Many techniques developed, especially for classification

# Feature Creation

- Create new attributes that can capture the important information in a data set much more efficiently than the original attributes
- Three general methodologies:
  - Feature extraction
    - Example: extracting edges from images
  - Feature construction
    - Example: dividing mass by volume to get density
  - Mapping data to new space
    - Example: Fourier and wavelet analysis

# Discretization

- **Discretization** is the process of converting a continuous attribute into an ordinal attribute
  - A potentially infinite number of values are mapped into a small number of categories
  - Discretization is commonly used in classification
  - Many classification algorithms work best if both the independent and dependent variables have only a few values

# Binarization

- Binarization maps a continuous or categorical attribute into one or more binary variables
- Typically used for association analysis
- Often convert a continuous attribute to a categorical attribute and then convert a categorical attribute to a set of binary attributes
  - Association analysis needs asymmetric binary attributes
  - Examples: eye color and height measured as {low, medium, high}



# Attribute Transformation

- An **attribute transform** is a function that maps the entire set of values of a given attribute to a new set of replacement values such that each old value can be identified with one of the new values
  - Simple functions:  $x^k$ ,  $\log(x)$ ,  $e^x$ ,  $|x|$
  - **Normalization**
    - Refers to various techniques to adjust to differences among attributes in terms of frequency of occurrence, mean, variance, range
    - Take out unwanted, common signal, e.g., seasonality
  - In statistics, **standardization** refers to subtracting off the means and dividing by the standard deviation

# Exercises-1

# Principal Component Analysis

Dimensionality Reduction

# Eigenvalues and Eigenvectors

- The eigenvector is a vector whose direction will not be affected by a linear transformation.
- Hence eigenvectors represents the direction of largest variance of data while the eigenvalue decides the magnitude of this variance in those directions.

# Computing eigenvalues and eigenvectors

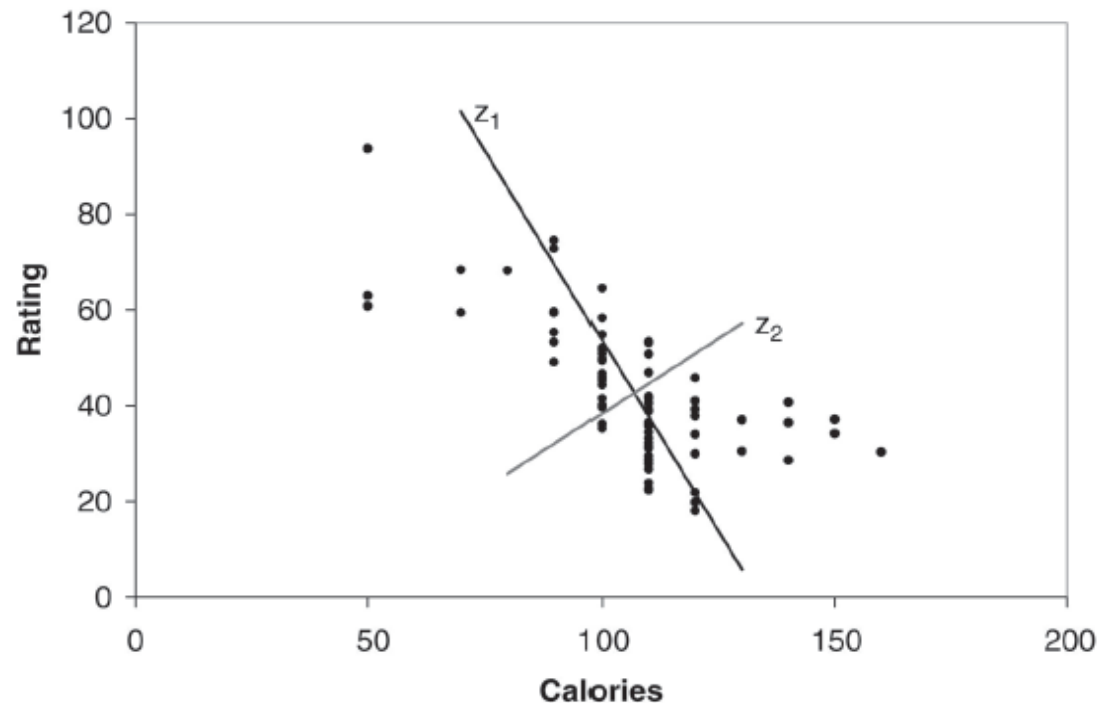
- Let  $A$  be a linear transformation represented by a matrix  $A$ 
  - If there is a vector  $X \in \mathbb{R}^n \neq 0$  such that  $AX = \lambda X$

# LDA

- Step-1: Standardize the data
  - To normalize the variances of data attributes
  - Avoids biased results
  - For any attribute, one way to do is to subtract the mean and divide by standard deviation
- Step-2: Covariance matrix computation
  - How are the attributes related to each other
  - Matrix is symmetric with diagonal values are variances
- Step-3: Compute Eigenvalues and Eigenvectors (that are principal components)
  - principal components represent the directions of the data that explain a **maximal amount of variance**
  - 10-dimensional data gives you 10 principal components
  - 1<sup>st</sup> component has the maximum information followed by 2<sup>nd</sup> component and so on.

# Using linear combinations to redistribute the variability

- $Z_1$  and  $Z_2$  are two linear combinations
- $Z_1$  has the highest variation or spread of values
- $Z_2$  has the lowest variation



# Exercises-2



# Case Study-1