Recap

- (Ch 12) Clustering
  - The curse of dimensionality
  - Multivariate normal distribution
  - The clustering problem
  - k-means algorithm

Today

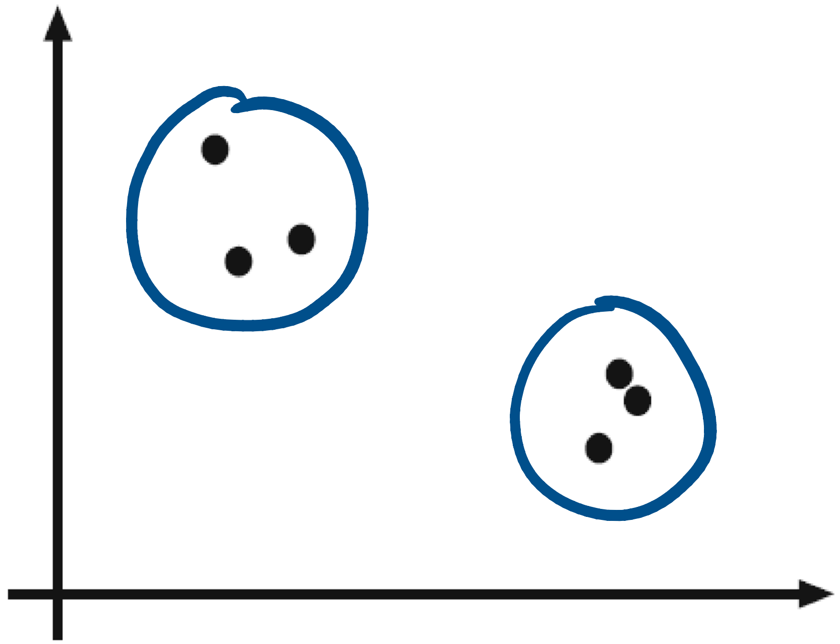
- (Ch 12) Clustering
  - k-means algorithm
  - Vector quantization

The clustering problem

- Given a dataset $\{\mathbf{x}\}$, separate the data items into clusters so that
  - Items within a cluster are close to each other
  - Items in different clusters are far from each other

- There are two problems to solve
  - Determine the number of clusters
  - Assign each item to a cluster

- Note that we are taking unlabeled data and assigning a class label to each item

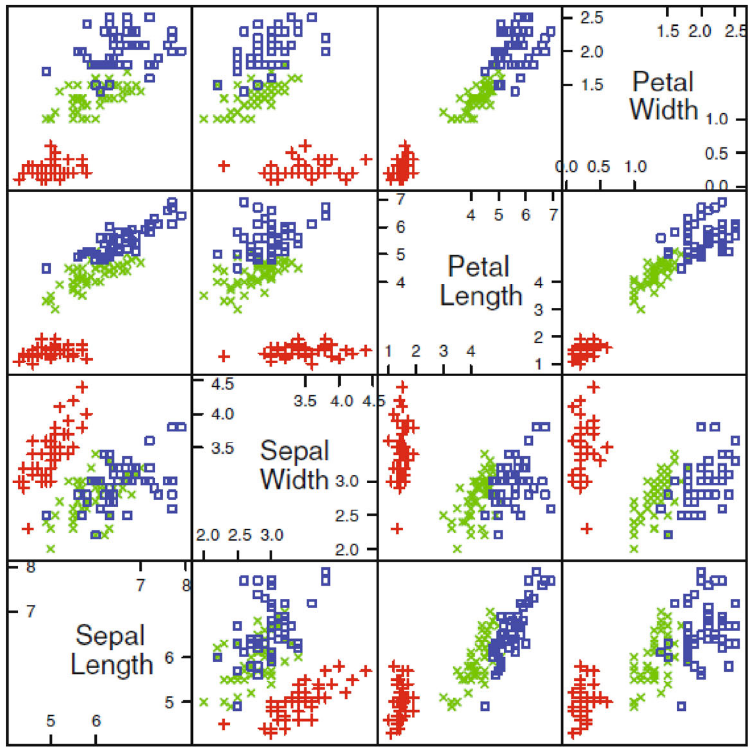


k-means clustering

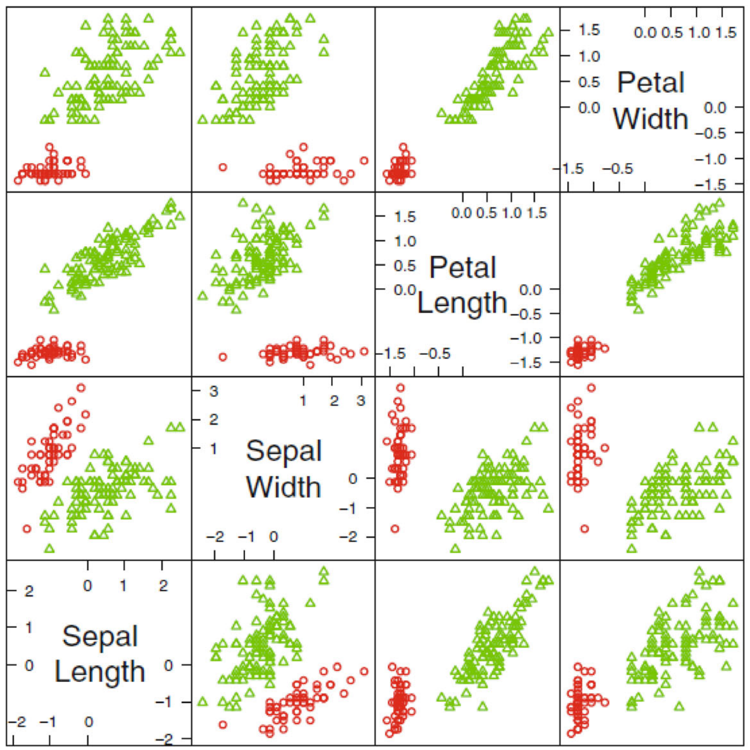
- Pick a value for k, which is the number of clusters
- Select k random cluster centers
- Iterate the following two steps until convergence
  - Assign each data item to the nearest cluster center
  - Update each cluster center as the mean of the items assigned to its cluster

k-means clustering result: iris example

true labels

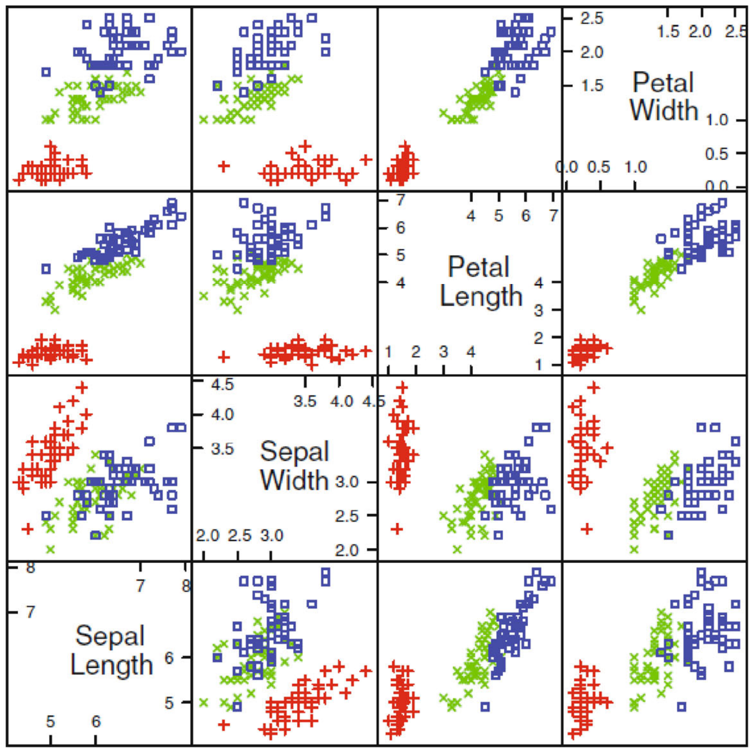


k-means with $k = 2$ clusters

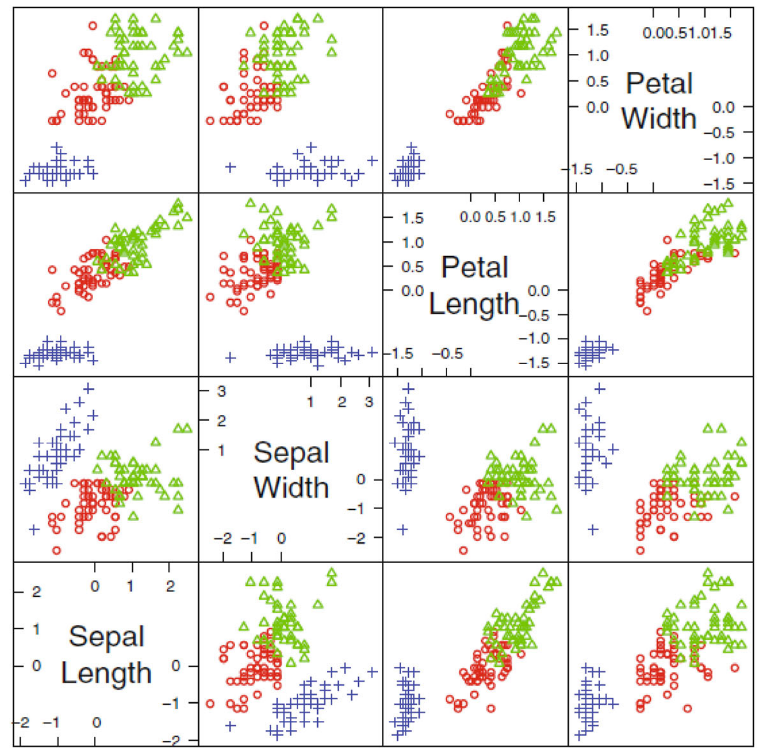


k-means clustering result: iris example

true labels



k-means with $k = 3$ clusters



Groceries in Portugal example

- The dataset consists of the annual grocery spending of 440 customers

  http://archive.ics.uci.edu/ml/datasets/Wholesale+customers

- Each customer's spending is recorded in 6 categories:

  fresh food, milk, grocery, frozen, detergents/paper, delicatessen

- Each customer is labeled by
  - Channel (Channel 1, Channel 2)
  - Region (Region 1, Region 2, Region 3)

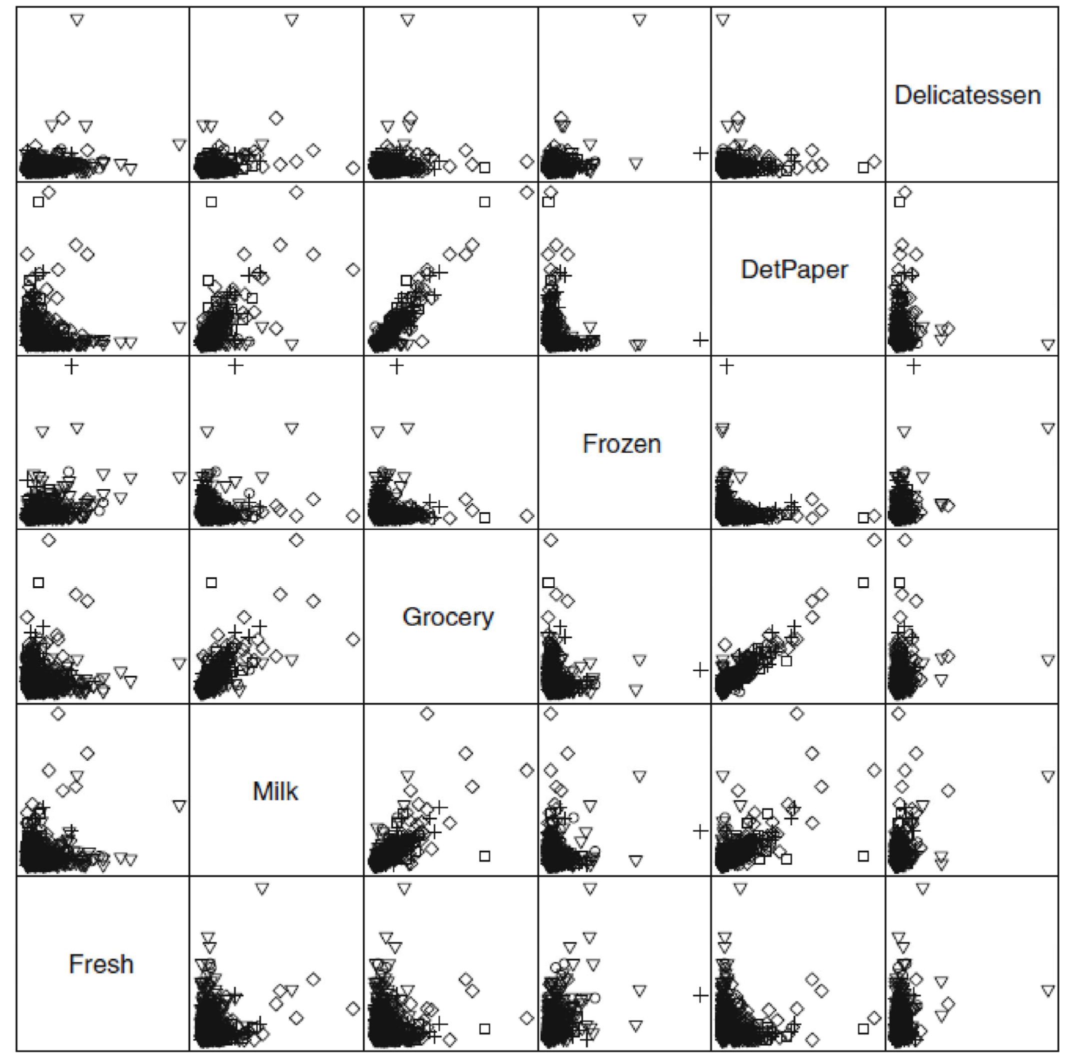
  for a total of 6 channel/region labels

Visualizing the data: groceries example

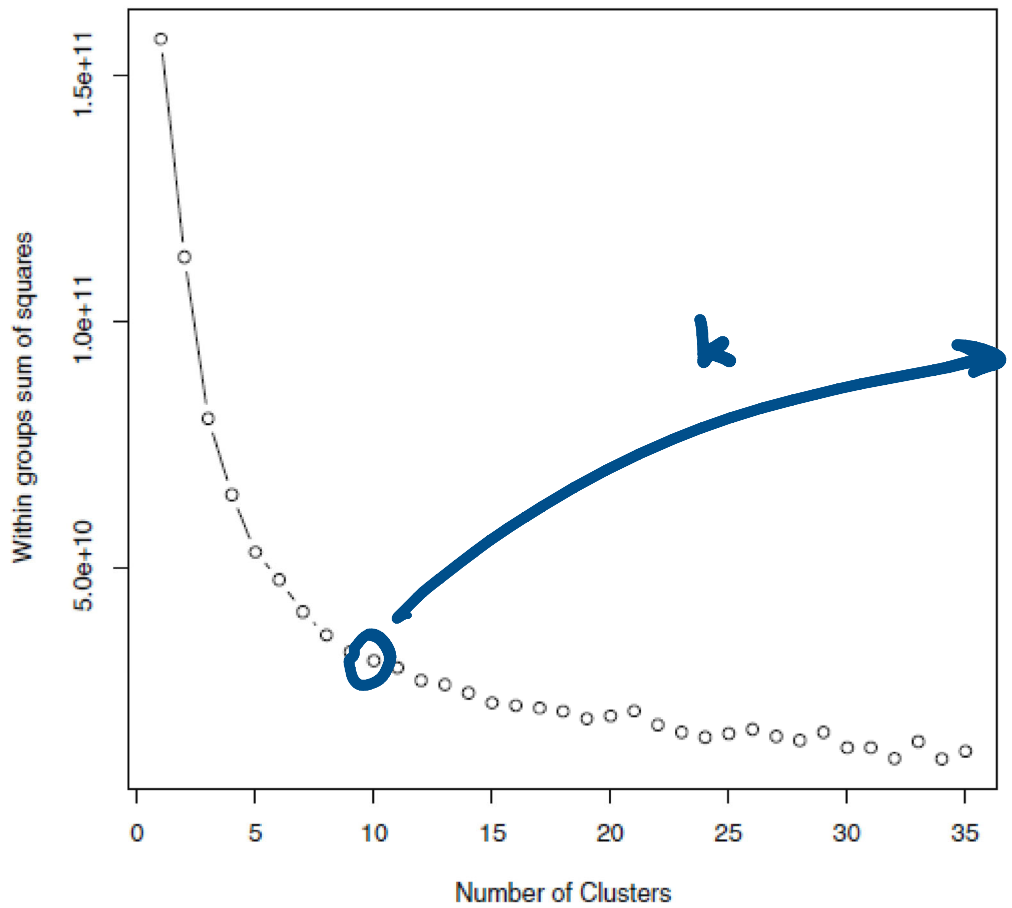
- The scatterplot matrix
  - along 6 spending dimensions
  - with 6 channel/region labels

  does not reveal any structure

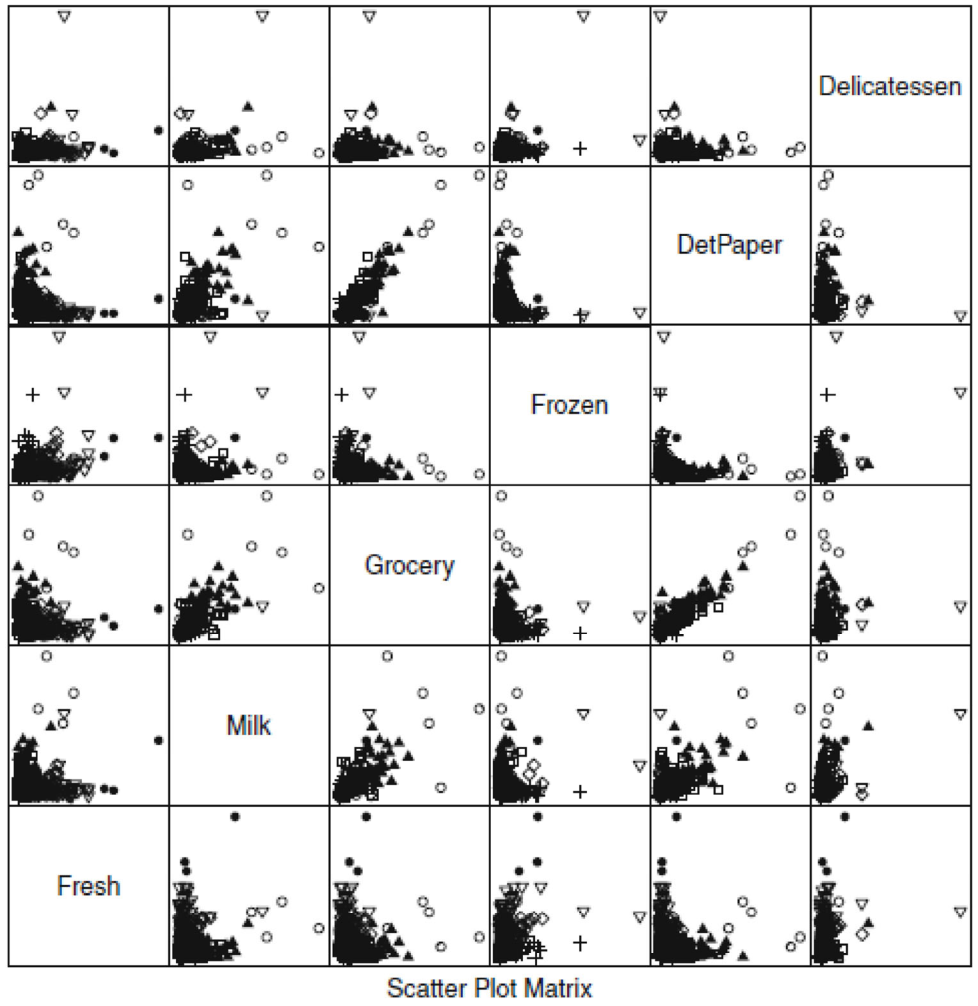
- At first glance, it does not look like clustering will help



k-means clustering: groceries example



k

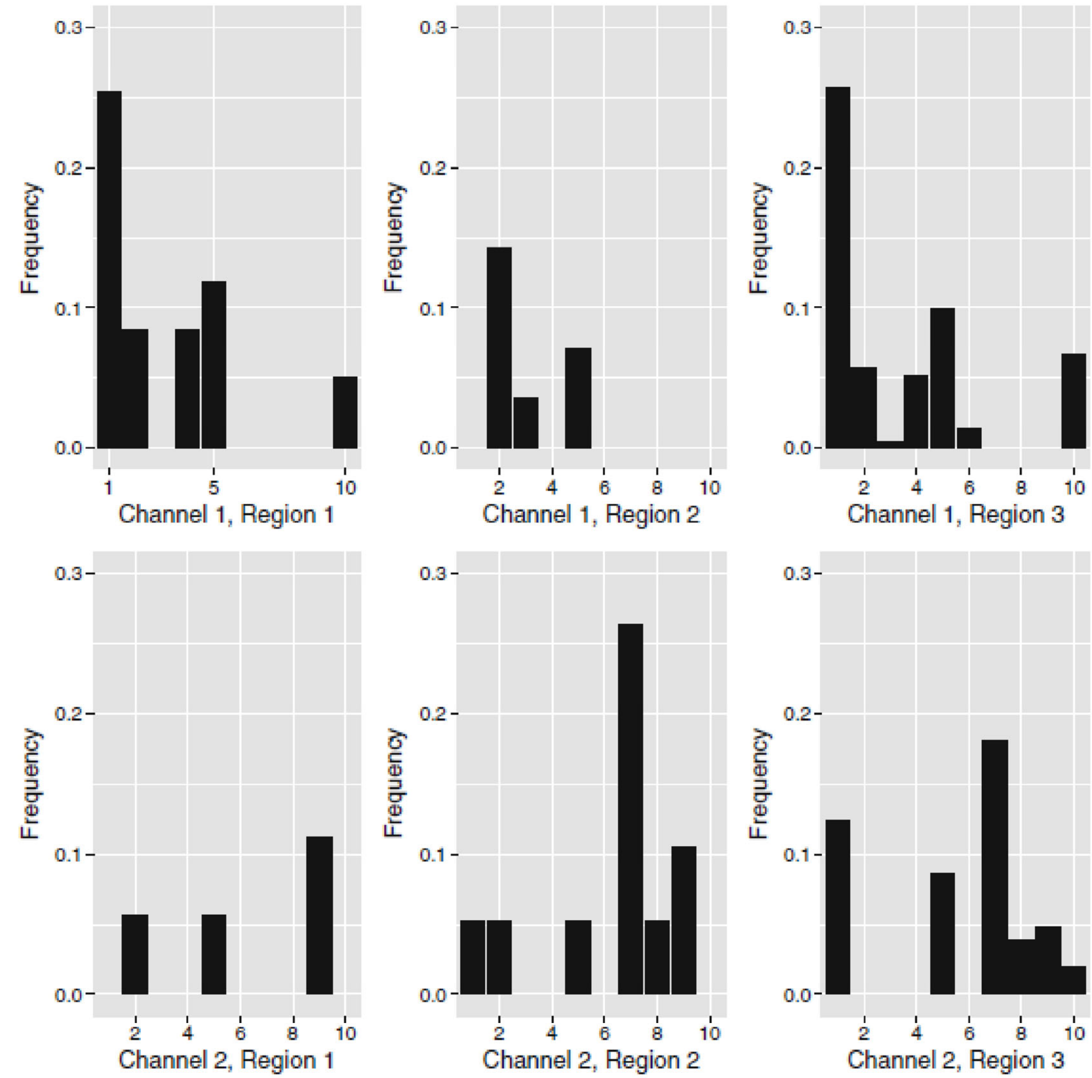


Trying to find structure: groceries example

- It is reasonable to think that there are certain customer “types”
  - Customers who cook meals at home would spend more on fresh food
  - Customers with children would spend more on milk
- We don’t know what these customer types are, but we can let the cluster centers stand for them
- Even though each channel/region has many types of customers, perhaps each of them has a characteristic mix of customer types

Cluster center histograms: groceries example

- For each channel/region, we make a histogram of customers that map to each of 10 cluster centers ("customer types")
- There is more similarity in the mix within channels than regions
- We can now classify a group of customers (of **arbitrary size**) from an unknown channel/region



Classifying data of varying size

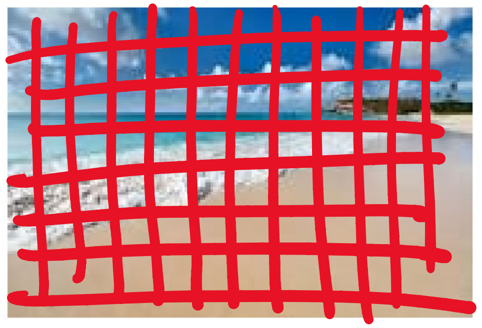
- The classifiers of Chapter 11 all assumed that each feature vector $\mathbf{x}$ had the same number of entries

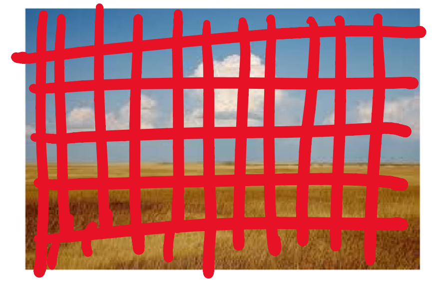
- Many datasets have items of different size
  - Images usually have different numbers of pixels
  - Audio signals (and other time series) usually have different durations

- We will use **vector quantization** to map variable length data to fixed-length feature vectors using cluster center histograms

Pattern vocabulary: conceptual example

- Suppose we want to classify images as either beach or prairie






- We slice each training image into 10×10 pixel subimages and cluster all subimages to construct a **pattern vocabulary** of k patterns

$k=4$
cluster centers


sand

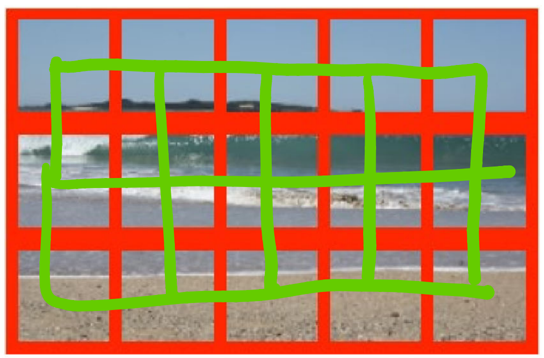

water

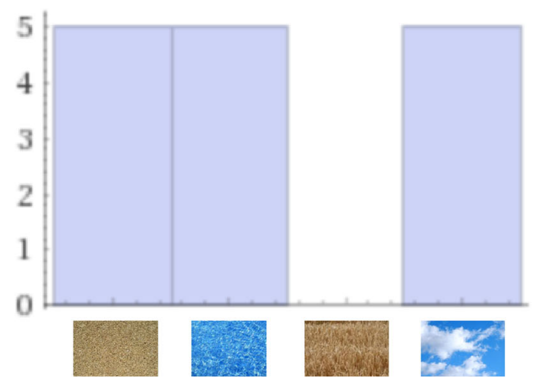

dry grass


clouds/sky

Feature vectors: conceptual example

- To represent an image as a fixed-length feature vector
  - Slice the image into 10×10 pixel subimages
  - Assign each subimage to the nearest of the k patterns (i.e. cluster centers)
  - The counts form a feature vector of dimension k





$$\mathbf{x}_i = \begin{bmatrix} 5 \\ 5 \\ 0 \\ 5 \end{bmatrix}$$

- These feature vectors are the fixed-length inputs for a classifier

Classification with vector quantization

- Build a pattern vocabulary
  - Slice the training set of signals into pieces of fixed size d
  - Cluster all the pieces and find k cluster centers (typically using k-means)

- Represent each signal as a feature vector
  - Slice each signal in the training and test sets into pieces of size d
  - Count the number of slices nearest each cluster center to obtain a k-dimensional feature vector

- Train a classifier using the training feature vectors and evaluate it using the test feature vectors

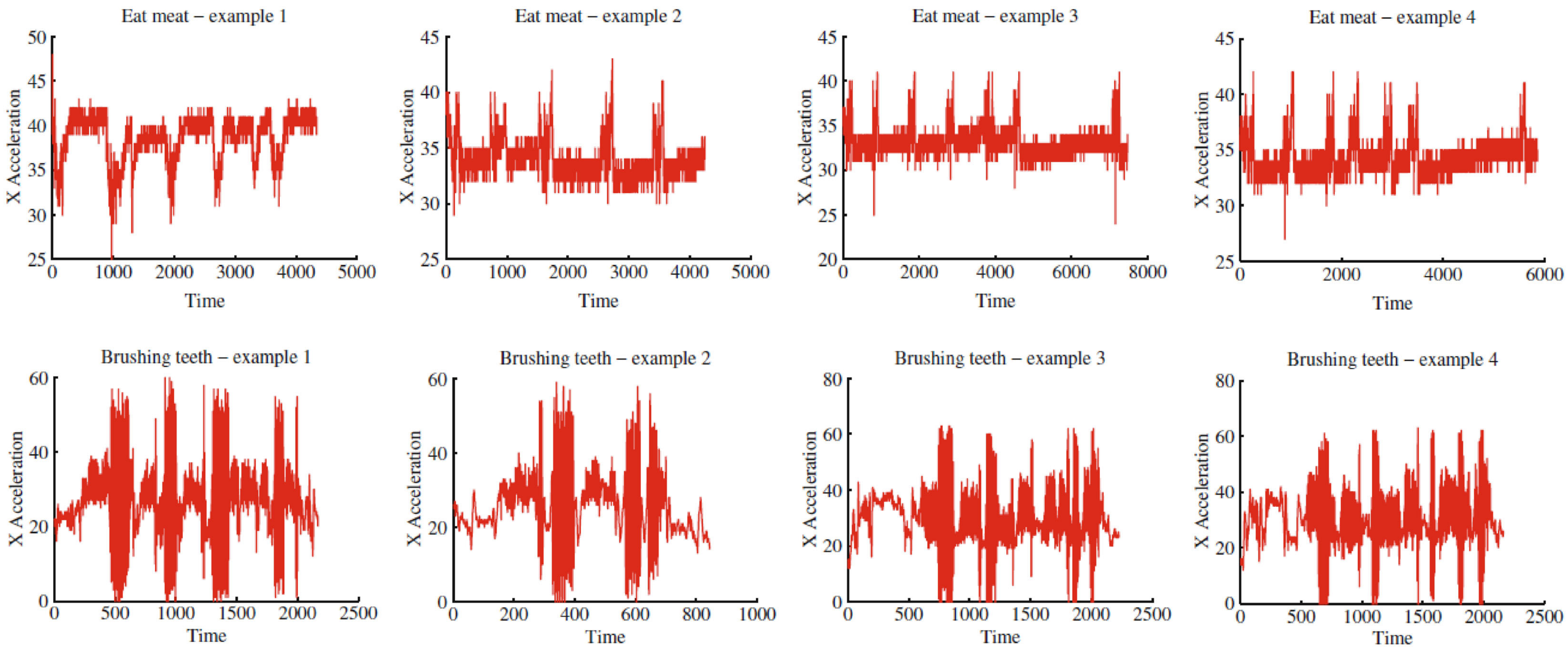
The project: activity from accelerometer data

- The dataset consists of Fitbit-like accelerometer signals, each of which
  - Can be of arbitrary length
  - Consists of 3 dimensions (x, y, z) of data sampled at 32 Hz
  - Is labeled with one of 14 activities, such as “brushing teeth”

https://archive.ics.uci.edu/ml/datasets/Dataset+for+ADL+Recognition+with+Wrist-worn+Accelerometer

- Your task is to train a classifier to take an accelerometer signal and map it to an activity

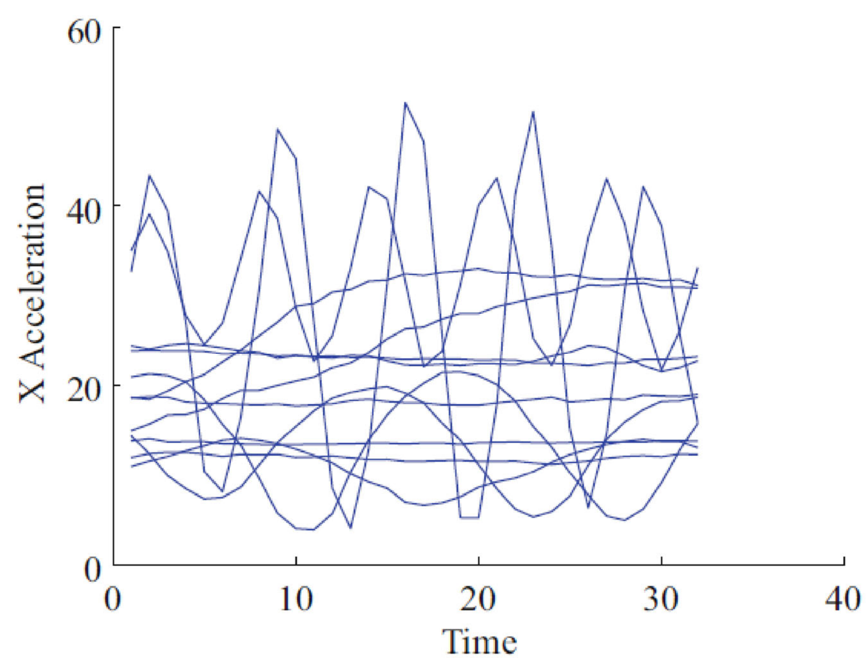
The project: looking at the raw data



The project: building a pattern vocabulary

- Slice each signal into non-overlapping pieces of 1 second duration, which gives you pieces of size $d = \underbrace{32}_{\text{samples}} \times \underbrace{3}_{x,y,z} = 96$
- Cluster the 96-dimensional vectors to k cluster centers using scikit-learn's k-means clustering algorithm ($k=480$)

Some cluster centers, x dimension only



The project: representation and classification

- Represent each signal as a k-dimensional feature vector

- Train a multiclass classifier such as scikit-learn's random forest on the training vectors

- Evaluate the classifier using the test vectors

- Improve the classifier by tuning parameters

d k

Some feature vectors