THE UNIVERSITY *of* EDINBURGH

Text Technologies for Data Science

INFR11145

Web Search

Instructor:
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01-Nov-2023

Pre-lecture

- Hopefully CW1 went fine (don’t share results)
- Your feedback in break!
- No lab for this week
- New lecturer next week:
  Bjorn Ross

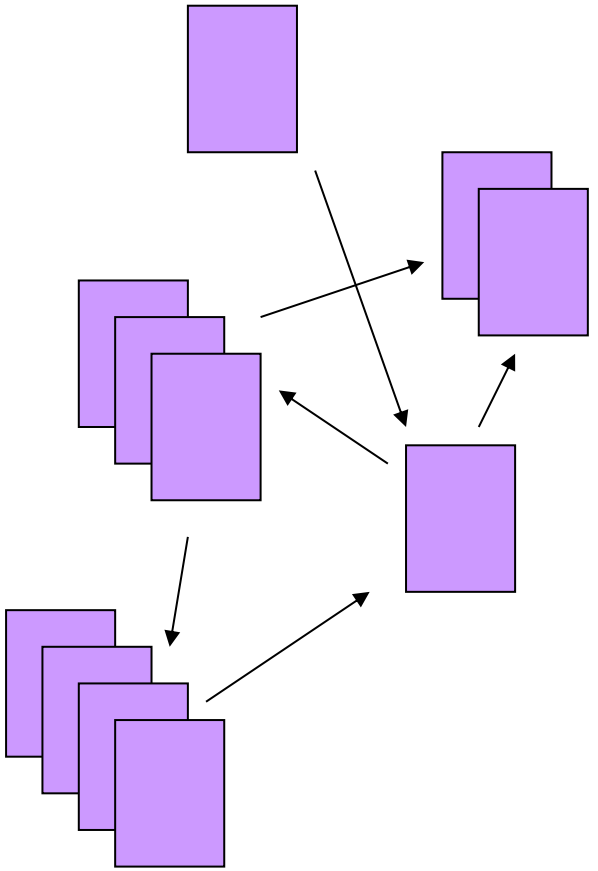
- CW marking is going on.
  - Hopefully results will be announced within 3 weeks

Lecture Objectives

- Learn about:
  - Working with Massive data
  - Link analysis (PageRank)
  - Anchor text

The Web Document Collection

- Huge / Massive
- Graph / Connected
- No design/co-ordination
- Distributed content publishing
- Content includes truth, lies, obsolete information, contradictions …
- Unstructured (text, html, …), semi-structured (XML, annotated photos), structured (DB) …
- Growth – slowed down from initial “volume doubling every few months” but still expanding
- Content can be dynamically generated



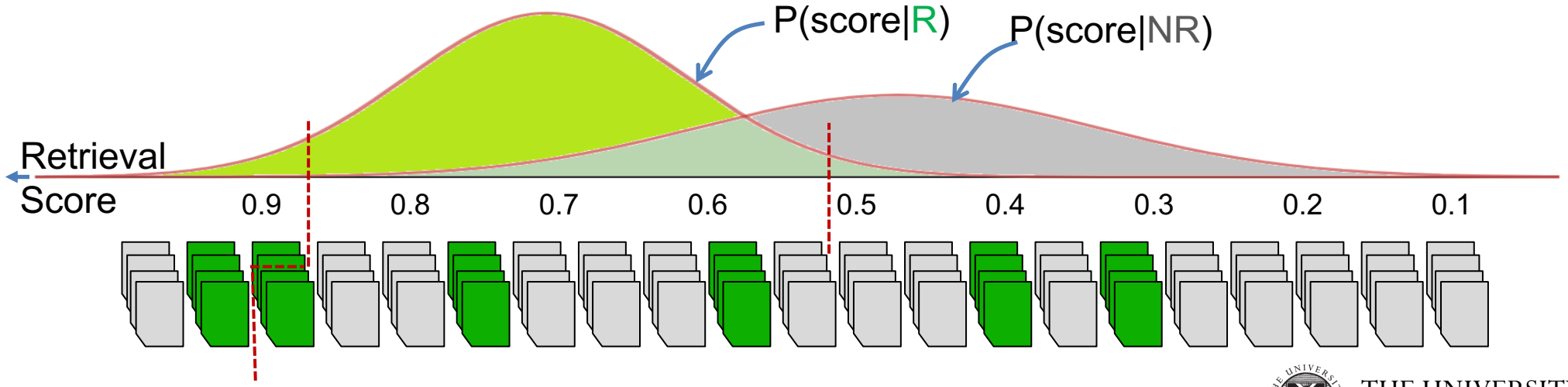
The Web

Effect of Massive data

- Web search engines work with huge amount of data
  - 20 PB/day in 2008 → 160 PB/day in 2013 → now??
  - 1 PB = 1,000 TB = 1,000,000 GB
- How this would affect a search engine?
  - Very challenging (storage, processing, networking, …)
  - Very useful still (makes stuff easier), how?

Effect of Massive data on Precision

- Assume two good search engines that collect two sub-sets of the web
  - Search engine A collected N docs → precision@10 = 40%
  - Search engine B collected 4N docs → precision@10??
    - Distribution of positive/negative scores stays the same
    - Precision/Recall at a given score stays the same
    - In any decent IR system: more relevant docs exist at the top → P@n ↑↑ ➔ precision@10 = 60% (increases)



Big Data or Clever Algorithm?

- For Web search, larger index usually would beat a better retrieval algorithm
  - Google Index vs Bing Index
- Similar to other applications
  - Google MT vs IBM MT
    - Statistical methods trained over 10x training data beat deep NLP methods with 1x training data
  - In general ML, the more data, the better the results
    - Tweets classification: using 100x of noisy training data beats 1x of well prepared training data, even with absence of stemming & stopping
  - Question answering task:
    - IBM Watson vs Microsoft experiment

Big Data or Clever Algorithm?

- Question answering task:
  - **Q**: Who created the character of Scrooge?
  - **A**: Scrooge, introduced by Charles Dickens in "A Chrismas Carol"
  - Requires heavy linguistic analysis, lots of research in TREC
- 2002, Microsoft
  - Identify (subj verb obj), rewrite as queries:
    - Q1: "created the character of Scrooge"
    - Q2: "the character of Scrooge was created by"
  - Search the web for exact phrase, get top 500 results
  - Extract phrase: ■Q1 or Q2■ , get most frequent ■
  - Very naive approach, ignores most answers patterns
  - Who cares!! Web is huge, you will find matches anyway

117	Dickens
78	Christmas Carol
75	Charles Dickens
72	Disney
54	Carl Banks
	…

Search “Microsoft”

Doc1

Microsoft.com

“Microsoft” mentioned 5 times

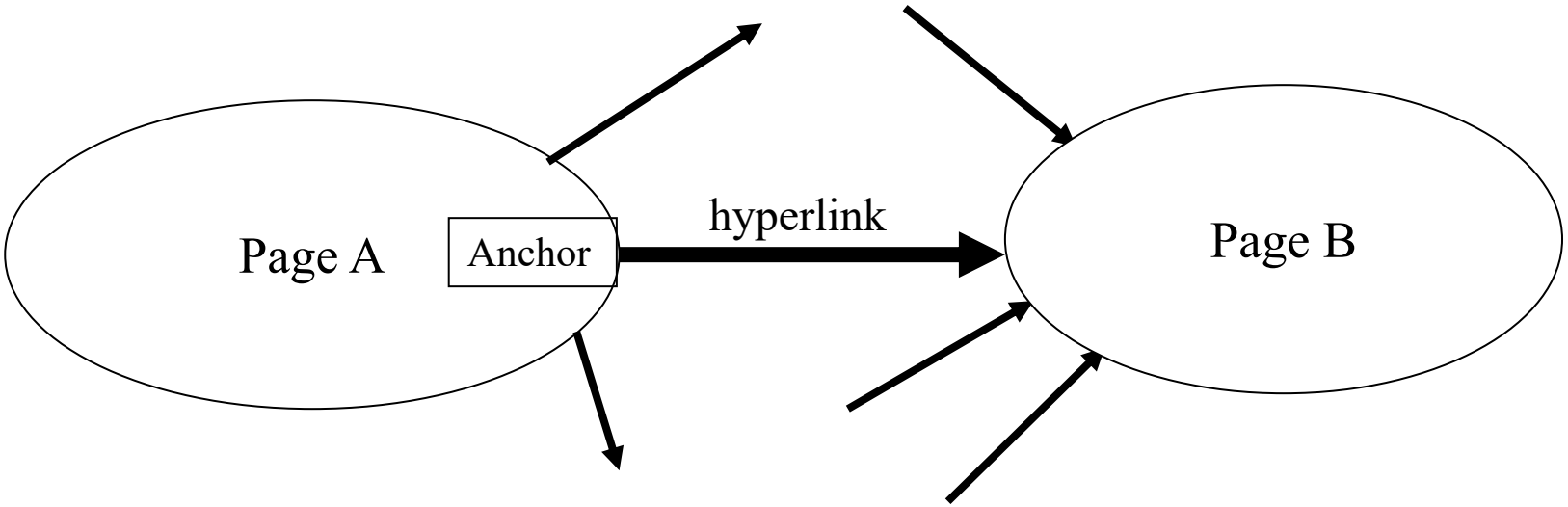
Doc2

Tutorial.com

Tutorial on MS word

“Microsoft” mentioned 35 times

The Web as a Directed Graph



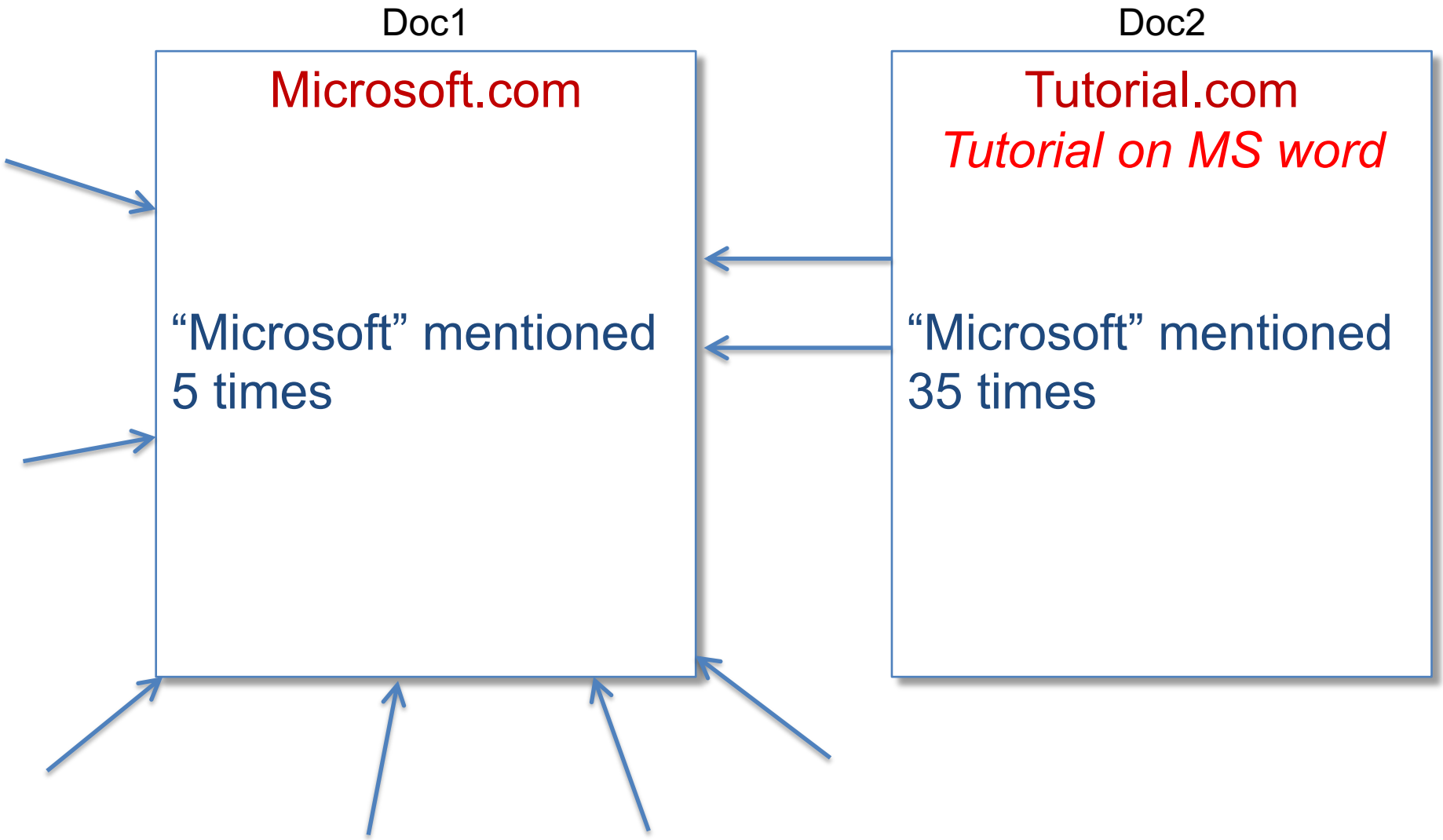
Assumption 1: A hyperlink between pages denotes author perceived relevance (quality signal)

Assumption 2: The text in the anchor of the hyperlink describes the target page (textual context)

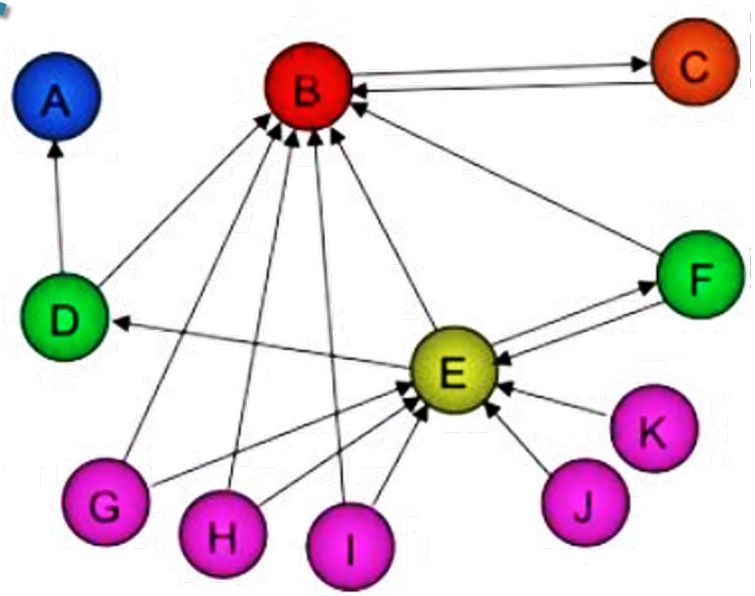
Links between Pages

- Google Description of **PageRank**:
  - Relies on the "uniquely democratic" nature of the web
  - Interprets a link from page A to page B as "a vote"
- A → B: means A thinks B worth something
  - "wisdom of the crowds": many links means B must be good
  - Content-independent measure of quality of B
- Use as ranking feature, combined with content
  - But not all pages that link to B are of equal importance!
    - Importance of a link from CNN >>> link from blog page
- Google PageRank, 1998
  - How many "good" pages link to B?

Search “Microsoft”



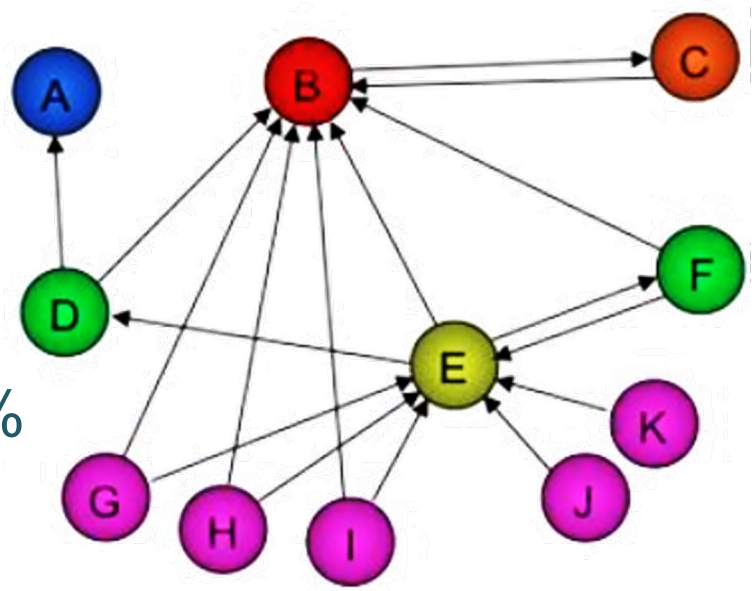
PageRank: Random Surfer



- Analogy:
  - User starts browsing at a random page
  - Pick a random outgoing link → goes there → repeat forever
  - Example: G → E → F → E → D → B → C
  - With probability 1-λ jump to a random page
    - Otherwise, can get stuck forever A, or B ↔ C
- **PageRank** of page x
  - Probability of being at page x at a random moment in time

PageRank: Algorithm

- Initialize $PR_0(x) = \frac{100\%}{N}$
  - *N*: total number of pages
  - $PR_0(A) = .. = PR_0(K) = \frac{100\%}{11} = 9.1\%$



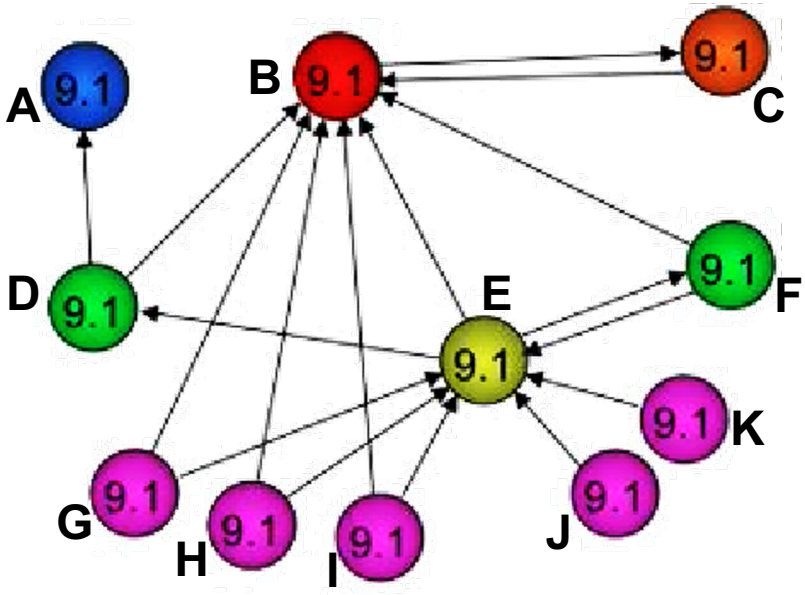
- For every page x

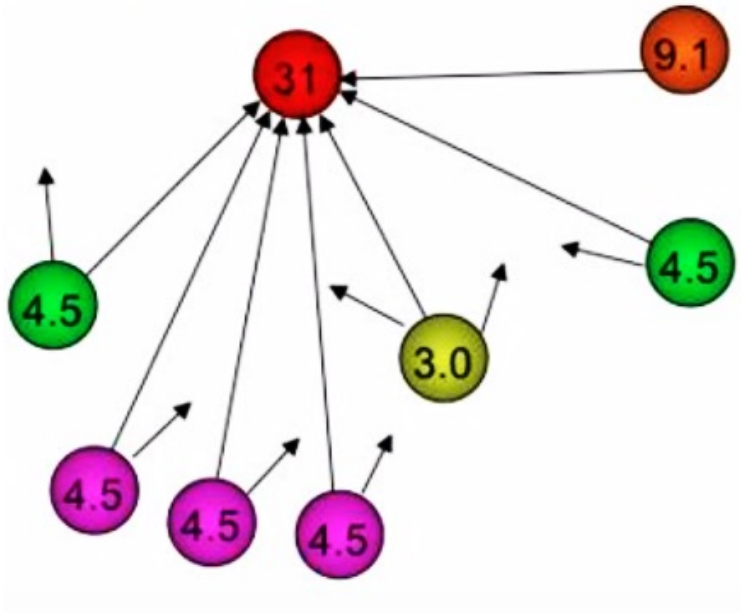
$$PR_{t+1}(x) = \frac{1-\lambda}{N} + \lambda \sum_{y \to x} \frac{PR_t(y)}{L_{out}(y)}$$

- $y \longrightarrow x$ contributes part of its PR to x
- Spread PR equally among out-links
- Iterate till converge

PageRank: Example

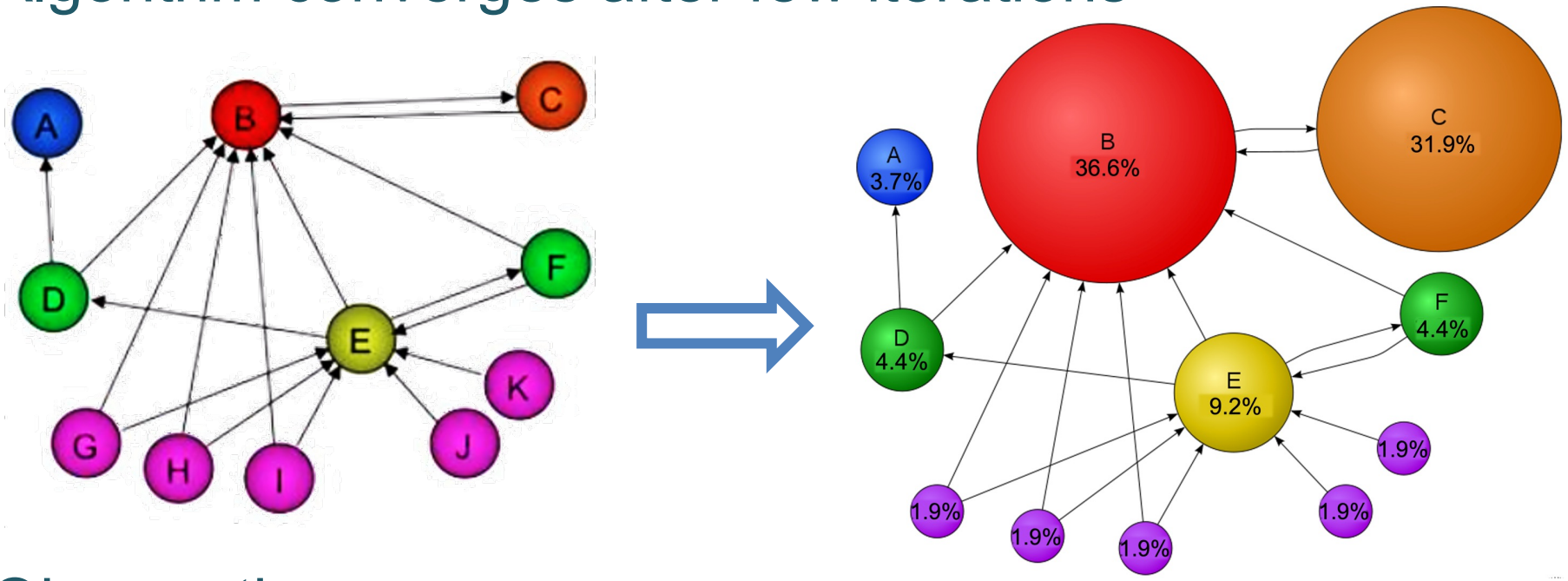
- Let $\lambda = 0.82$
- $PR(B) = \frac{0.18}{11} + 0.82 \times [PR(C) + \frac{1}{2}PR(D) + \frac{1}{3}PR(E) + \frac{1}{2}PR(F) + \frac{1}{2}PR(G) + \frac{1}{2}PR(H) + \frac{1}{2}PR(I)]$
  $\approx 0.31 = 31\%$
- $PR(C) = \frac{0.18}{11} + 0.82 \times PR(B)$
  $= 0.18 \times 9.1\% + 0.82 \times 9.1\%$
  $= 9.1\%$
- $PR_{t+1}(C) = 0.18 \times 9.1\% + 0.82 \times 31\%$
  $\approx 26\%$





PageRank: Example result

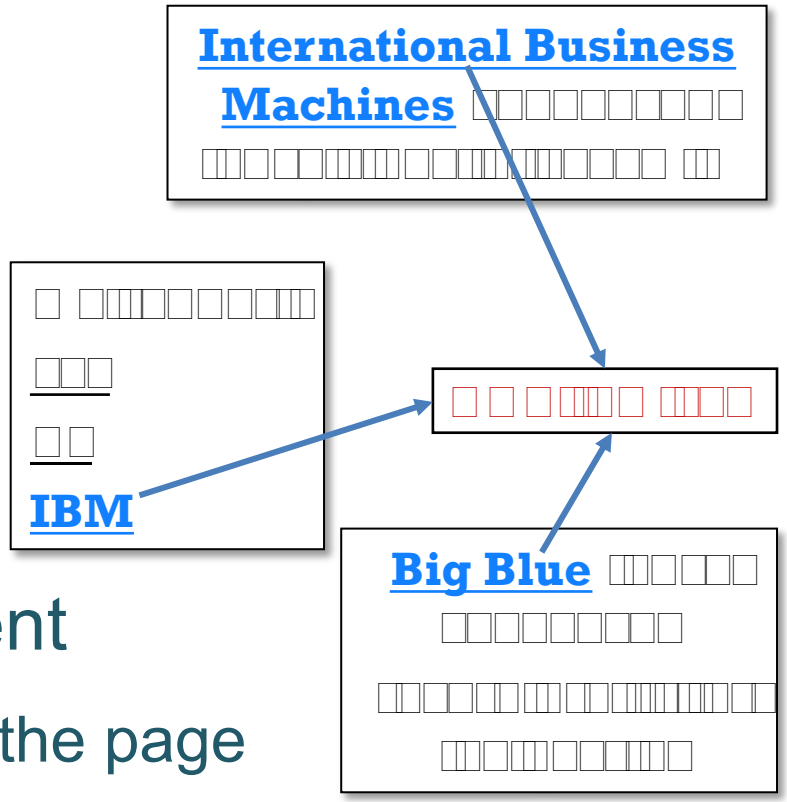
- Algorithm converges after few iterations



- Observations
  - Pages with no inlinks: PR = $(1 - \lambda)/N$= 0.18/11 = 1.6%
  - Same (or symmetric) inlinks → same PR (e.g. **D** and **F**)
  - One inlink from high PR >> many from low PR (e.g. **C** vs **E**)

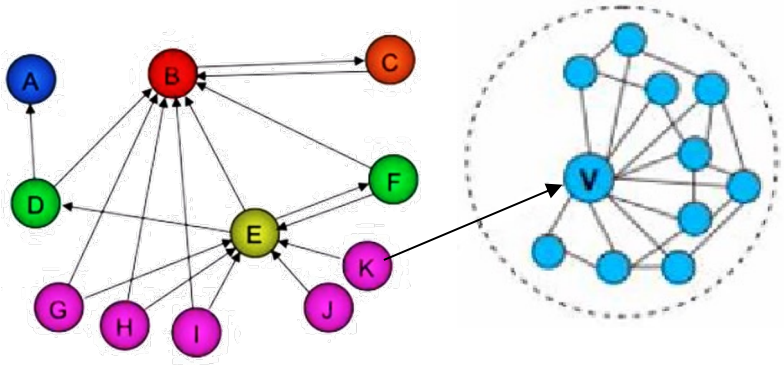
Anchor Text

- Anchor Text (text of a link):
  - Description of destination page
  - Short, descriptive like a query
  - Re-formulated in different ways
    - Human "query expansion"
- Used when indexing page content
  - Add text of all anchor text linking the page
  - Different weights for different anchor text
    - Weighted according to PR of linking page
- Significantly improves retrieval



Link Spam

- Trackback links (blogs that link to me)
  - Based on `$HTTP_REFERER`
  - Artificial feedback loops
    - Similar to "*follow back*" in Twitter
- Links from comments on sites with high PR
  - Links in comments on CNN
  - One solution: insert `rel=nofollow` into links
    - Link ignored when computing PR
- Link farms
  - Fake densely-connected graph
  - Hundreds of web domains / IPs can be hosted on one machine



The Reality

- **PageRank** is used in Google, but is hardly the full story of ranking
  - A big hit when initially proposed, but just one feature now
  - Many sophisticated features are used
  - Machine-learned ranking heavily used
    - Learning to Rank (L2R)
    - Many features are used, including PR
  - Still counted as a very useful feature

Summary

- Web data is massive
  - Challenging for efficiency, but useful for effectiveness
- PageRank:
  - Probability that random surfer is currently on page x
  - The more powerful pages linking to x, the higher the PR
- Anchor text:
  - Short concise description of target page content
  - Very useful for retrieval
- Link Spam
  - Trackable links, link farms

How Search Engine Works?

Resources

- Text book 1: Intro to IR, Section 21.1
- Text Book 2: IR in Practice: 4.5, 10.3
- Page Rank Paper:
  Page, L., Brin, S., Motwani, R., & Winograd, T. (1999).
  The PageRank citation ranking: Bringing order to the web.
  Stanford InfoLab.
- Additional reading:
  Dumais, S., Banko, M., Brill, E., Lin, J., & Ng, A. (2002)
  Web question answering: Is more always better?.
  SIGIR 2002.
- YouTube Video: How Search Works
  https://www.youtube.com/watch?v=BNHR6IQJGZs