

## Big Data Algorithmic Introduction

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## Logistics

- Contact: [shavitt@eng.tau.ac.il](mailto:shavitt@eng.tau.ac.il)
- Final grade:
  - 4-6 home assignments (will try to include programming assignments as well): 20%
  - Exam 80%

## Big Data

- Today we have huge datasets:
  - Social networks
  - Biological networks
  - Consumer data
  - Transportation data
  - Internet data
- Their analysis require new approaches

## How many *objects* do we store?

### The Cloud Scales: Amazon S3 Growth

Quarter	Total Number of Objects
Q4 2006	2.9 Billion
Q4 2007	14 Billion
Q4 2008	40 Billion
Q4 2009	102 Billion
Q4 2010	262 Billion
Q4 2011	762 Billion
Q1 2012	905 Billion

## LinkedIn

### LinkedIn Growth 2006-2011

Year	Number of Users (Approximate)
2006	10,000,000
2007	15,000,000
2008	25,000,000
2009	40,000,000
2010	70,000,000
2011	140,000,000

<http://dstevenwhite.com>

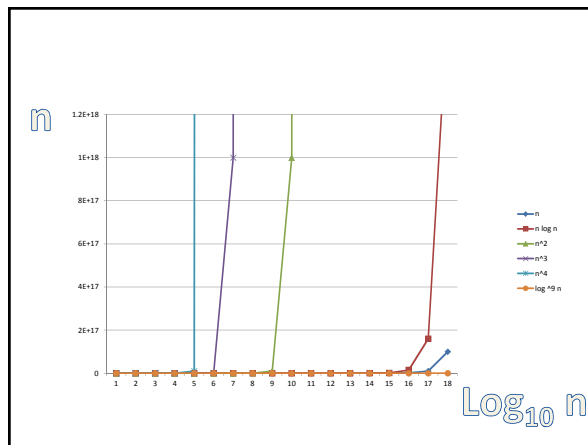
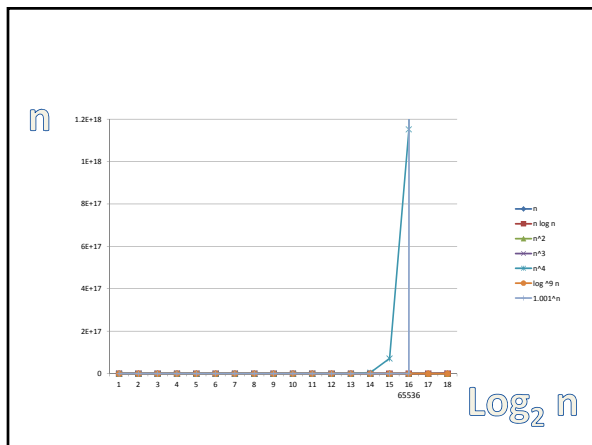
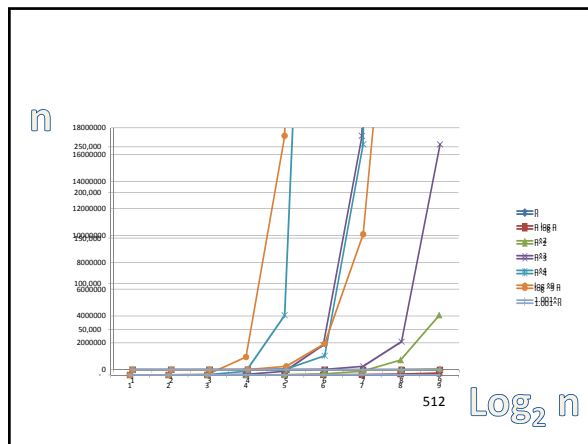
## Analyzing the Facebook graph?

### Facebook Users In Millions

Date	Number of Users (Millions)
Dec-04	1
Apr-05	3.5
Dec-05	5.5
Apr-06	12
Dec-06	20
Apr-07	50
Dec-07	100
Apr-08	150
Dec-08	200
Apr-09	300
Dec-09	450
Apr-10	550
Dec-10	650
Apr-11	750
Dec-11	850
Apr-12	900
Dec-12	1,090

### Complexity Basics

- We are interested in algorithms that are efficient
  - $O(n)$  is better than  $O(n^2)$
  - $O(n)$  is better than  $O(n \log n)$
  - $O(\log^5 n)$  is better than  $O(n)$
  - $O(n^3)$  is better than  $O((1+\epsilon)^n)$



### When Data is Large?

- Definition 1: When data cannot be stored on the machine RAM
- If the algorithm is not sequential
- Definition 2: When “regular” algorithms fail
- Too slow
    - An  $O(n^2)$  algorithm when  $n=2,000,000$  will run for 8 hours if the  $O$  constant is 1
  - Too deep stack

### Where is Our Data?

- Centralized
  - oracle
- Distributed
- Streamed

### Thinking about Algorithms

- Our thinking about algorithm is 80 years old
- Worst case analysis
  - Average case is marginalized
  - No attempt to define working regimes
  - Constants are ignored (even logs  $\hat{O}()$ )

### Shortest Path

- Given a graph  $G(V,E)$  with non-negative edge weights, find the shortest path between two vertices.
- Best algorithm?
- Dijkstra with complexity  $O(V \log V+E)$ 
  - $|V|$  times we select the node closest to source
    - Costs  $O(V)$

### Shortest Path

- Given a graph  $G(V,E)$  with non-negative edge weights, find the shortest paths from a vertice to all others.
- Best algorithm?
- Dijkstra with complexity  $O(V \log V+E)$

### Dijkstra

- Complexity  $O(V \log V+E)$ 
  - $|V|$  times we select the node closest to source
    - Costs  $O(V)$
  - $|E|$  we relax and edge
- Why not  $O(V^2+E)$ ?
  - Q can be implemented with a *Binary heap*
    - $O(E \log V)$
  - Q can be implemented with a *Fibonacci heap*
    - $O(V \log V+E)$

```

Dijkstra(G, w, s)
1 INITIALIZE-SINGLE-SOURCE(G, s)
2 S ← ∅
3 Q ← V[G]
4 while Q ≠ ∅
5   do u ← EXTRACT-MIN(Q)
6     S ← S ∪ {u}
7   for each vertex v ∈ Adj[u]
8     do RELAX(u, v, w)
    
```

### But wait, what does the bible say?

heaps.

From a practical point of view, however, the constant factors and programming complexity of Fibonacci heaps make them less desirable than ordinary binary (or  $k$ -ary) heaps for most applications. Thus, Fibonacci heaps are predominantly of theoretical interest. If a much simpler data structure with the same amortized time bounds as Fibonacci heaps were developed, it would be of great practical use as well.

$V$  is a binomial heap. A Fibonacci heap is a collection of trees. Fibonacci

This leaves us with a complexity of  $O(E \log V)$  and we still have to implement the heap

### Shortest Path with Bellman-Ford

```

procedure BellmanFord(list vertices, list edges, vertex source)
//Step 1: initialize graph
for each vertex v in vertices:
  if v is source then distance[v] := 0
  else distance[v] := infinity
  predecessor[v] := null
// Step 2: relax edges repeatedly
for i from 1 to size(vertices)-1:
  for each edge (u, v) with weight w in edges:
    if distance[u] + w < distance[v]:
      distance[v] := distance[u] + w
      predecessor[v] := u
    
```

$O(V E)$

### B-F Discussion

- $O(V E)$  is worse even than  $O(E \log V)$

// Step 2: relax edges repeatedly

```
for i from 1 to size(V)-1: D+1
  for each edge (u, v) with weight w in edges:
    if distance[u] + w < distance[v]:
      distance[v] := distance[u] + w
      predecessor[v] := u
```

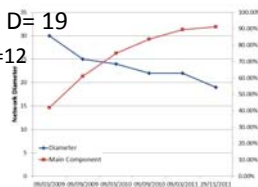
What is the diameter of a *real* graph?

$\log V$  (or less)

Easy to implement – no hidden costs

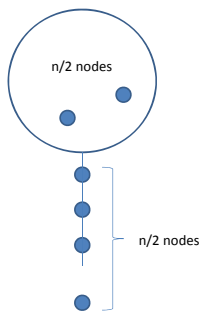
### Example: The STEAM Network

- A network of gamers
- $|V|=9,000,000$   $|E|= 82,000,000$   
 $|E|/|V|=18.2$
- LCC has 8,244,178 nodes
- Approximated Diameter:  $D= 19$   
– Removing 22 nodes  $\Rightarrow D=12$



### It is easy to build a bad graph

- But do such graphs exist?
  - In our facebook graph?
  - LinkedIn graph?
  - Any real data graph?
- Maybe in a future graph?



### Algorithmic Approaches

- Find better exact algorithms
  - Maybe for special cases: sparse graphs, bounded degree, bounded diameter, ...
- Approximation algorithms
  - $\epsilon$ , constant, logarithmic approximation
  - Polynomial running time
- Probabilistic approximation
  - Sometimes sublinear
- heuristics

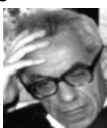
### $(\epsilon, \delta)$ – Approximation

- An algorithm for estimating  $f$  is an  $(\epsilon, \delta)$ -approximation if it takes an input instance and two real values  $\epsilon, \delta$  and produces an output  $y$  such that

$$\Pr[(1-\epsilon) \cdot f \leq y \leq (1+\epsilon) \cdot f] \geq 1-2\delta$$

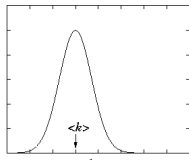
Graphs

### Random graphs in Mathematics The Erdős-Rényi model



- Generation:
  - create  $n$  nodes.
  - each possible link is added with probability  $p$ .
- Number of links:  $np$
- If we want to keep the number of links linear, what happen to  $p$  as  $n \rightarrow \infty$ ?

Poisson distribution

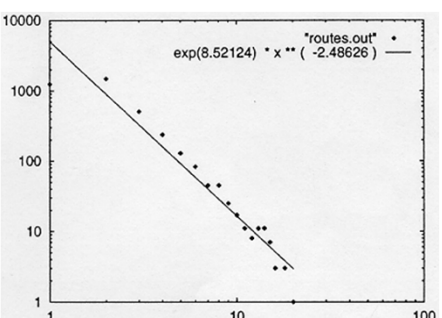


### The Barabasi-Albert Model

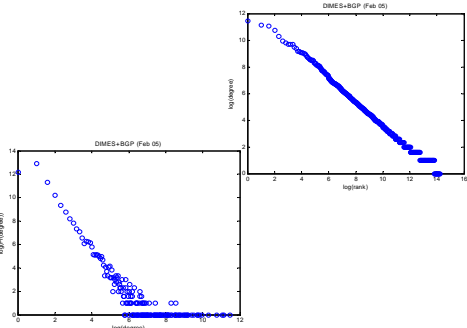
- Noticed that many graphs have a similar structure
  - No characteristic degree
  - Most nodes have small degree
  - The number of nodes with high degree declines polynomially (not exponentially)
    - Long tail

### The Faloutsos Graph 1995 Internet router topology

3888 nodes, 5012 edges,  $\langle k \rangle = 2.57$



### Degree Dist. & Zipf Plot



### ACTOR CONNECTIVITIES

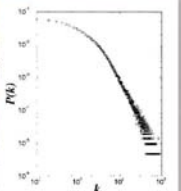
nodes: actors  
edges: casted jointly

IMDb Internet Movie Database

Days of Thunder (1990)  
Far and Away (1992)  
Eyes Wide Shut (1999)

$N = 212,250$  actors  
 $\langle k \rangle = 28.78$

$P(k) \sim k^{-\gamma}$   
 $\gamma = 2.3$



### SCIENCE CITATION INDEX

1,000 Most Cited Physicists, 1981-June 1997

Check out more 5000,000 Scientists

Nodes: papers  
Links: citations

Witten-Sander  
PRL 1981

1736 PRL papers (1988)

$P(k) \sim k^{-\gamma}$   
 $\gamma = 3$

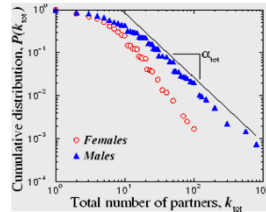
Author(s)	Year	Journal	Citations	Rank	Normalized Rank	Normalized Citations
Witten	1981	Physical Review Letters	1234	1	1.000	1234.0
Sander	1981	Physical Review Letters	25	25	0.040	48.5
Witten	1981	Physical Review Letters	2212	2	0.500	2468.0
Sander	1981	Physical Review Letters	1234	25	0.040	48.5

(S. Redner, 1998)

### Sex-web

**Nodes:** people (Females; Males)  
**Links:** sexual relationships

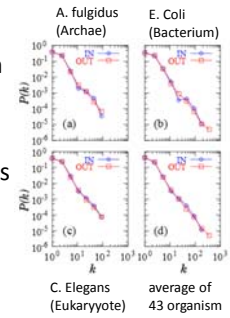
4781 Swedes; 18-74;  
 59% response rate.



Liljeros et al. Nature 2001

### Metabolic Network

- A graph representation of the biochemical reaction in a metabolic network
- nodes= substrates
- Edges = metabolic reactions
- Node degree
  - In = participate as product
  - Out = participate as educt



Jeong et al. Nature 2000

### SCALE-FREE NETWORKS

**(1) The number of nodes (N) is NOT fixed.**

Networks continuously expand by the addition of new nodes

Examples:  
 WWW : addition of new documents  
 Citation : publication of new papers

**(2) The attachment is NOT uniform.**

A node is linked with higher probability to a node that already has a large number of links.

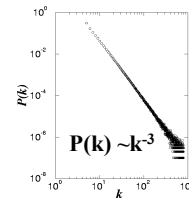
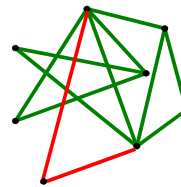
Examples :  
 WWW : new documents link to well known sites (CNN, YAHOO, NewYork Times, etc)  
 Citation : well cited papers are more likely to be cited again

### Scale-free model

**(1) GROWTH :**  
 At every timestep we add a new node with  $m$  edges (connected to the nodes already present in the system).

**(2) PREFERENTIAL ATTACHMENT :**  
 The probability  $\Pi$  that a new node will be connected to node  $i$  depends on the connectivity  $k_i$  of that node

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}$$



A.-L.Barabási, R. Albert, Science 286, 509 (1999)