Internet Measurement and Data Analysis (11)

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review of previous class

Class 10 Anomaly detection and machine learning (6/20)

- Anomaly detection
- Machine Learning
- SPAM filtering and Bayes theorem
- exercise: naive Bayesian filter

today's topics

Class 11 Data Mining

- Pattern extraction
- Classification
- Clustering
- exercise: clustering

data mining

- huge volume of data
  - difficult to handle with traditional methods
  - need to extract information hidden in data that is not readily evident
- Data Mining
  - huge volume, multi-dimensional diverse data, non-trivial distributions
  - methods often derived from ideas in machine learning, AI, pattern recognition, statistics, database, signal processing
- data processing becomes practical by growing computing power (e.g., cloud computing)

Data Mining methods

definition: non-trivial extraction of implicit, previously unknown and potentially useful information from data

- pattern extraction: find existing models and patterns in data
  - correlation
  - time-series
- classification: automatically create new classes that do not exist in the original data
  - rule-based methods
  - naive Bayesian filter
  - neural networks
  - support vector machine (SVM)
  - dimensionality reduction (e.g., PCA)
- clustering: compute the distance (or similarity) between data points and group them
  - distance based, density based, graph based
  - k-means, DBSCAN
- anomaly detection: find deviation from normal state using statistical methods
  - univariate, multivariate
  - outlier detection

distances (review)

various distances

- Euclidean distance
- standardized Euclidean distance
- Minkowski distance
- Mahalanobis distance

similarities

- binary vector similarities
- n-dimensional vector similarities

clustering

important technique for classifying data with complex relationship

compute the distance (or similarity) of variables to make them into groups

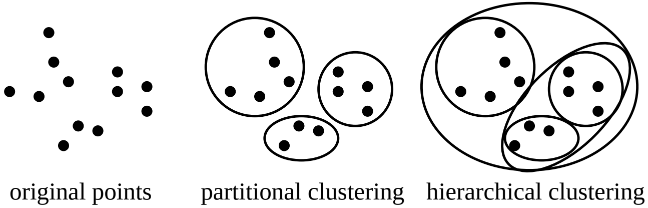
- to classify and understand data
- to summarize data

various applications

- business: grouping customers for marketing purposes
- meteorology: finding patterns in complex weather data
- biology: classifying genes and proteins
- medical science and pharmacy: complex relationship of symptoms and effects

clustering methods

- partitional clustering
  - k-means method
- hierarchical clustering
  - MST method
  - DBSCAN method



k-means method

- partitional clustering
- specify the number of cluster, k
- basic algorithm is simple
  - each cluster has centroid (usually mean)
  - assign each object to the closest cluster
  - repeat re-computation of centroids and cluster assignments
- limitations
  - need to specify the number of clusters, k, beforehand
  - sensitive to the selection of initial points
  - clusters are supposed to have similar sizes and densities, and a round shape
  - sensitive to outliers

basic k-means algorithm:

1: select k points randomly as the initial centroids
2: **repeat**
3: form k clusters by assigning all points to the closest centroid
4: recompute the centroid of each cluster
5: **until** the centroids don't change

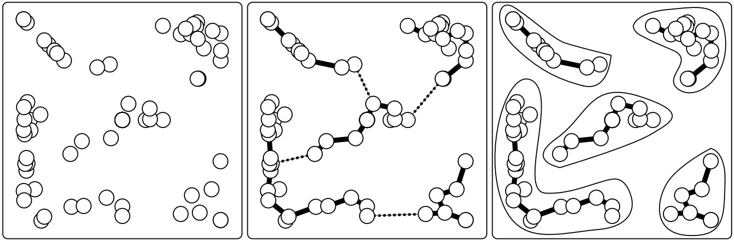
hierarchical clustering

- generate clusters using a tree structure
  - the cluster structure can be explained by the tree
- no need to specify the number of clusters beforehand
- 2 approaches
  - agglomerative: start with data points as individual clusters, and repeat merging the closest clusters
  - divisive: start with one all-inclusive cluster, and repeat splitting clusters

MST clustering

Minimum Spanning Tree clustering

- divisive hierarchical clustering
- start with an arbitrary point, and create MST
- repeat dividing clusters by removing the longest edge



(1) (2) (3)

DBSCAN

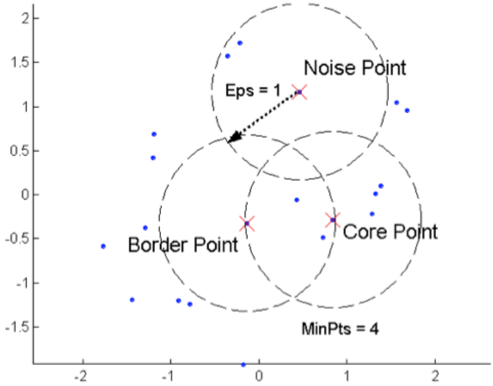
Density-Based Spatial Clustering

- density-based: combine data points within the specified distance
- can extract arbitrary (non-round) shapes of clusters
- robust against noise and outliers
- distance threshold Eps and point threshold $MinPts$
  - Core points: within the distance Eps, more than $MinPts$ neighbors exist
  - Border points: not Core, but have a core within the distance Eps
  - Noise points: have no core within the distance Eps
- limitations: clusters with different densities, or with large number of parameters

DBSCAN algorithm:

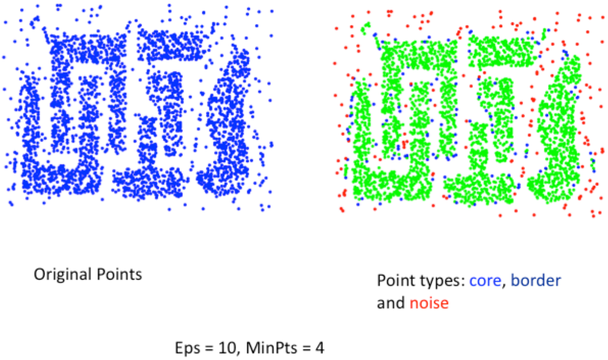
1: label all points as core, border, or noise points
2: eliminate noise points
3: put an edge between all core points that are within Eps of each other
4: make each group of connected core points into a separate cluster
5: assign each border point to one of the clusters of its associated core points

DBSCAN: Core, Border, and Noise Points



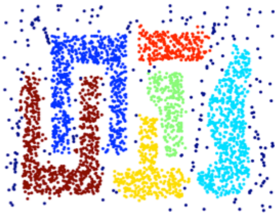
source: Tan, Steinbach, Kumer. Introduction to Data Mining

DBSCAN: example of Core, Border, and Noise Points



source: Tan, Steinbach, Kumer. Introduction to Data Mining

DBSCAN: example clusters

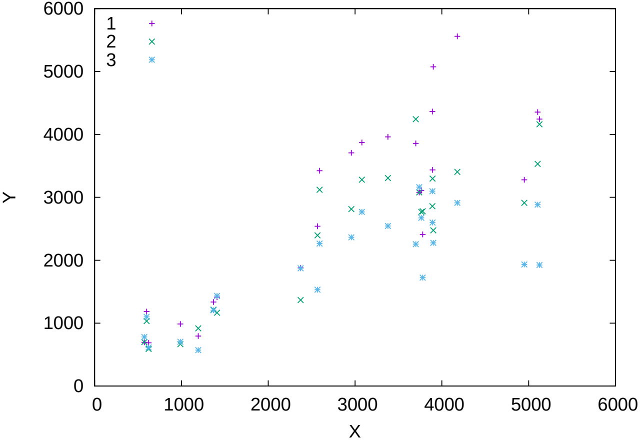


Clusters

source: Tan, Steinbach, Kumer. Introduction to Data Mining

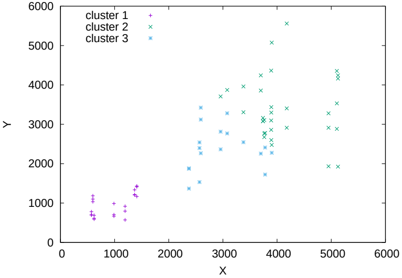
today's exercise: k-means clustering

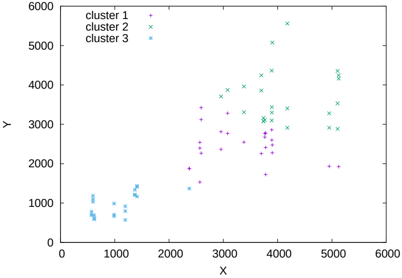
```
% ruby k-means.rb km-data.txt > km-results.txt
```



k-means clustering results

- different results by different initial values





k-means code (1/2)

```
k = 3   # k clusters
re = /^(\d+)\s+(\d+)/
INFINITY = 0x7fffffff

# read data
nodes = Array.new       # array of array for data points: [x, y, cluster_index]
centroids = Array.new   # array of array for centroids: [x, y]
ARGF.each_line do |line|
  if re.match(line)
    c = rand(k)  # randomly assign initial cluster
    nodes.push [$1.to_i, $2.to_i, c]
  end
end

round = 0
begin
  updated = false

  # assignment step: assign each node to the closest centroid
  if round != 0  # skip assignment for the 1st round
    nodes.each do |node|
      dist2 = INFINITY  # square of dsistance to the closest centroid
      cluster = 0 # closest cluster index
      for i in (0 .. k - 1)
        d2 = (node[0] - centroids[i][0])**2 + (node[1] - centroids[i][1])**2
        if d2 < dist2
          dist2 = d2
          cluster = i
        end
      end
      node[2] = cluster
    end
  end
```

k-means code (2/2)

```
  # update step: compute new centroids
  sums = Array.new(k)
  clsize = Array.new(k)
  for i in (0 .. k - 1)
    sums[i] = [0, 0]
    clsize[i] = 0
  end
  nodes.each do |node|
    i = node[2]
    sums[i][0] += node[0]
    sums[i][1] += node[1]
    clsize[i] += 1
  end

  for i in (0 .. k - 1)
    newcenter = [Float(sums[i][0]) / clsize[i], Float(sums[i][1]) / clsize[i]]
    if round == 0 || newcenter[0] != centroids[i][0] || newcenter[1] != centroids[i][1]
      centroids[i] = newcenter
      updated = true
    end
  end

  round += 1

end while updated == true

# print the results
nodes.each do |node|
  puts "#{node[0]}\t#{node[1]}\t#{node[2]}"
end
```

gnuplot script

```
set key left
set xrange [0:6000]
set yrange [0:6000]
set xlabel "X"
set ylabel "Y"

plot    "km-results.txt" using 1:($3==0?$2:1/0) title "cluster 1" with points, \
        "km-results.txt" using 1:($3==1?$2:1/0) title "cluster 2" with points, \
        "km-results.txt" using 1:($3==2?$2:1/0) title "cluster 3" with points
```

previous exercise: SPAM filtering

- SPAM filtering using naive bayesian classifier
  - based on the code from “Programming Collective Intelligence” Chapter 6

```
% ruby naivebayes.rb
classifying "quick rabbit" => good
classifying "quick money" => bad
```

naive bayesian classifier for the exercise

compute the propbability of a document to be classified into a specific category by words appearing in the dicument

$$P(C)\prod_{i=1}^{n}P(x_i|C)$$

- $P(C)$: the probability of the category
- $\prod_{i=1}^{n}P(x_i|C)$: product of the conditional probability of each word in the category

select the category with the highest probability

- threshold： the probability of the best category should be $thresh$ times higher than that of the second best category

SPAM classifier script

- training and classifier

```
# create a classifier instance
cl = NaiveBayes.new

# training
cl.train('Nobody owns the water.','good')
cl.train('the quick rabbit jumps fences','good')
cl.train('buy pharmaceuticals now','bad')
cl.train('make quick money at the online casino','bad')
cl.train('the quick brown fox jumps','good')

# classify
sample_data = [ "quick rabbit", "quick money" ]

sample_data.each do |s|
  print "classifying \"#{s}\" => "
  puts cl.classify(s, default="unknown")
end
```

script: Classifier Class (1/2)

```
# feature extraction
def getwords(doc)
  words = doc.split(/\W+/)
  words.map!{|w| w.downcase}
  words.select{|w| w.length < 20 && w.length > 2 }.uniq
end

# base class for classifier
class Classifier
  def initialize
    # initialize arrays for feature counts, category counts
    @fc, @cc = {}, {}
  end

  def getfeatures(doc)
    getwords(doc)
  end

  # increment feature/category count
  def incf(f, cat)
    @fc[f] ||= {}
    @fc[f][cat] ||= 0
    @fc[f][cat] += 1
  end

  # increment category count
  def incc(cat)
    @cc[cat] ||= 0
    @cc[cat] += 1
  end

  ...
```

script: Classifier Class (2/2)

```
  def fprob(f,cat)
    if catcount(cat) == 0
      return 0.0
    end

    # the total number of times this feature appeared in this
    # category divided by the total number of items in this category
    Float(fcount(f, cat)) / catcount(cat)
  end

  # when the sample size is small, fprob is not reliable.
  # so, make it start with 0.5 and converge to fprob as the number grows
  def weightedprob(f, cat, weight=1.0, ap=0.5)
    # calculate current probability
    basicprob = fprob(f, cat)
    # count the number of times this feature has appeared in all categories
    totals = 0
    categories.each do |c|
      totals += fcount(f,c)
    end
    # calculate the weighted average
    ((weight * ap) + (totals * basicprob)) / (weight + totals)
  end

  def train(item, cat)
    features = getfeatures(item)
    features.each do |f|
      incf(f, cat)
    end
    incc(cat)
  end
end
```

script: NaiveBayes Class

```
# naive baysian classifier
class NaiveBayes < Classifier
  def initialize
    super   # inherit from parent class
    @thresholds = {}
  end

  def docprob(item, cat)
    features = getfeatures(item)
    # multiply the probabilities of all the features together
    p = 1.0
    features.each do |f|
      p *= weightedprob(f, cat)
    end
    return p
  end

  def prob(item, cat)
    catprob = Float(catcount(cat)) / totalcount
    docprob = docprob(item, cat)
    return docprob * catprob
  end

  def classify(item, default=nil)
    # find the category with the highest probability
    probs, max, best = {}, 0.0, nil
    categories.each do |cat|
      probs[cat] = prob(item, cat)
      if probs[cat] > max
        max = probs[cat]
        best = cat
      end
    end
    # make sure the probability exceeds threshold*next best
```

debug: dumping the feature probabilities

internal states after the training:

```
fprob for "nobody":    good:0.333 bad:0.000
fprob for "owns":      good:0.333 bad:0.000
fprob for "the":       good:1.000 bad:0.500
fprob for "water":     good:0.333 bad:0.000
fprob for "quick":     good:0.667 bad:0.500
fprob for "rabbit":    good:0.333 bad:0.000
fprob for "jumps":     good:0.667 bad:0.000
fprob for "fences":    good:0.333 bad:0.000
fprob for "buy":       good:0.000 bad:0.500
fprob for "pharmaceuticals":   good:0.000 bad:0.500
fprob for "now":       good:0.000 bad:0.500
fprob for "make":      good:0.000 bad:0.500
fprob for "money":     good:0.000 bad:0.500
fprob for "online":    good:0.000 bad:0.500
fprob for "casino":    good:0.000 bad:0.500
fprob for "brown":     good:0.333 bad:0.000
fprob for "fox":       good:0.333 bad:0.000
```

assignment 2: twitter data analysis

- purpose: processing realworld big data
- data sets:
  - twitter data for about 40M users by Kwak et al. in July 2009
    - http://an.kaist.ac.kr/traces/WWW2010.html
  - twitter_degrees.zip (164MB, 550MB uncompressed)
    - user_id, followings, followers
  - numeric2screen.zip (365MB, 756MB uncompressed)
    - user_id, screen_name
- items to submit
  1. CCDF plot of the distributions of twitter users' followings/followers
     - log-log plot, the number of followings/followers on X-axis
  2. list of the top 30 users by the number of followers
     - rank, user_id, screen_name, followings, followers
  3. optional
     - other analysis of your choice
  4. discussion
     - describe what you observe from the data
- submission: upload your report in the PDF format via SFC-SFS
- submission due: 2016-06-21 (Tue)

twitter data sets

twitter_degrees.zip (164MB, 550MB uncompressed)

```
# id followings followers

12      586     1001061
13      243     1031830
14      106     8808
15      275     14342
16      273     218
17      192     6948
18      87      6532
20      912     1213787
21      495     9027
22      272     3791
...
```

numeric2screen.zip (365MB, 756MB uncompressed)

```
# id screenname

12 jack
13 biz
14 noah
15 crystal
16 jeremy
17 tonystubblebine
18 Adam
20 ev
21 dom
22 rabble
...
```

items to submit

CCDF plot

- log-log plot, the number of followings/followers on X-axis
- plot the 2 distributions in a single graph

list of the top 30 users by the number of followers

- rank, user_id, screen_name, followings, followers
- you need to sort and merge 2 files

```
# rank   id             screenname    followings followers

1       19058681        aplusk          183      2997469
2       15846407        TheEllenShow    26       2679639
3       16409683        britneyspears   406238   2674874
4       428333          cnnbrk          18       2450749
5       19397785        Oprah           15       1994926
6       783214          twitter         55       1959708
...
```

sort command

sort command: sorts lines in a text file

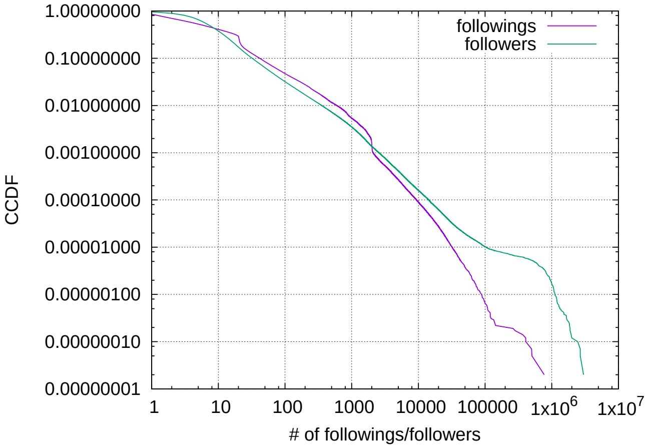
```
$ sort [options] [FILE ...]
```

- options (relevant to the assignment)
  - -n : compare according to string numerical value
  - -r : reverse the result of comparisons
  - -k POS1[,POS2] : start a key at POS1, end it at POS 2 (origin 1)
  - -t SEP : use SEP instead of non-blank as the field-separator
  - -m : merge already sorted files
  - -T DIR : use DIR for temporary files

example: sort “file” using the 3rd field as numeric value in the reverse order , use “/usr/tmp” for temporary files

```
$ sort -nr -k3,3 -T/usr/tmp file
```

assignment 2 answer: CCDF plot



list of the top 30 users by the number of followers

# rank	id	screenname	followings	followers
1	19058681	aplusk	183	2997469
2	15846407	TheEllenShow	26	2679639
3	16409683	britneyspears	406238	2674874
4	428333	cnnbrk	18	2450749
5	19397785	Oprah	15	1994926
6	783214	twitter	55	1959708
7	16190898	RyanSeacrest	137	1885782
8	813286	BarackObama	770155	1882889
9	19757371	johncmayer	64	1844499
10	17461978	THE_REAL_SHAQ	563	1843561
11	25365536	KimKardashian	73	1790771
12	19554706	mrskutcher	99	1691919
13	15485441	jimmyfallon	131	1668193
14	18220175	iamdiddy	173	1657119
15	16727535	lancearmstrong	103	1651207
16	807095	nytimes	177	1524048
17	18863815	coldplay	2633	1517067
18	27104736	mileycyrus	54	1477423
19	14075928	TheOnion	369569	1380160
20	17220934	algore	8	1377332
21	18091904	ashleytisdale	75	1318909
22	18222378	50cent	13	1318378
23	20536157	google	162	1278103
24	21879024	tonyhawk	118	1277163
25	19329393	PerezHilton	328	1269341
26	16827333	souljaboytellem	94	1241331
27	20	ev	912	1213787
28	972651	mashable	1934	1210996
29	26885308	ashsimpsonwentz	32	1200472
30	6273552	MCHammer	27413	1195089

ways to merge the files

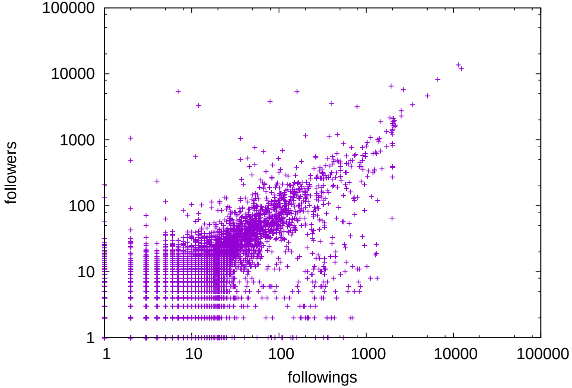
- method 1: extract the top 30 user IDs first, then match only these user IDs against screennames
- method 2: use UNIX join command
  - example below
- method 3: ...

```
$ join -a1 -a2 -e NULL -o '0,1.2,2.2,2.3' numeric2screen twitter_degrees.txt > joined.txt
$ head -n 10 joined.txt
12 jack 586 1001061
13 biz 243 1031830
14 noah 106 8808
15 crystal 275 14342
16 jeremy 273 218
17 tonystubblebine 192 6948
18 Adam 87 6532
20 ev 912 1213787
21 dom 495 9027
22 rabble 272 3791
```

scatter plot of sampled twitter users' followings/followers

scatter plot

- extract 10,000 sample users, then, plot them on a log-log scale, followings on X-axis and followers on Y-axis



discussions

from CCDF

- both distributions follow power-law
  - except extreme users on both ends
  - both distribution change the slope at 100k
- for followings, there are gaps at around 20 and 2000
  - 20: on sign up, the system recommends 20 people to follow
  - 2000: there used to be this limit on the max number of followings

from the scatter plot

- users' followings/followers are not symmetric, especially for the tail
- most users have less than 200 followings/followers, but some are huge
- we cannot see the distribution from the scatter plot, since the majority of users in the bottom left region are plotted on same points

summary

Class 11 Data Mining

- Pattern extraction
- Classification
- Clustering
- exercise: clustering

next class

Class 12 Search and Ranking (7/4)

- Search systems
- PageRank
- exercise: PageRank algorithm
- **the final report**