Internet Measurement and Data Analysis (12)

Kenjiro Cho

2012-12-19

review of previous class

Class 11 Data Mining (12/12)

- Pattern extraction
- Classification
- Clustering
- exercise: clustering

today's topics

Class 12 Search and Ranking

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

history of search engines

most Internet users use search engines everyday

- 1994 Yahoo! portal started
  - a pioneer of potal sites (directory-based)
  - initially, they published their favorite sites for others
- 1995 Altavista
  - a pioneering search engine with crawling robot, and multi-language support
  - issues with quality degradation by SPAM
- 1998 Google was established
  - automated search engine by the PageRank algorithm
  - web pages are scored based on the popularity of the pages

search engine mechanisms

- directory based
  - manual registration and classification
  - high quality, but it does not scale
- robot based
  - automatically crawl web sites and create database
  - becomes the mainstream as the number of web pages increases

robot-based search engine

- collect web pages
  - crawling
- manage database of collected information
  - index generation
- match web pages with a serach query
  - search ranking

index generation

- extract keywords from web pages
- create inverted index from keywords to web pages

search ranking

when a search server receives a search query, it

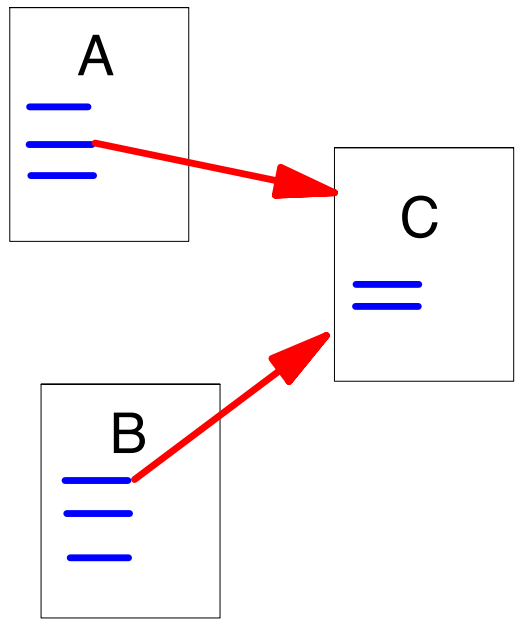
- obtains a list of related web pages by looking up the inverted index with the keywords
- orders the list by ranking, and send it back to the user

web page ranking

- requires a metric to show the importance of a web page
- PageRank: the ranking method proposed by Google

PageRank: basic idea

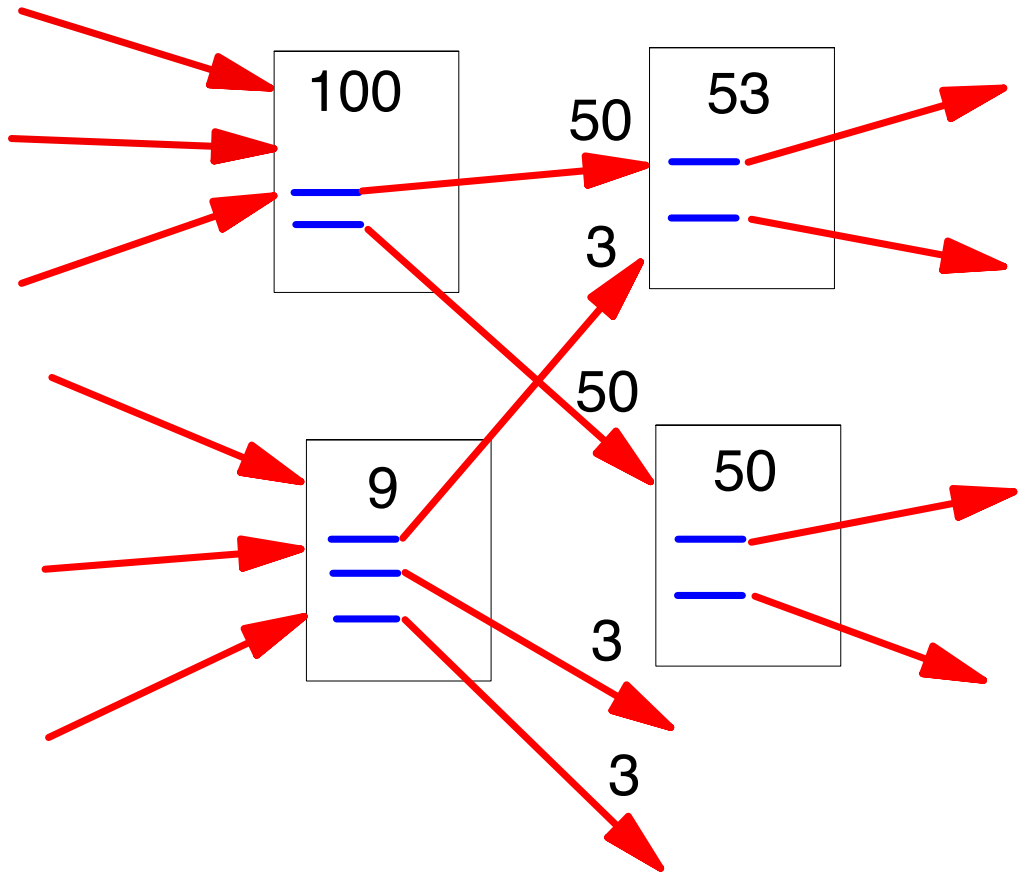
- score web pages only from the link relationship of web pages
  - it does not look at content at all



source: L. Page, et al. The pagerank citation ranking: Bringing order to the web. 1998.

PageRank: insights

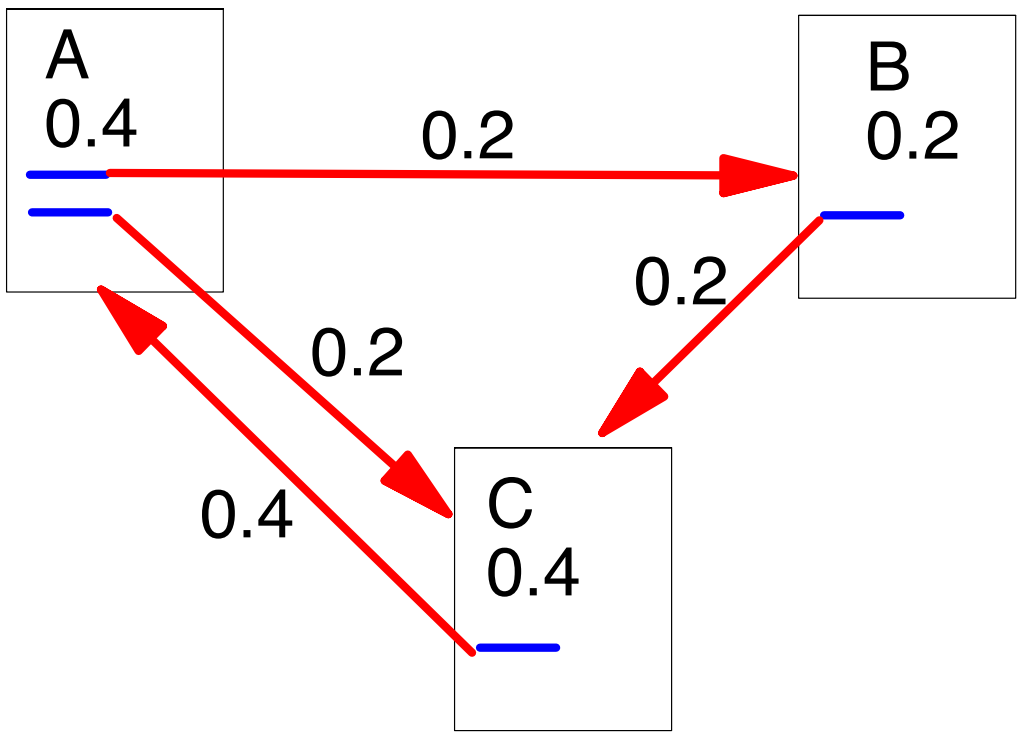
- high quality web pages are linked from many web pages
- a link from higher quality web page is more valuable
- as the number of links within a web page increases, the value of each link decreases



source: L. Page, et al. The pagerank citation ranking: Bringing order to the web. 1998.

PageRank: model

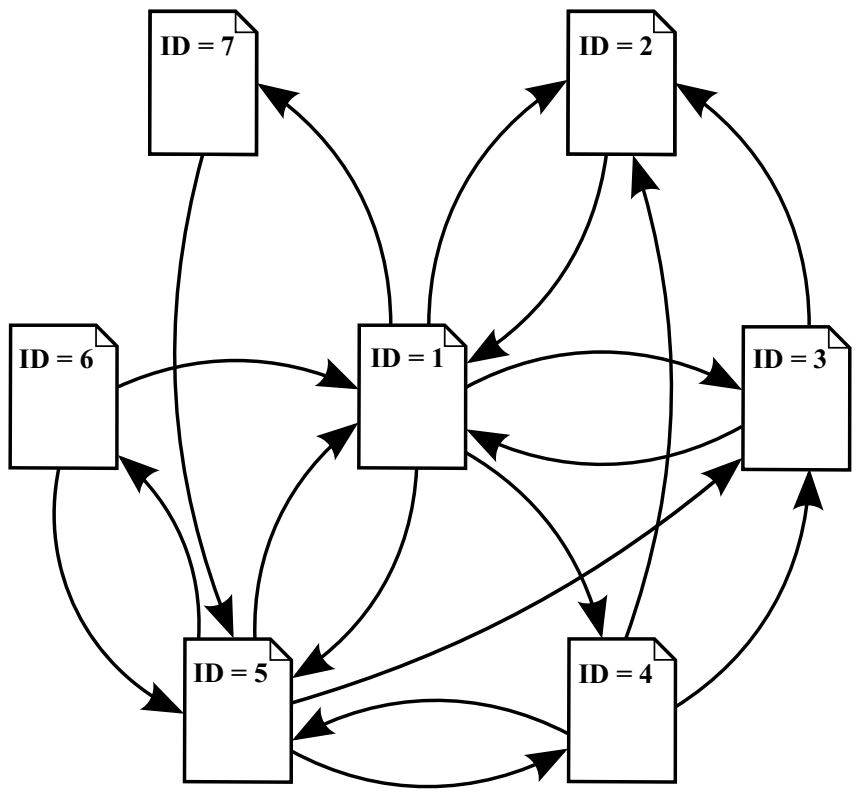
- web pages linked from high quality web pages are high quality
- random surfer model
  - a user clicks links within the same web page with the same probability



source: L. Page, et al. The pagerank citation ranking: Bringing order to the web. 1998.

PageRank example

Page ID	OutLinks
1	2, 3, 4, 5, 7
2	1
3	1, 2
4	2, 3, 5
5	1, 3, 4, 6
6	1, 5
7	5



matrix model

Matrix Notation (src $\rightarrow$ dst)

$$A^\top = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

Transition Matrix (dst $\leftarrow$ src): the sum of column is 1

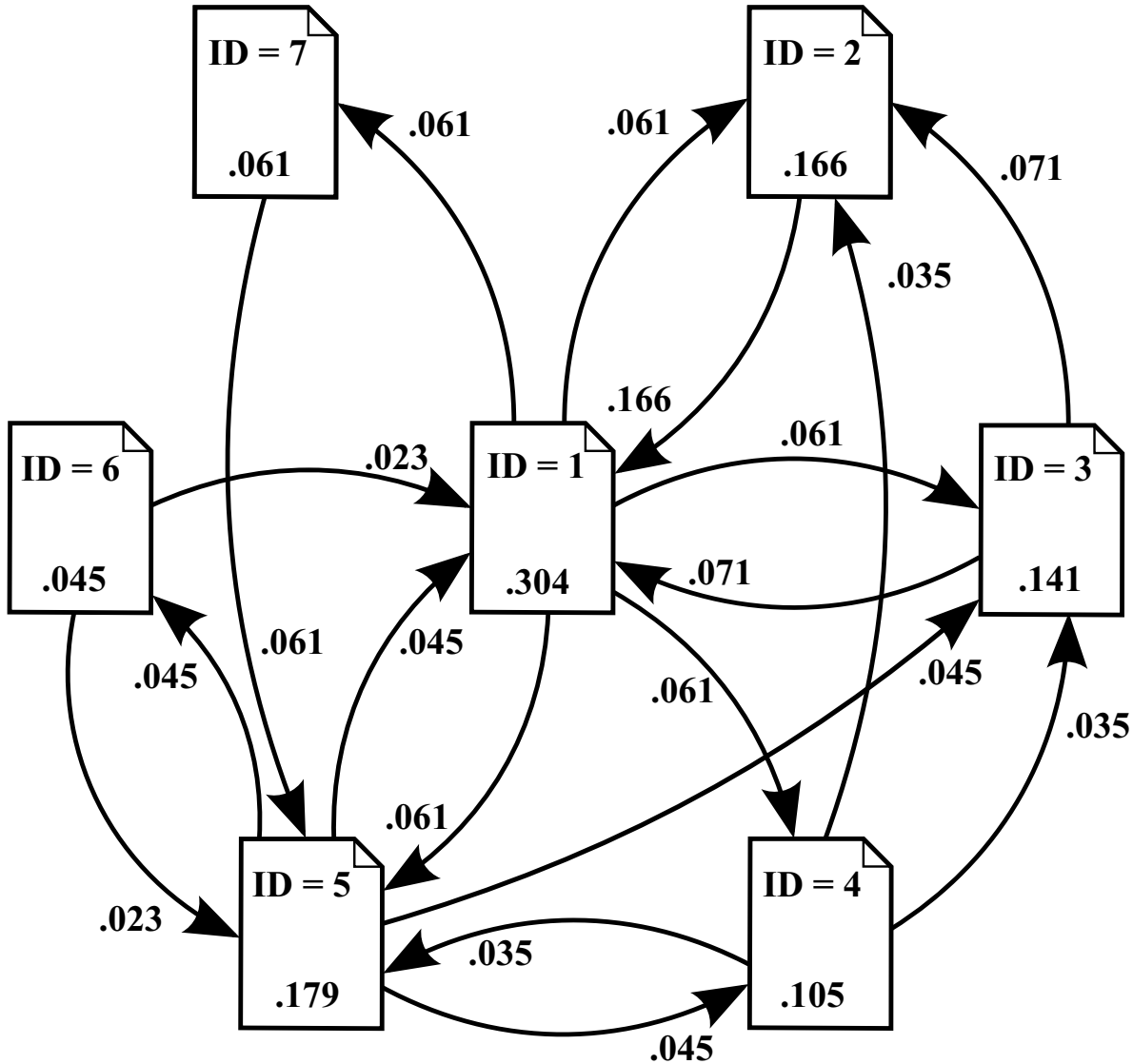
$$A = \begin{bmatrix} 0 & 1 & 1/2 & 0 & 1/4 & 1/2 & 0 \\ 1/5 & 0 & 1/2 & 1/3 & 0 & 0 & 0 \\ 1/5 & 0 & 0 & 1/3 & 1/4 & 0 & 0 \\ 1/5 & 0 & 0 & 0 & 1/4 & 0 & 0 \\ 1/5 & 0 & 0 & 1/3 & 0 & 1/2 & 1 \\ 0 & 0 & 0 & 0 & 1/4 & 0 & 0 \\ 1/5 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\mathsf{R} = c\mathsf{AR}$$

pagerank vector R is an eigen vector of Transition Matrix A, c is a reciprocal of the eigen value

PageRank example: result

can be obtained by eigen value computation



issues with simple PageRank model

- in reality
  - there exist nodes without outgoing links (dangling node)
  - there exist nodes without incoming links
  - there exist loops
- transition probability model is Markov chain's transition matrix
  - eventually converges to the equilibrium state
- convergence condition: the matrix is recurrent and irreducible
  - directed graph is strongly connected (there is a directed path from each node to every other nodes)
  - there exists one principal eigen vector

solution: add behavior to jump to random pages with a certain probability

PageRank algorithm

start from an arbitrary initial state, and repeat transitions until the ranks of all pages converge

- case: node with outlinks (> 0)
  - randomly select a link within the page with probability d
  - jump to a random page with probability $(1 - d)$
- case: dangling node (no outlink)
  - jump to a random page

$$\text{A'} = d\text{A} + (1 - d)[1/N]$$

d: damping factor ($= 0.85$)

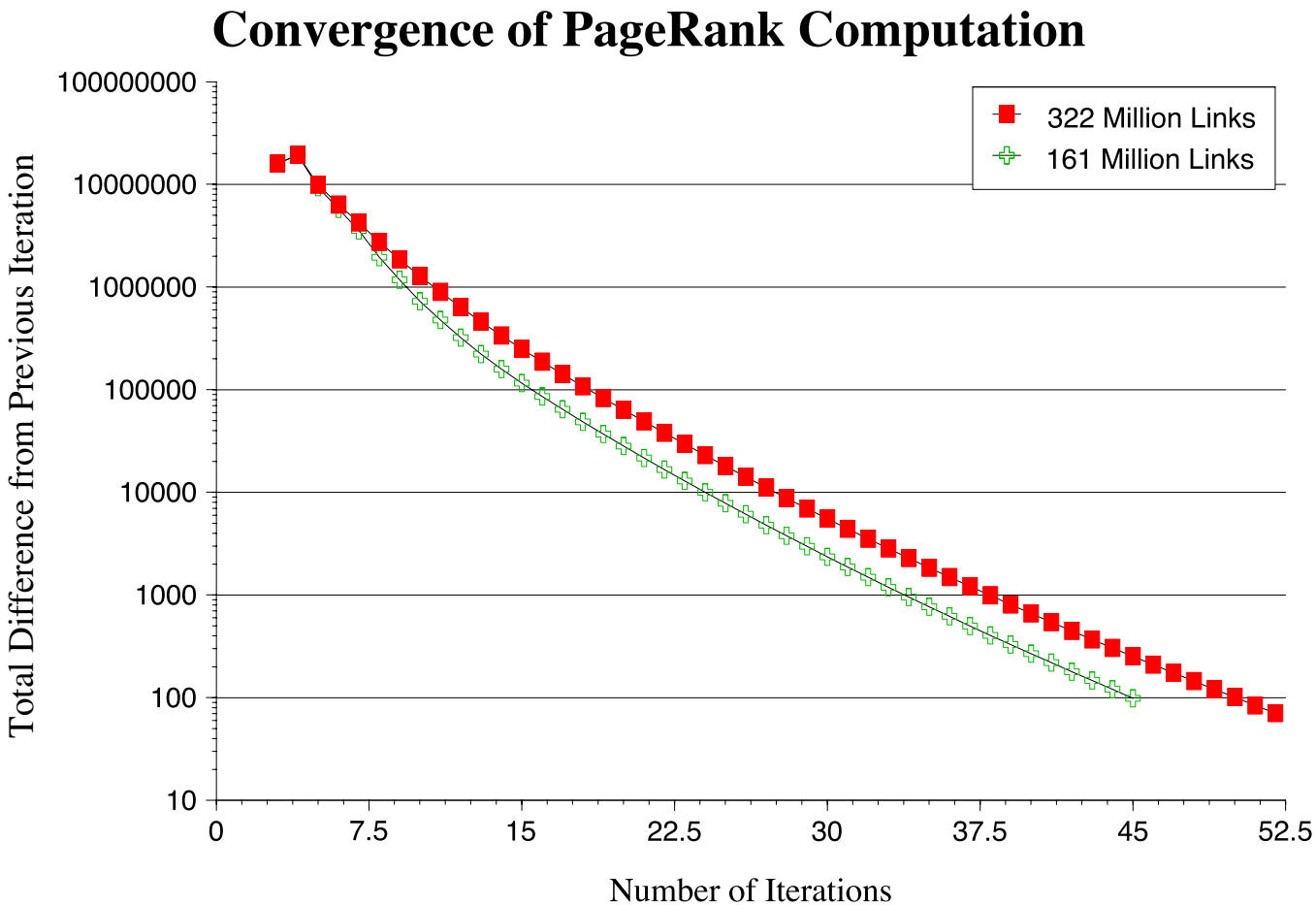
computation by power iteration method

- eigenvalue computation is not practical for a large matrix
- but can be approximated by power iteration method

```
parameters:
    d: dampig_factor = 0.85
    thresh: convergence_threshold = 0.000001
initialize:
    for i
        r[i] = 1/N
loop:
    e = 0
    for i
        new_r[i] = d * (sum_inlink(r[j]/degree[j]) + sum_dangling(r[j])/N)
                   + (1 - d)/N
        e += |new_r[i] - r[i]|
    r = new_r
while e > thresh
```

PageRank convergence

- evaluation results show logarithmic convergence even for a large number of web pages



source: L. Page, et al. The pagerank citation ranking: Bringing order to the web. 1998.

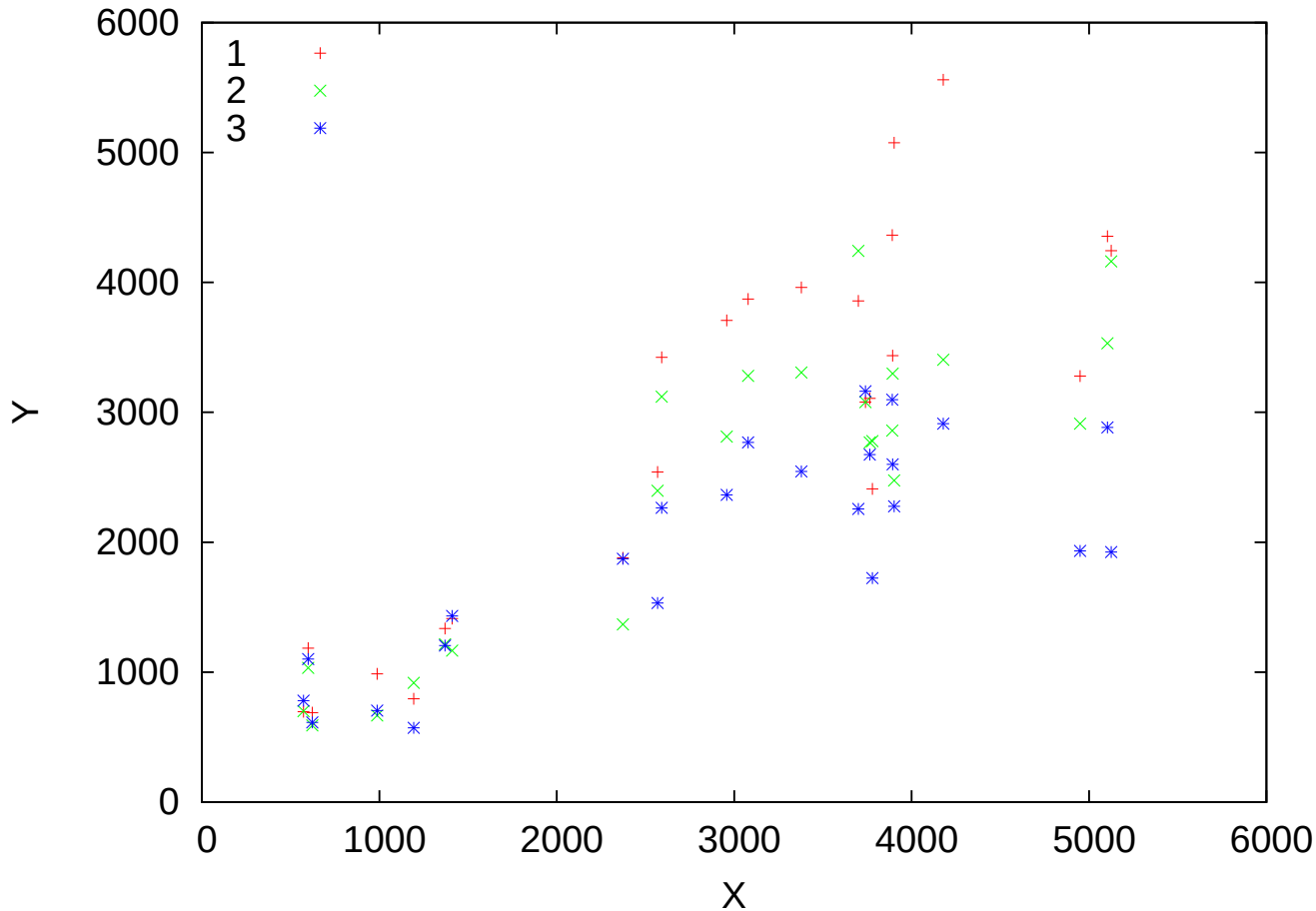
PageRank summary

- simple idea
  - web pages linked from high quality web pages are high quality
- formalize the idea by the transition matrix of Markov chain, and make it converge
- build a scalable implementation, and prove the effectiveness by real data
- start business, and become a top company

- note: this algorithm was introduced in 1998. the current algorithm used by Google must have evolved significantly since then.

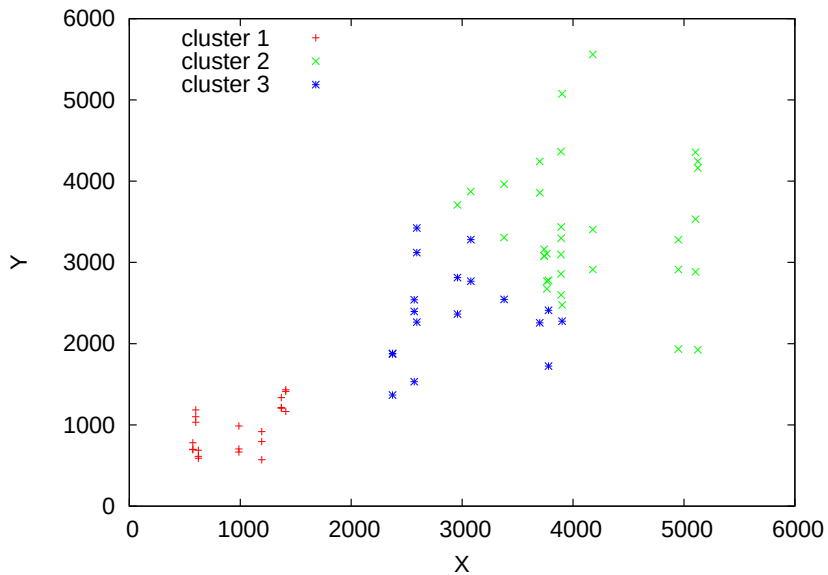
previous exercise: k-means clustering

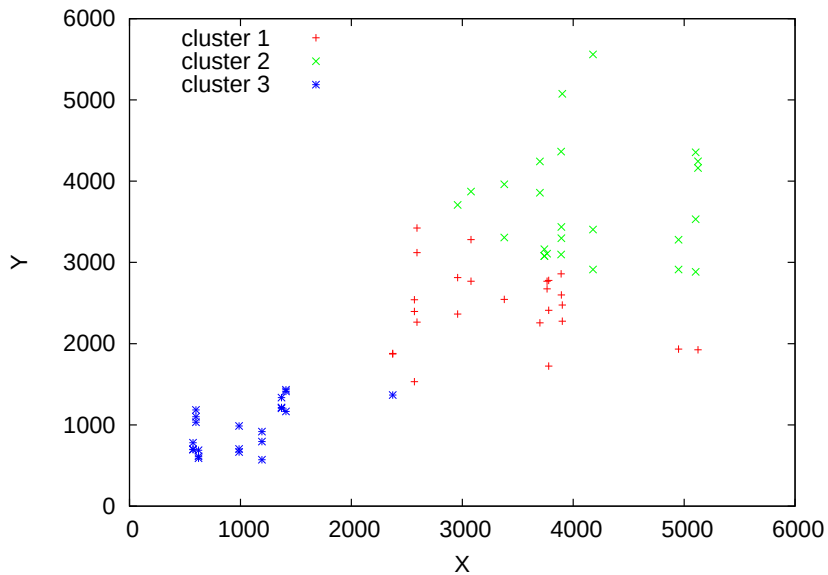
```
% ruby k-means.rb km-data.txt > km-results.txt
```



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
```

today's exercise: PageRank

```
% cat sample-links.txt
# PageID: OutLinks
1:      2       3       4       5       7
2:      1
3:      1       2
4:      2       3       5
5:      1       3       4       6
6:      1       5
7:      5
% ruby pagerank.rb -f 1.0 sample-links.txt
reading input...
initializing... 7 pages dampingfactor:1.00 thresh:0.000001
iteration:1  diff_sum:0.661905 rank_sum: 1.000000
iteration:2  diff_sum:0.383333 rank_sum: 1.000000
...
iteration:20  diff_sum:0.000002 rank_sum: 1.000000
iteration:21  diff_sum:0.000001 rank_sum: 1.000000
[1] 1 0.303514
[2] 5 0.178914
[3] 2 0.166134
[4] 3 0.140575
[5] 4 0.105431
[6] 7 0.060703
[7] 6 0.044728
```

PageRank code (1/4)

```
require 'optparse'

d = 0.85   # damping factor (recommended value: 0.85)
thresh = 0.000001 # convergence threshold

OptionParser.new {|opt|
  opt.on('-f VAL', Float) {|v| d = v}
  opt.on('-t VAL', Float) {|v| thresh = v}
  opt.parse!(ARGV)
}

outdegree = Hash.new # outdegree[id]: outdegree of each page
inlinks = Hash.new # inlinks[id][src0, src1, ...]: inlinks of each page
rank = Hash.new # rank[id]: pagerank of each page
last_rank = Hash.new # last_rank[id]: pagerank at the last stage
dangling_nodes = Array.new # dangling pages: pages without outgoing link

# read a page-link file: each line is "src_id  dst_id_1 dst_id_2 ..."
ARGF.each_line do |line|
  pages = line.split(/\D+/)  # extract list of numbers
  next if line[0] == ?# || pages.empty?

  src = pages.shift.to_i  # the first column is the src
  outdegree[src] = pages.length
  if outdegree[src] == 0
    dangling_nodes.push src
  end
  pages.each do |pg|
    dst = pg.to_i
    inlinks[dst] ||= []
    inlinks[dst].push src
  end
end
```

PageRank code (2/4)

```
# initialize
# sanity check: if dst node isn't defined as src, create one as a dangling node
inlinks.each_key do |j|
  if !outdegree.has_key?(j)
    # create the corresponding src as a dangling node
    outdegree[j] = 0
    dangling_nodes.push j
  end
end

n = outdegree.length # total number of nodes
# initialize the pagerank of each page with 1/n
outdegree.each_key do |i|  # loop through all pages
  rank[i] = 1.0 / n
end
$stderr.printf " %d pages dampingfactor:%.2f thresh:%f\n", n, d, thresh
```

PageRank code (3/4)

```
# compute pagerank by power method
k = 0 # iteration number
begin
  rank_sum = 0.0  # sum of pagerank of all pages: should be 1.0
  diff_sum = 0.0  # sum of differences from the last round
  last_rank = rank.clone  # copy the entire hash of pagerank

  # compute dangling ranks
  danglingranks = 0.0
  dangling_nodes.each do |i| # loop through dangling pages
    danglingranks += last_rank[i]
  end

  # compute page rank
  outdegree.each_key do |i|  # loop through all pages
    inranks = 0.0
    # for all incoming links for i, compute
    #    inranks = sum (rank[j]/outdegree[j])
    if inlinks[i] != nil
      inlinks[i].each do |j|
        inranks += last_rank[j] / outdegree[j]
      end
    end

    rank[i] = d * (inranks + danglingranks / n) + (1.0 - d) / n
    rank_sum += rank[i]

    diff = last_rank[i] - rank[i]
    diff_sum += diff.abs
  end

  k += 1
  $stderr.printf "iteration:%d  diff_sum:%f rank_sum: %f\n", k, diff_sum, rank_sum
end while diff_sum > thresh
```

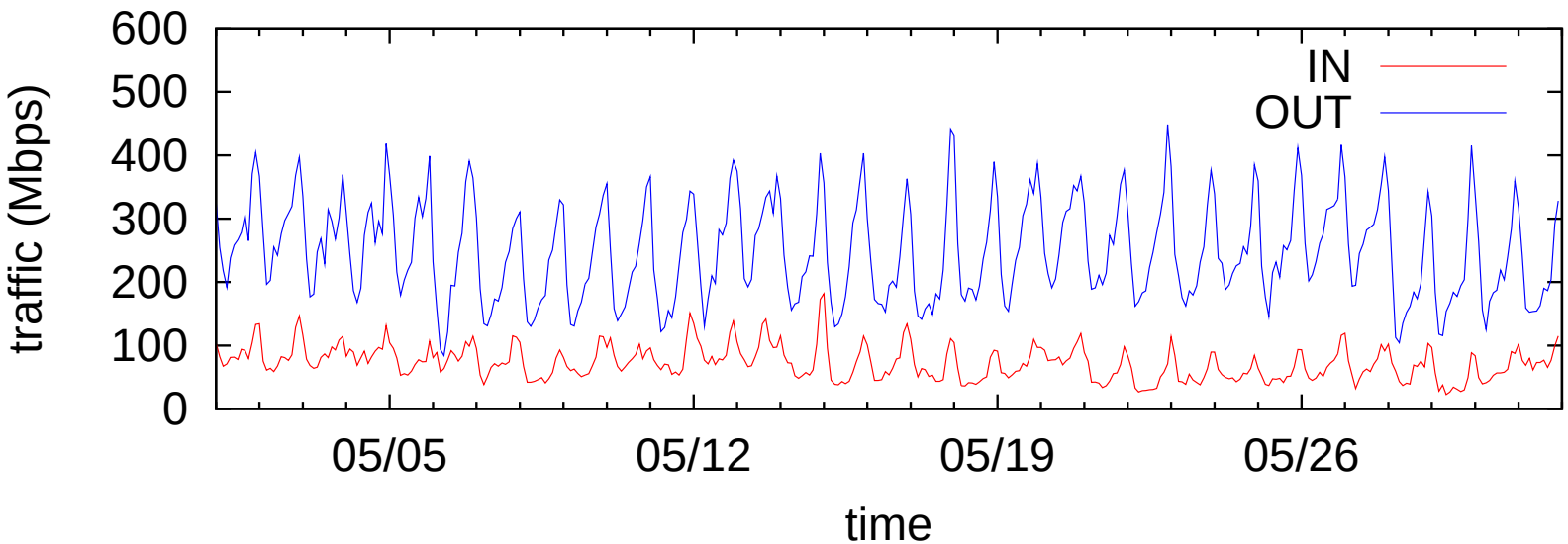
PageRank code (4/4)

```
# print pagerank in the decreasing order of the rank
# format: [position]  id  pagerank
i = 0
rank.sort_by{|k, v| -v}.each do |k, v|
  i += 1
  printf "[%d] %d %f\n", i, k, v
end
```

assignment 2 answer: traffic analysis

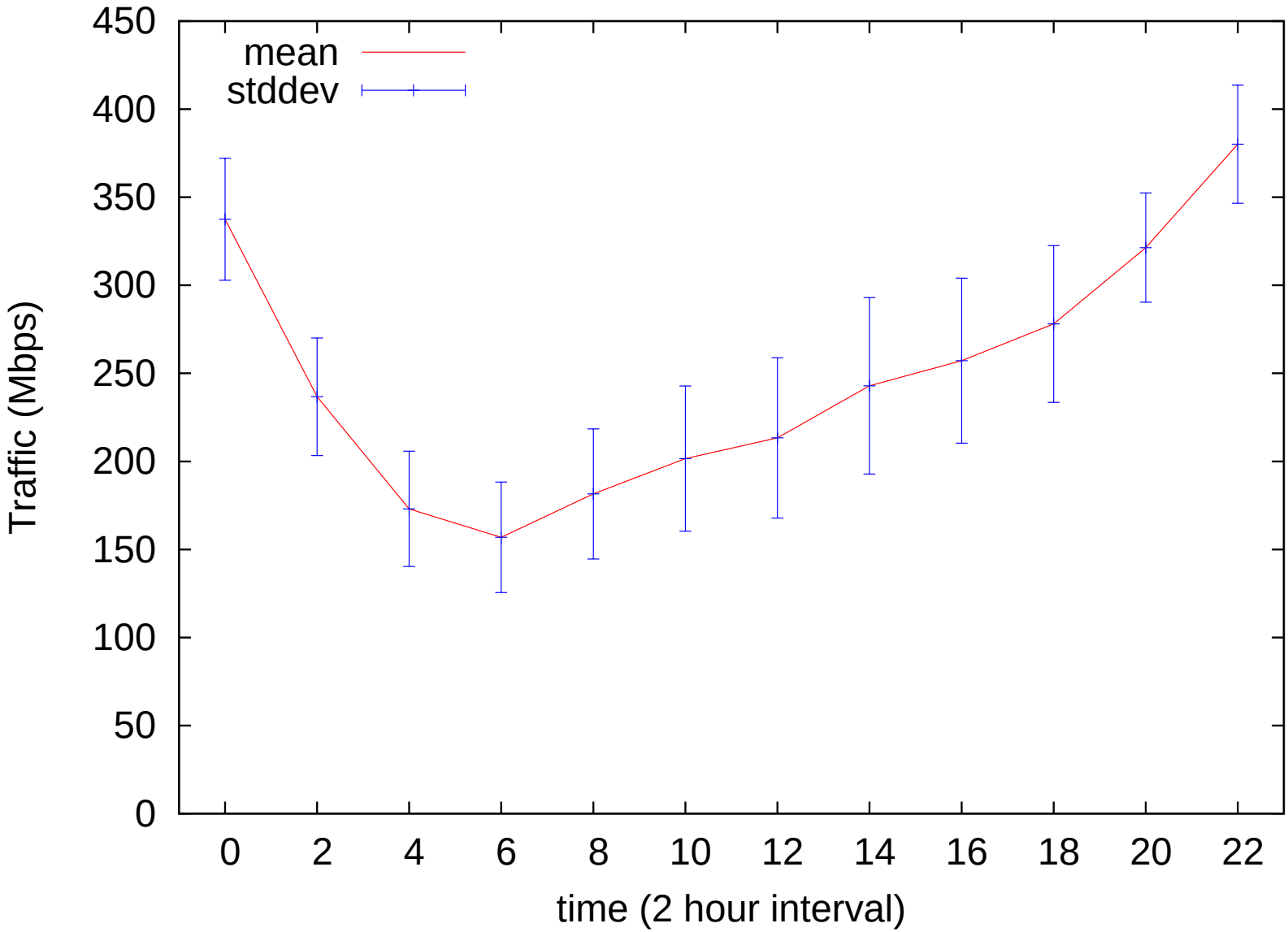
- purposes: analyzing real time-series data
- data: ifbps-2012.txt (the same interface counter for the exercise 2 but for 2012)
  - interface counter values from a router providing services to broadband users
  - one month data from May 2012, with 2-hour resolution
  - format: time IN(bits/sec) OUT(bits/sec)
- items to submit
  1. IN/OUT traffic plot for the entire month with 2 hour resolution
  2. time-of-day traffic of OUT
     - plot mean and standard deviation for each time of day
  3. time-of-day traffic plot of OUT for each day of the week
  4. correlation coefficient matrix of OUT among days of the week
  5. option
     - other analysis (e.g., IN vs. OUT, 2011 vs. 2012)
  6. discussion
     - describe your observations about the data and plots
- submission format: a single PDF file including item 1-6
- submission method: upload the PDF file through SFC-SFS
- submission due: 2012-12-07

IN/OUT traffic for the entire month

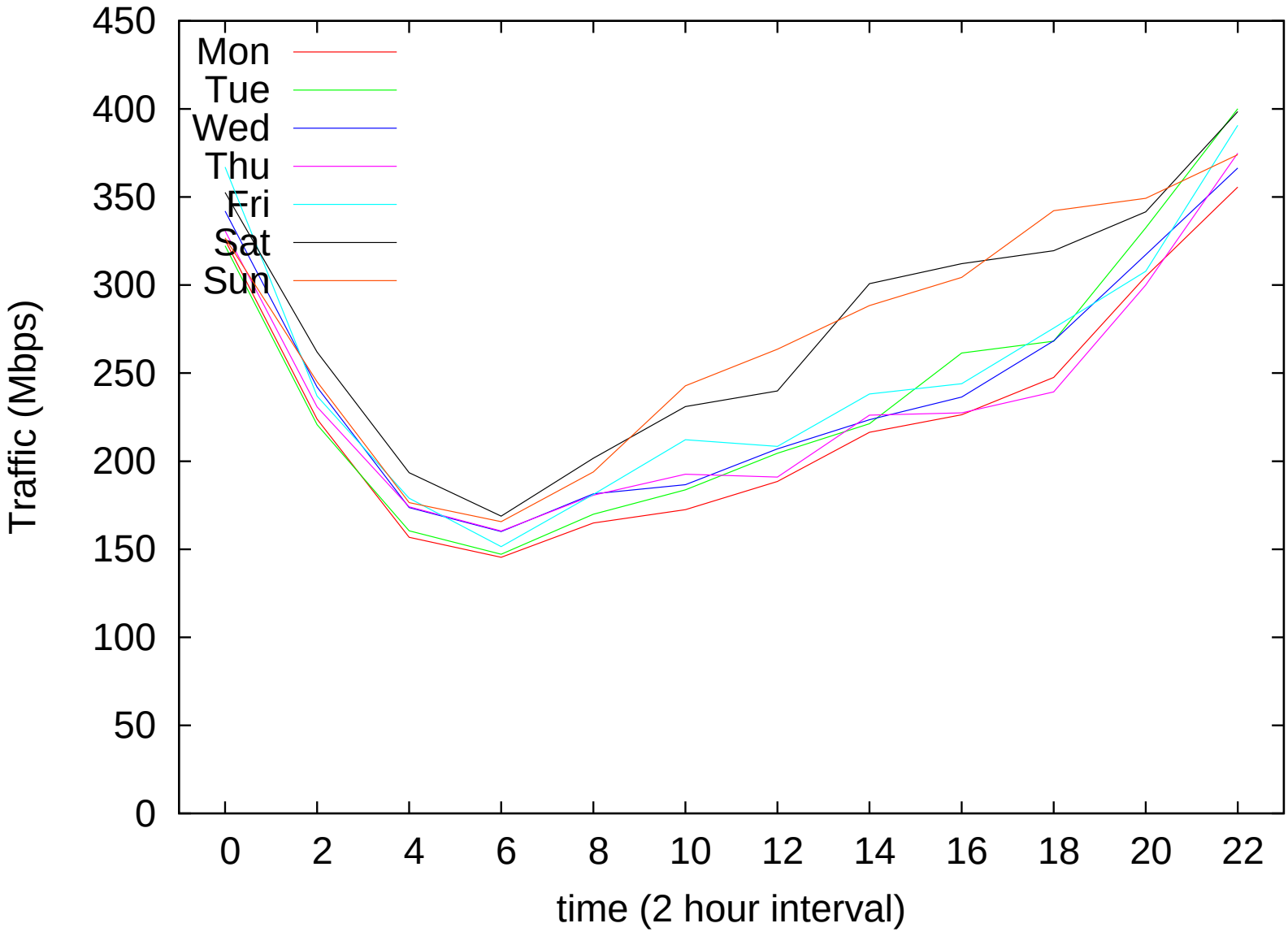


time-of-day traffic of OUT

- plot mean and standard deviation for each time of day



time-of-day traffic of OUT for each day of the week



correlation coefficient matrix of OUT among days of the week

- correlation matrix among days of week

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	1.000	0.985	0.998	0.991	0.988	0.955	0.901
Tue	0.985	1.000	0.981	0.975	0.969	0.964	0.927
Wed	0.998	0.981	1.000	0.987	0.987	0.946	0.897
Thu	0.991	0.975	0.987	1.000	0.988	0.933	0.859
Fri	0.988	0.969	0.987	0.988	1.000	0.951	0.896
Sat	0.955	0.964	0.946	0.933	0.951	1.000	0.971
Sun	0.901	0.927	0.897	0.859	0.896	0.971	1.000

on the final report

- select A or B
  - A. PageRank computation of Wikipedia
  - B. free topic
- up to 8 pages in the PDF format
- submission via SFC-SFS by 2013-01-25 (Fri) 23:59

final report topics

A. PageRank computation of Wikipedia

- data: link data within Wikipedia English version (5.7M pages)
- A-1 investigate the distribution of pages
  - A-1-1 plot CDF and CCDF of the outdegree of pages
  - A-1-2 discussion on the outdegree distribution of Wikipedia pages
- A-2 PageRank computation
  - A-2-1 compute PageRank, and show the top 30 of the results
  - A-2-2 other analysis (optional)
  - A-2-3 discussion on the results

B. free topic

- select a topic by yourself
- the topic is not necessarily on networking
- but the report should include some form of data analysis and discussion about data and results

note: you may work with a classmate on programming. but, if you work with someone, make it clear in the report. still, you must write discussions by yourself.

A. PageRank computation of Wikipedia

data: link data of Wikipedia English version (5.7M pages)

- created by Henry Haselgrove (http://haselgrove.id.au/wikipedia.htm)
  - a local copy is avaialble from the class web page
  - a test data set (a subset of 100K pages)
- links-simple-sorted.zip: link data (323MB compressed, 1GB uncompressed)
  - each page has an unique integer ID
  - format: $from : to_1, to_2, ...to_n$
- titles-sorted.zip: title data (28MB compressed, 106MB uncompresed)
  - $n-$th line: the title of page ID n (1 origin)

```
% head -3 links-simple-sorted.txt
1: 1664968
2: 3 747213 1664968 1691047 4095634 5535664
3: 9 77935 79583 84707 564578 594898 681805 681886 835470 ...
%
% sed -n '2713439p' titles-sorted.txt
Keio-Gijuku_University
```

A-1 investigate the distribution of pages

A-1 investigate the distribution of pages

- A-1-1 plot CDF and CCDF of the outdegree of pages
  - include pages with outdegree 0
- A-1-2 discussion on the outdegree distribution of Wikipedia pages
  - optional other analysis
  - hint: you may compare low-degree pages and high-degree pages

A-2 PageRank computation

A-2 PageRank computation

- A-2-1 compute PageRank, and show top 30 of the results
  - format: rank PageRank_value page_ID page_title
  - you may use the script for the exercise
    - use damping factor:0.85 thresh:0.000001
  - takes 5 hours with iMac with 8GB memory (requiring at least 4GB memory)
- A-2-2 other analysis (optional)
  - examples:
  - how to reduce the processing time
  - implement an improved verion of the PageRank algorithm
- A-2-3 discussion on the results

summary

Class 12 Search and Ranking

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

next class

Class 13 Scalable measurement and analysis (12/26)

- Distributed parallel processing
- Cloud computing technology
- MapReduce
- exercise: MapReduce algorithm