CC5212-1

Procesamiento Masivo de Datos

Otoño 2021

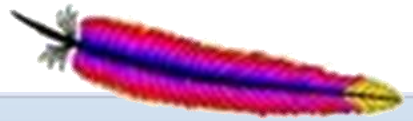
Lecture 8

Information Retrieval: Ranking

Aidan Hogan

aidhog@gmail.com

Apache Lucene



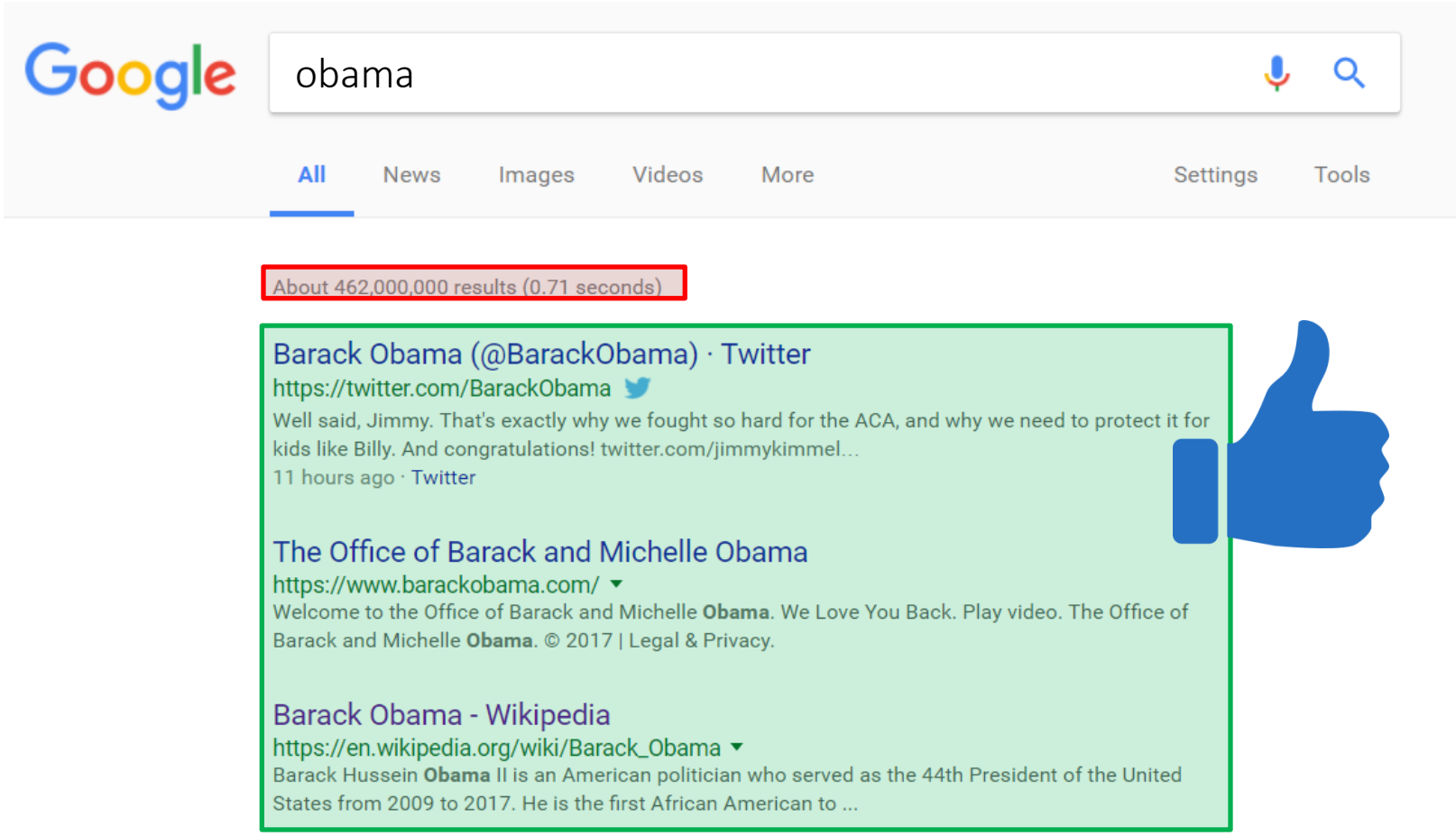
Tasks | Console

SearchWikiIndex [Java Application] C:\Program Files\Java\jre1.8.0_65\bin\javaw.exe (03-05-2017 12:45:22 a. m.)

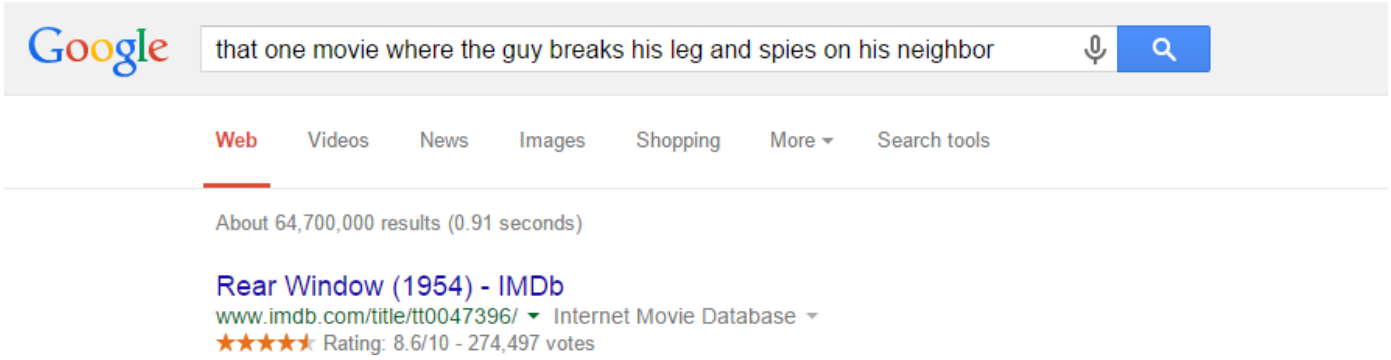
```
Opening directory at  lucene
Enter a keyword search phrase:
obama
Running query: obama
Parsed query: TITLE:obam^5.0 ABSTRACT:obam
Matching documents: 255
Showing top 10 results
1       http://es.wikipedia.org/wiki/Obama_Republican   Obama Republican
2       http://es.wikipedia.org/wiki/Obama_(Fukui)      Obama (Fukui)
3       http://es.wikipedia.org/wiki/Republicanos_por_Obama     Republicanos por Obama
4       http://es.wikipedia.org/wiki/Engonga_Obame      Engonga Obame
5       http://es.wikipedia.org/wiki/Barack_Obama       Barack Obama
6       http://es.wikipedia.org/wiki/Michelle_Obama     Michelle Obama
7       http://es.wikipedia.org/wiki/Cartel_%22Hope%22_de_Obama Cartel "Hope" de Obama
8       http://es.wikipedia.org/wiki/Transición_presidencial_de_Barack_Obama    Transición presidencial de Barack Obama
9       http://es.wikipedia.org/wiki/Por_qué_Obama_ganará_en_2008_y_en_2012     Por qué Obama ganará en 2008 y en 2012
10      http://es.wikipedia.org/wiki/Ricardo_Mangue_Obama_Nfubea        Ricardo Mangue Obama Nfubea
```

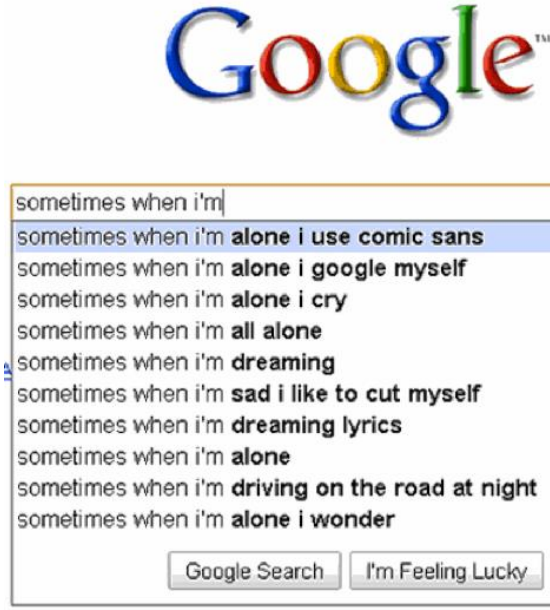
Information Retrieval: Ranking

How Does Google Get Such Good Results?



How does Google Get Such Good Results?



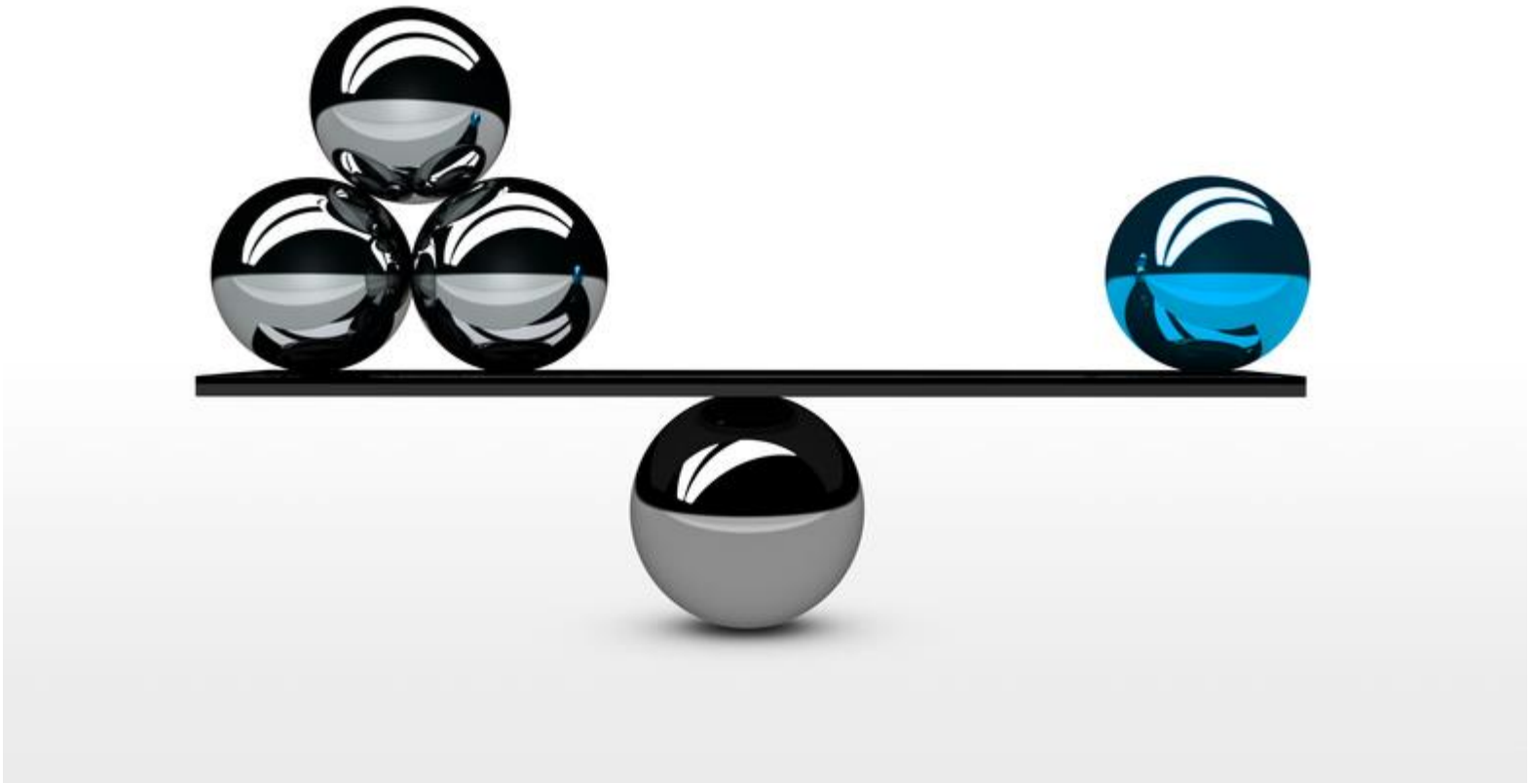


Two aspects of ranking: Relevance vs. Importance

Two Sides to Ranking: Relevance

Two Sides to Ranking: Importance

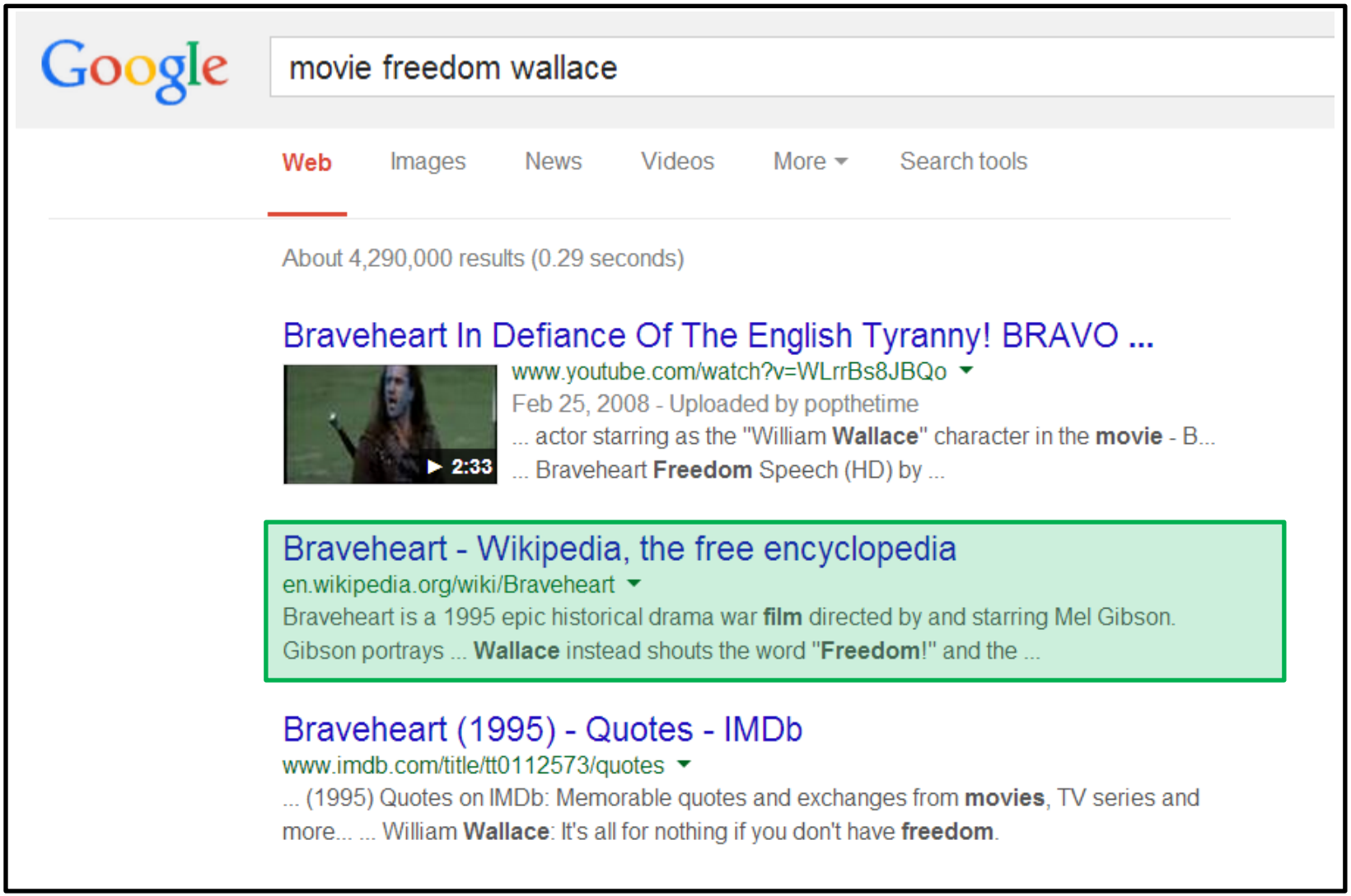
Relevance vs. Importance: A Balancing Act



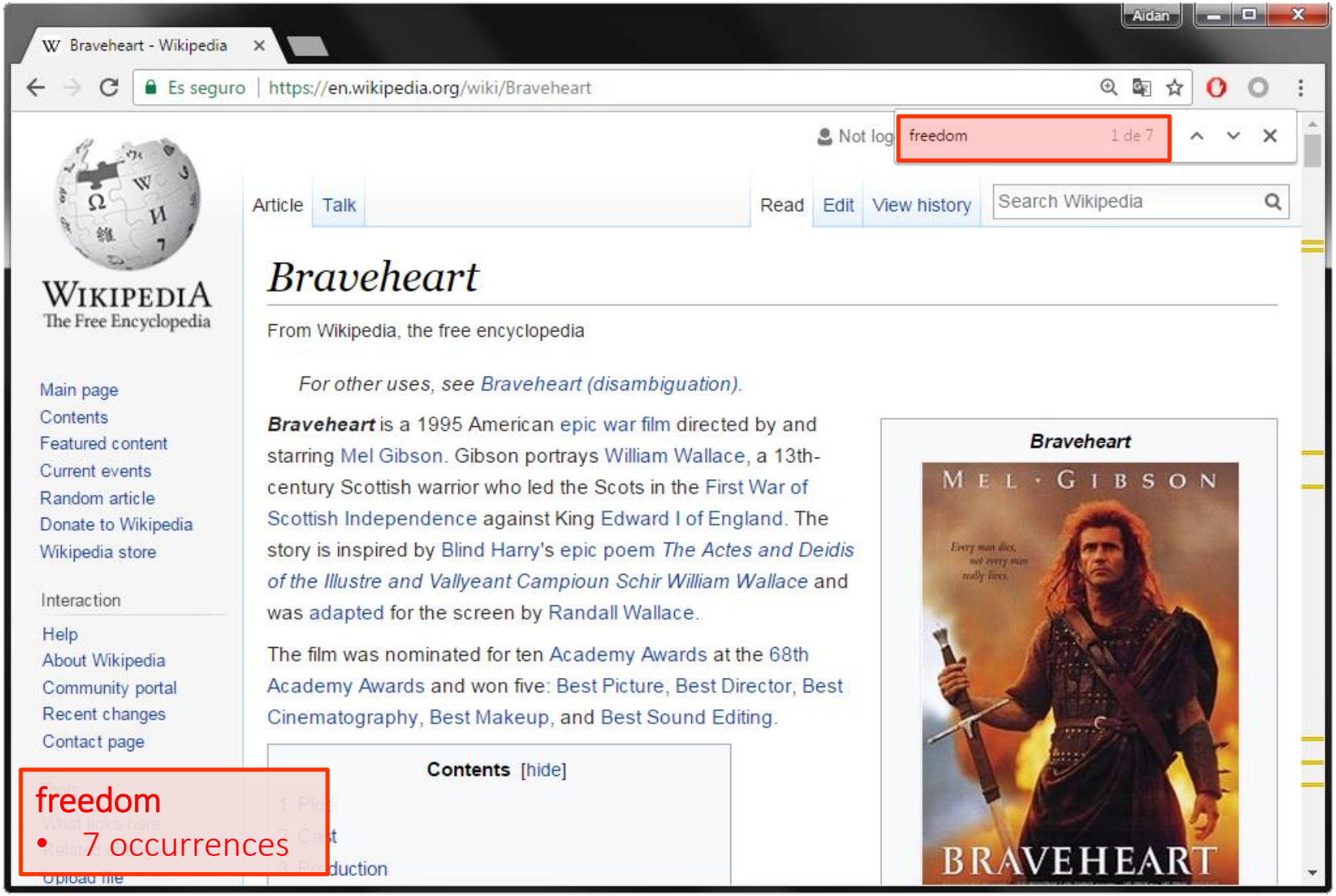
Ranking:
Relevance

Example Query

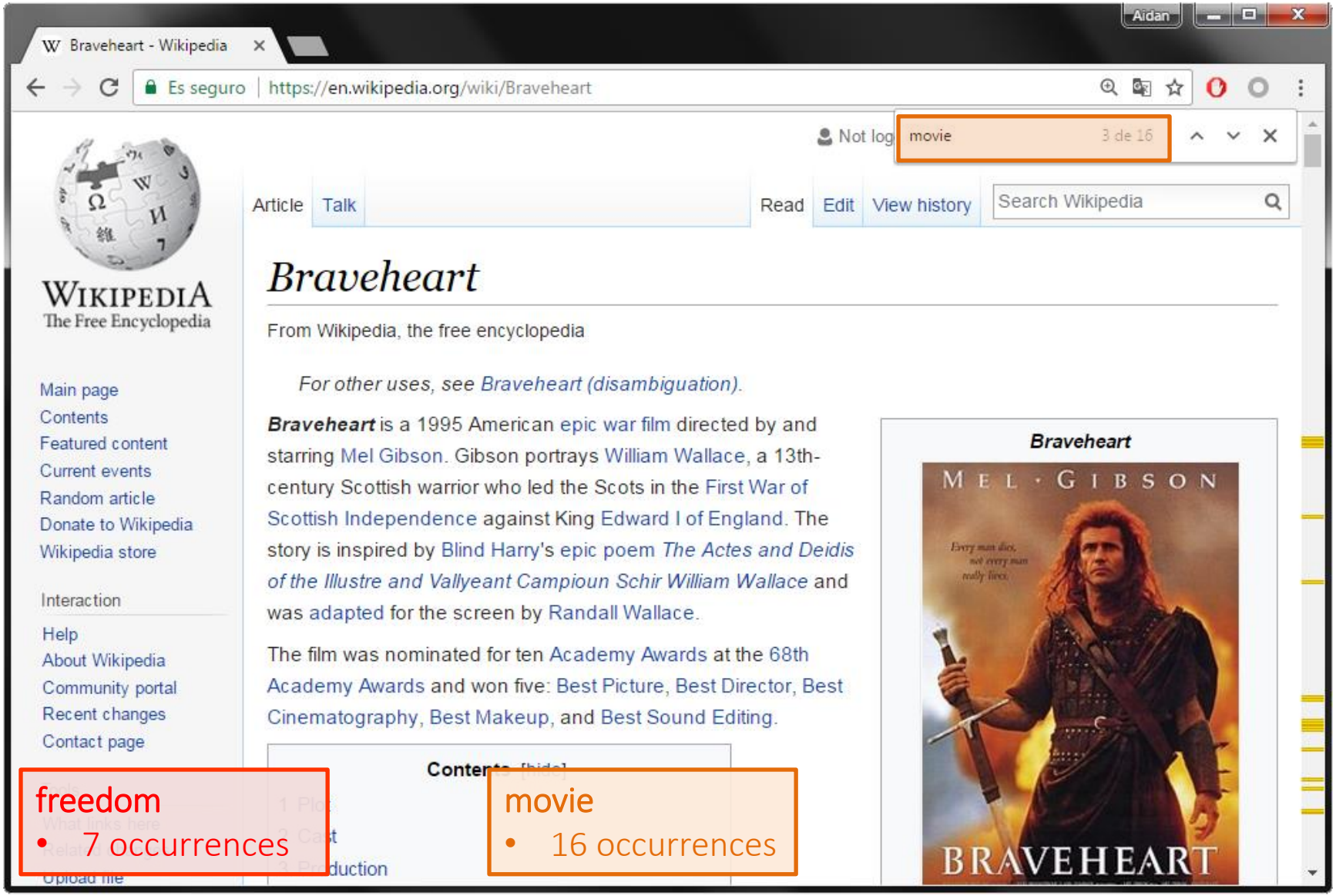
Which of these three keyword terms is most “important”?



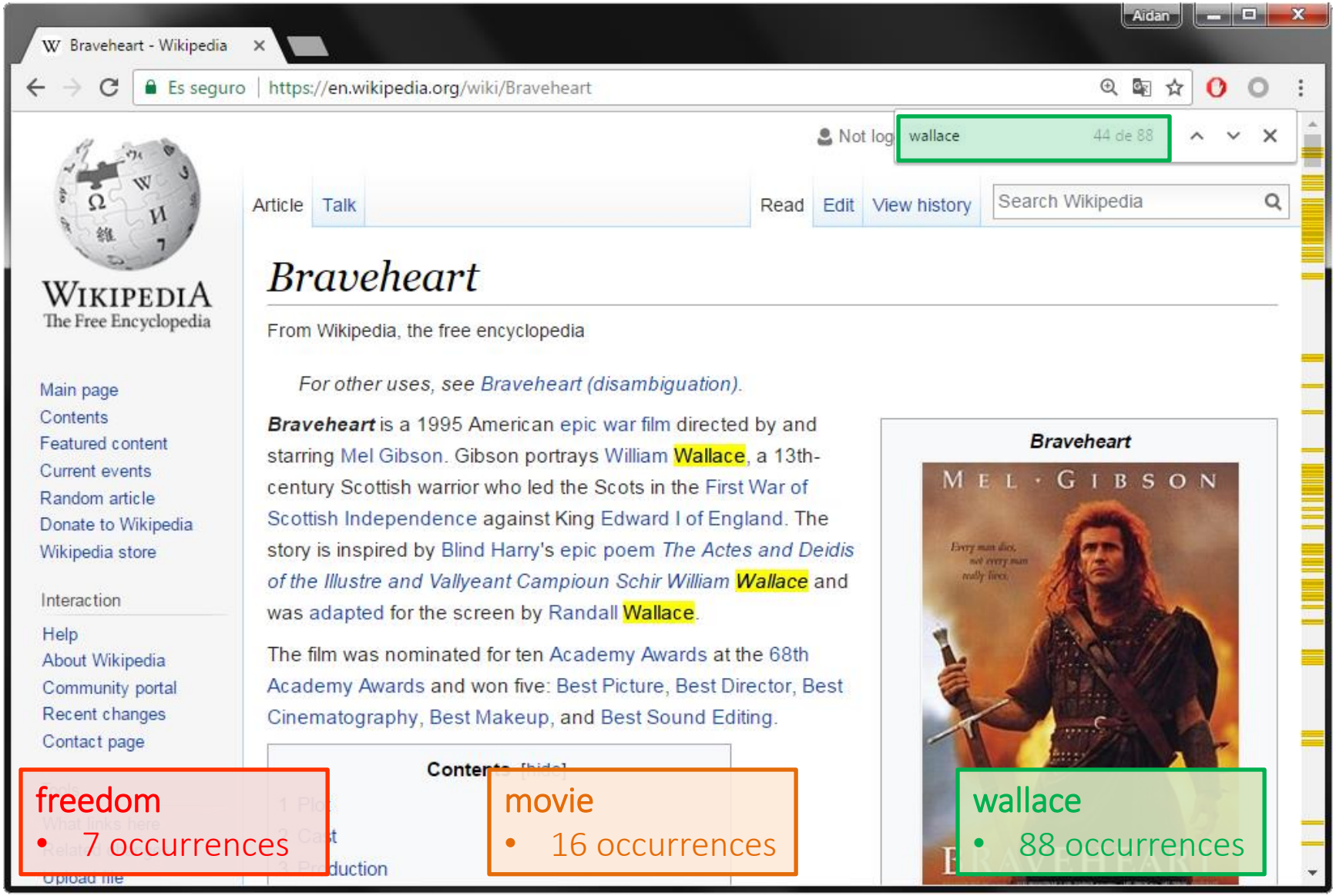
Matches in a Document



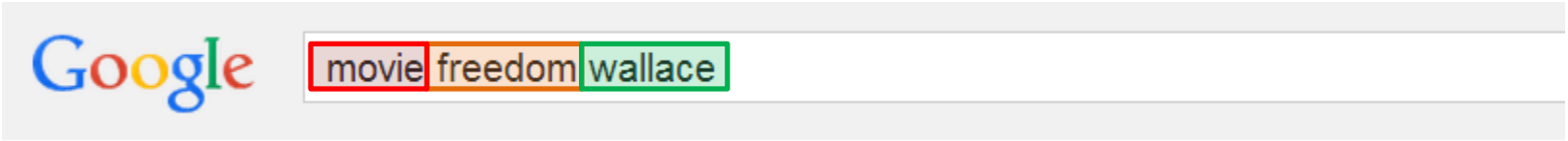
Matches in a Document

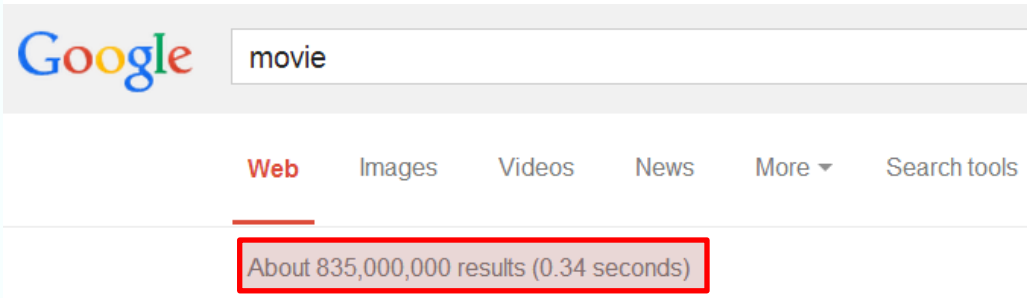


Matches in a Document



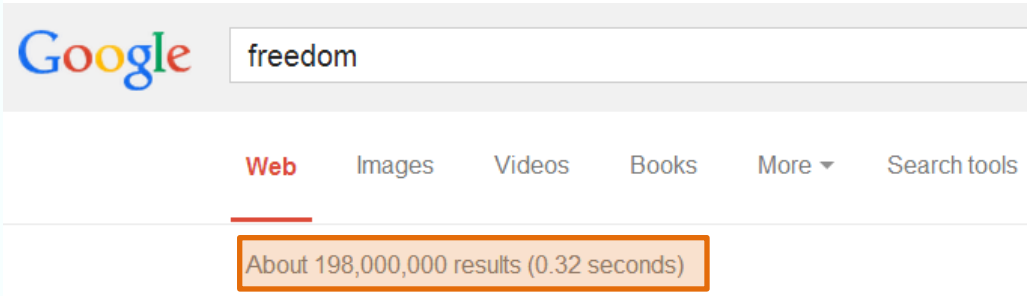
Usefulness of Words





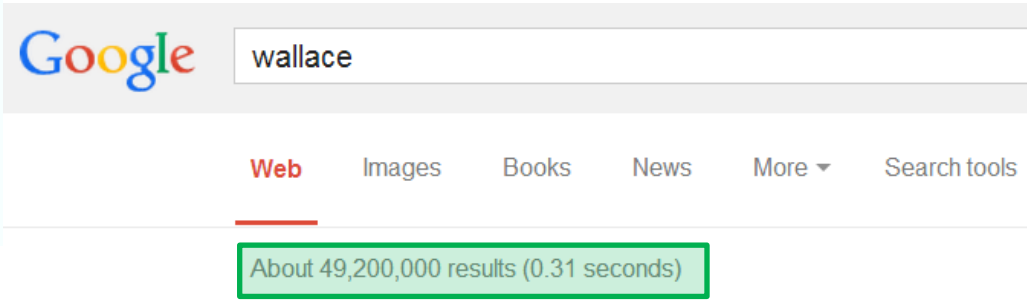
movie

- occurs very frequently



freedom

- occurs frequently



wallace

- occurs occassionally

Estimating Relevance

- Rare words more important than common words
  - wallace (49M) more important than freedom (198M) more important than movie (835M)
- Words occurring more frequently in a document indicate higher relevance
  - wallace (88) more matches than movie (16) more matches than freedom (7)

Relevance Measure: TF–IDF

- TF: Term Frequency
  - Measures occurrences of a term in a document
  - $\mathrm{tf}(t, d)$ … various options
    - Raw count of occurrences

$$\mathrm{tf}(t, d) = \mathrm{count}(t, d)$$

    - Logarithmically scaled

$$\mathrm{tf}(t, d) = \log(\mathrm{count}(t, d) + 1)$$

    - Normalised by document length

$$\mathrm{tf}(t, d) = \frac{\mathrm{count}(t,d)}{\sum_{t' \in d} \mathrm{count}(t',d)}$$

$$\mathrm{tf}(t, d) = \frac{\mathrm{count}(t,d)}{\max_{t' \in d} \mathrm{count}(t',d)}$$

    - A combination / something else ☺

Relevance Measure: TF–IDF

- IDF: Inverse Document Frequency
  - How common a term is across **all** documents
  - $\mathrm{idf}(t, D)$ ...
    - Logarithmically scaled document occurrences

$$\mathrm{idf}(t, D) = \log\left(\frac{|D|+1}{|\{d \in D : t \in d\}|+1}\right)$$

    - Note: The more rare, the larger the value

Relevance Measure: TF–IDF

- TF–IDF: Combine Term Frequency and Inverse Document Frequency:

$$\text{tf-idf}(t, d) = \text{tf}(t, d) \times \text{idf}(t, D)$$

- Score for a query
  - Let query $q = (t_1, \ldots, t_n)$
  - Score for a query: $\text{score}(q, d) = \sum_{t \in q} \text{tf-idf}(t, d)$

  (There are other possibilities)

Relevance Measure: TF–IDF

Term Frequency

$$\mathrm{tf}(t,d) = \mathrm{count}(t,d)$$

Inverse Document Frequency

$$\mathrm{idf}(t,D) = \log_2\left(\frac{|D|+1}{|\{d \in D : t \in d\}|+1}\right)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D)$$

t	$\mathrm{tf}(t,d)$
movie	16
freedom	7
wallace	43

Relevance Measure: TF–IDF

Term Frequency

$$\mathrm{tf}(t,d) = \mathrm{count}(t,d)$$

Inverse Document Frequency

$$\mathrm{idf}(t,D) = \log_2\left(\frac{|D|}{|\{d \in D : t \in d\}|+1}\right)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D)$$

t	$\mathrm{tf}(t,d)$	$\lvert\{d \in D : t \in d\}\rvert$
movie	16	835,000,000
freedom	7	198,000,000
wallace	43	49,200,000

Relevance Measure: TF–IDF

Term Frequency

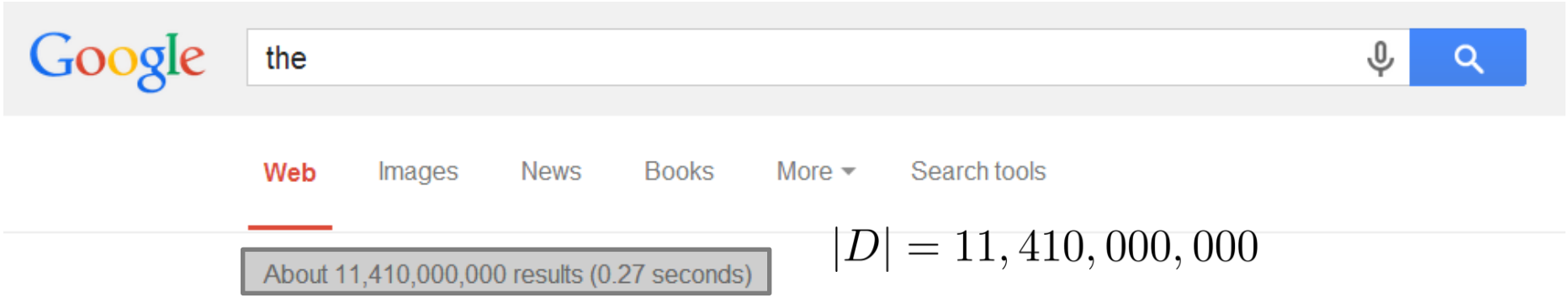
$$\mathrm{tf}(t,d) = \mathrm{count}(t,d)$$

Inverse Document Frequency

$$\mathrm{idf}(t,D) = \log_2\left(\frac{|D|}{|\{d \in D : t \in d\}|+1}\right)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D)$$

t	$\mathrm{tf}(t,d)$	$\lvert\{d \in D : t \in d\}\rvert$	$\frac{\lvert D\rvert+1}{\lvert\{d \in D : t \in d\}\rvert+1}$
movie	16	835,000,000	
freedom	7	198,000,000	
wallace	43	49,200,000	



$$|D| = 11,410,000,000$$

Relevance Measure: TF–IDF

Term Frequency

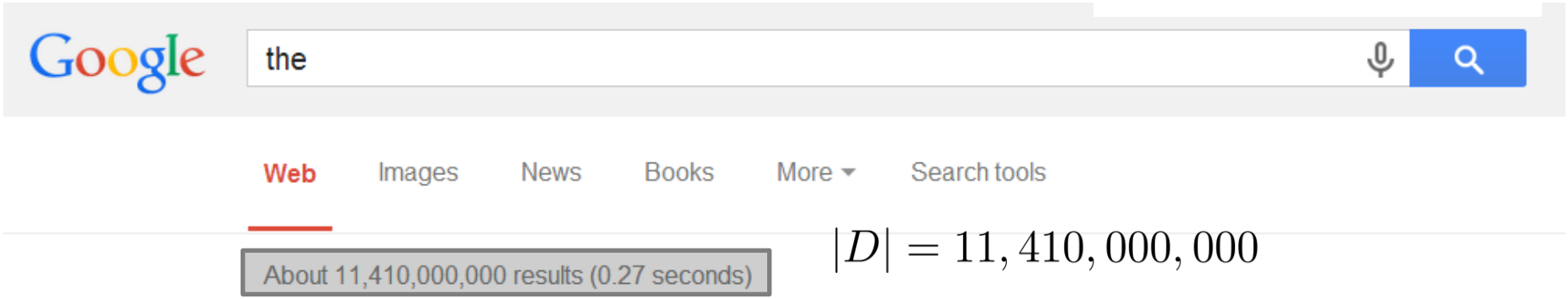
$$\mathrm{tf}(t,d) = \mathrm{count}(t,d)$$

Inverse Document Frequency

$$\mathrm{idf}(t,D) = \log_2\left(\frac{|D|}{|\{d \in D : t \in d\}|+1}\right)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D)$$

t	$\mathrm{tf}(t,d)$	$\lvert\{d \in D : t \in d\}\rvert$	$\frac{\lvert D\rvert+1}{\lvert\{d \in D : t \in d\}\rvert+1}$
movie	16	835,000,000	13.66
freedom	7	198,000,000	57.63
wallace	43	49,200,000	231.91



$$|D| = 11,410,000,000$$

Relevance Measure: TF–IDF

Term Frequency

$$\mathrm{tf}(t,d) = \mathrm{count}(t,d)$$

Inverse Document Frequency

$$\mathrm{idf}(t,D) = \log_2\left(\frac{|D|}{|\{d \in D : t \in d\}|+1}\right)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D)$$

t	$\mathrm{tf}(t,d)$	$\lvert\{d \in D : t \in d\}\rvert$	$\frac{\lvert D\rvert+1}{\lvert\{d \in D : t \in d\}\rvert+1}$	$\mathrm{idf}(t,d)$
movie	16	835,000,000	13.66	3.77
freedom	7	198,000,000	57.63	5.85
wallace	43	49,200,000	231.91	7.86

Relevance Measure: TF–IDF

Term Frequency

$$\mathrm{tf}(t,d) = \mathrm{count}(t,d)$$

Inverse Document Frequency

$$\mathrm{idf}(t,D) = \log_2\left(\frac{|D|}{|\{d \in D : t \in d\}|+1}\right)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D)$$

t	$\mathrm{tf}(t,d)$	$\lvert\{d \in D : t \in d\}\rvert$	$\frac{\lvert D\rvert+1}{\lvert\{d \in D : t \in d\}\rvert+1}$	$\mathrm{idf}(t,d)$	$\text{tf-idf}(t,d)$
movie	16	835,000,000	13.66	3.77	60.36
freedom	7	198,000,000	57.63	5.85	40.94
wallace	43	49,200,000	231.91	7.86	337.87

Relevance Measure: TF–IDF

Term Frequency

$$\mathrm{tf}(t,d) = \mathrm{count}(t,d)$$

Inverse Document Frequency

$$\mathrm{idf}(t,D) = \log_2\left(\frac{|D|}{|\{d \in D : t \in d\}|+1}\right)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D)$$

t	$\mathrm{tf}(t,d)$	$\lvert\{d \in D : t \in d\}\rvert$	$\frac{\lvert D\rvert+1}{\lvert\{d \in D : t \in d\}\rvert+1}$	$\mathrm{idf}(t,d)$	$\text{tf-idf}(t,d)$
movie	16	835,000,000	13.66	3.77	60.36
freedom	7	198,000,000	57.63	5.85	40.94
wallace	43	49,200,000	231.91	7.86	337.87

$$\mathrm{score}(q,d) = \sum_{t \in q} \text{tf-idf}(t,d)$$

$$\mathrm{score}\big((\text{movie}, \text{freedom}, \text{wallace}), \text{http://en.wikipedia.org/Braveheart}\big) \approx 439.17$$

Two Sides to Ranking: Relevance

Field-Based Boosting

- Not all text is equal: titles, headers, etc.

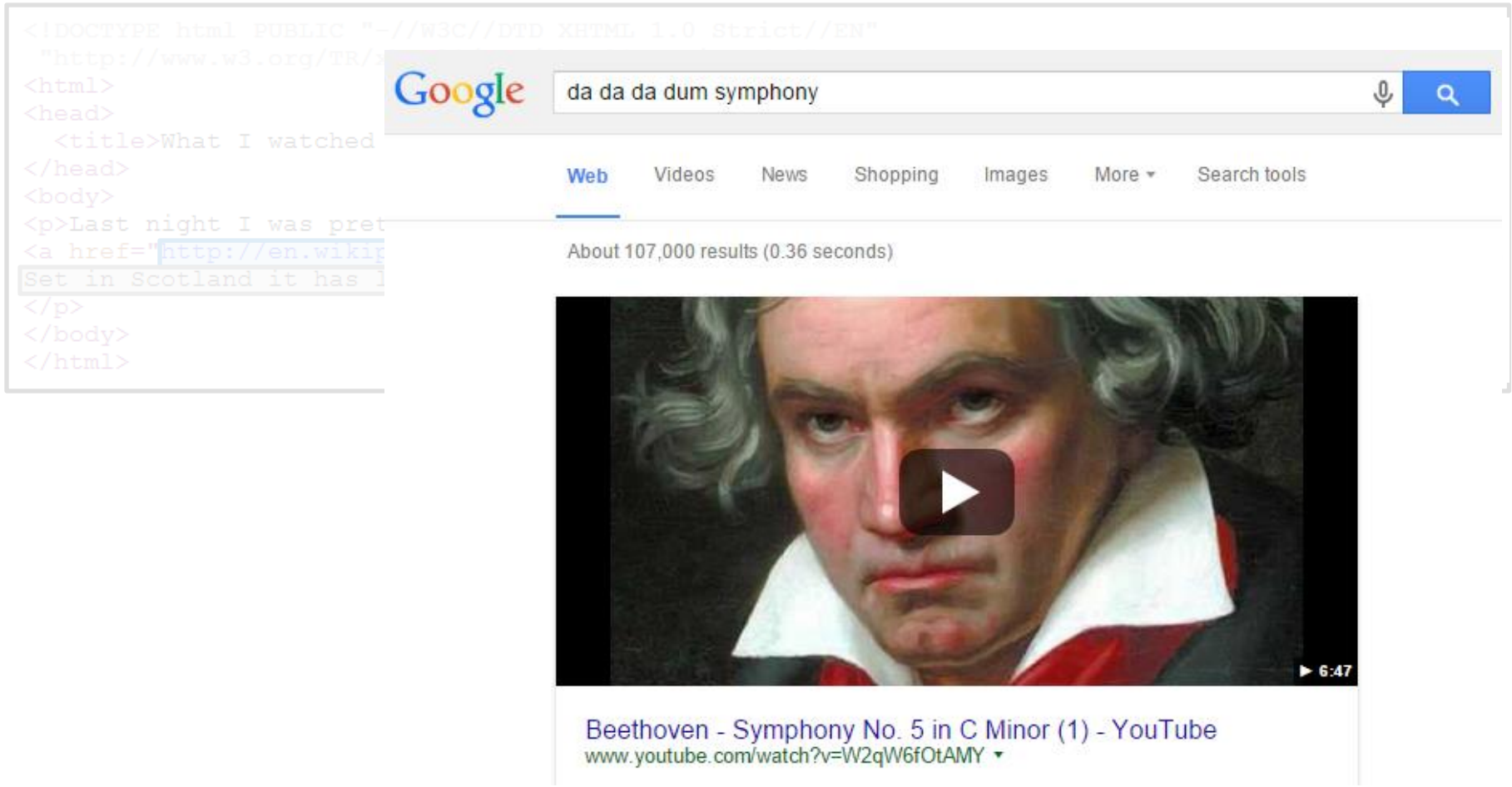
Anchor Text

- See how the Web views/tags a page

```
<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Strict//EN"
 "http://www.w3.org/TR/xhtml1/DTD/xhtml1-strict.dtd">
<html>
<head>
  <title>What I watched last night ...</title>
</head>
<body>
<p>Last night I was pretty bored so I made some popcorn and watched
<a href="http://en.wikipedia.org/Braveheart">a movie about William Wallace called Braveheart</a>.
Set in Scotland it has lots of blood and gore.
</p>
</body>
</html>
```

Anchor Text

- See how the Web views/tags a page



Lucene uses relevance scoring

Tasks Console

SearchWikiIndex [Java Application] C:\Program Files\Java\jre1.8.0_65\bin\javaw.exe (03-05-2017 12:45:22 a. m.)

```
Opening directory at  lucene
Enter a keyword search phrase:
obama
Running query: obama
Parsed query: TITLE:obam^5.0 ABSTRACT:obam
Matching documents: 255
Showing top 10 results
1       http://es.wikipedia.org/wiki/Obama_Republican   Obama Republican
2       http://es.wikipedia.org/wiki/Obama_(Fukui)      Obama (Fukui)
3       http://es.wikipedia.org/wiki/Republicanos_por_Obama     Republicanos por Obama
4       http://es.wikipedia.org/wiki/Engonga_Obame      Engonga Obame
5       http://es.wikipedia.org/wiki/Barack_Obama       Barack Obama
6       http://es.wikipedia.org/wiki/Michelle_Obama     Michelle Obama
7       http://es.wikipedia.org/wiki/Cartel_%22Hope%22_de_Obama Cartel "Hope" de Obama
8       http://es.wikipedia.org/wiki/Transición_presidencial_de_Barack_Obama    Transición presidencial de Barack Obama
9       http://es.wikipedia.org/wiki/Por_qué_Obama_ganará_en_2008_y_en_2012     Por qué Obama ganará en 2008 y en 2012
10      http://es.wikipedia.org/wiki/Ricardo_Mangue_Obama_Nfubea        Ricardo Mangue Obama Nfubea
```

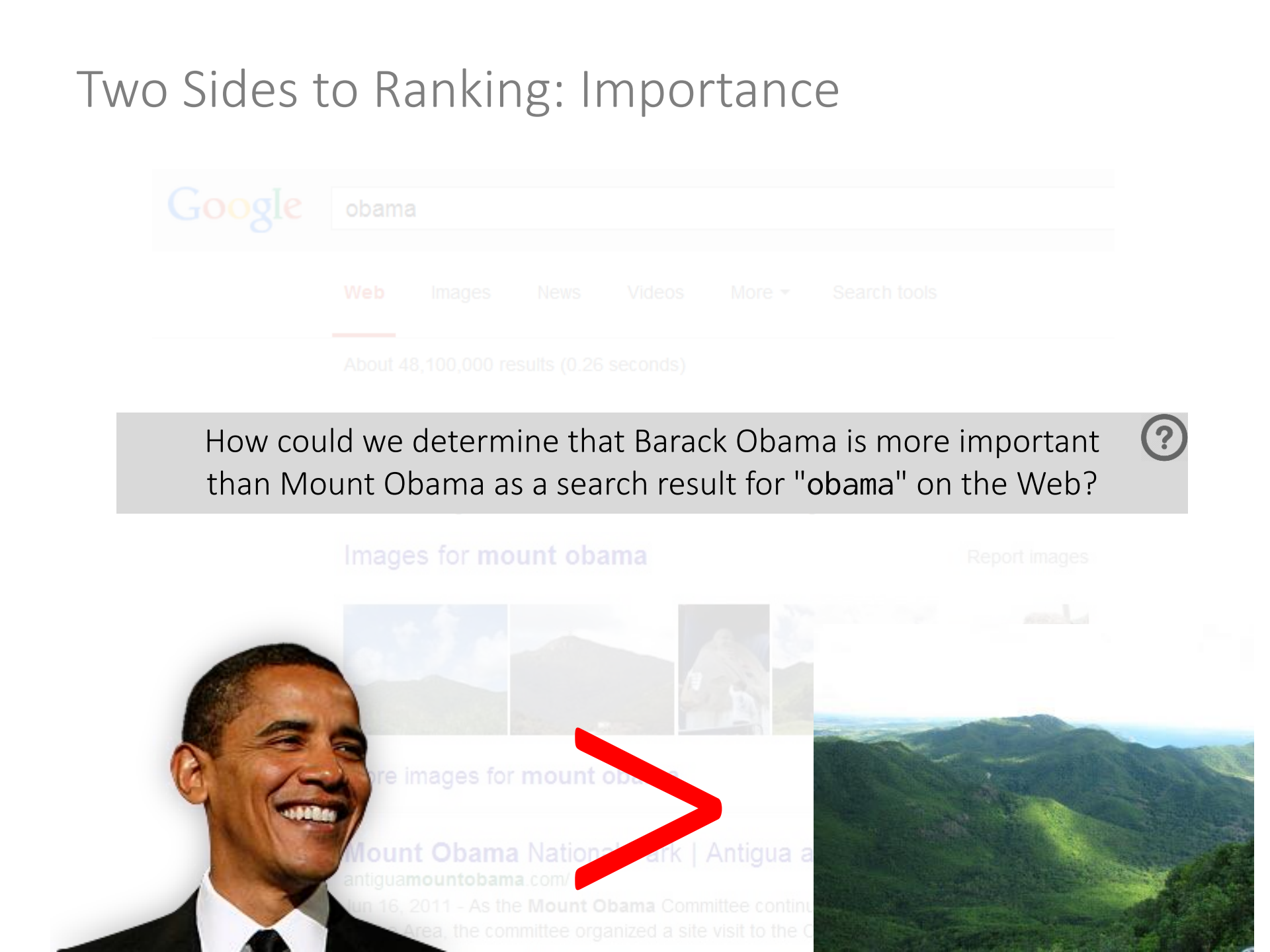
elasticsearch

… and Elasticsearch uses Lucene

Ranking:
Importance

Two Sides to Ranking: Importance

How could we determine that Barack Obama is more important than Mount Obama as a search result for "obama" on the Web?

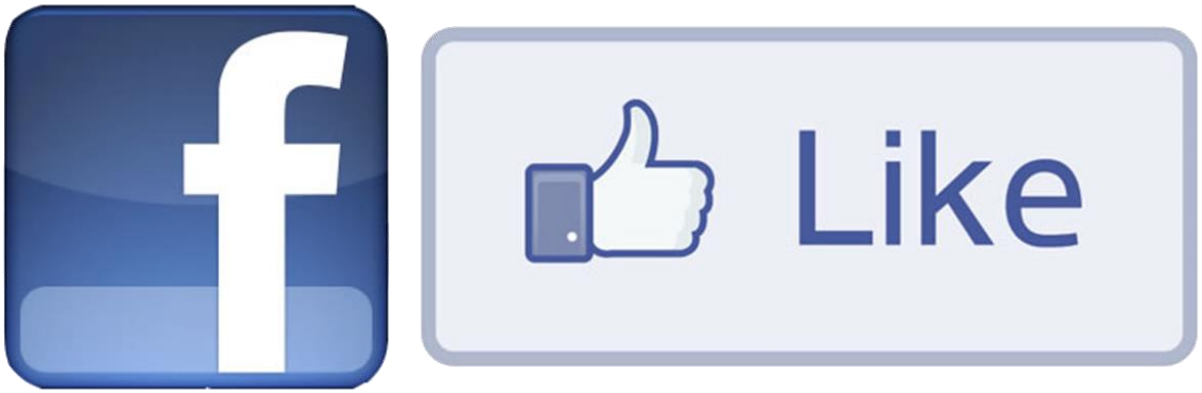


Link Analysis

Which will have more links from other pages?
The Wikipedia article for Mount Obama?
The Wikipedia article for Barack Obama?

Link Analysis

- Consider links as votes of confidence in a page
- A hyperlink is the open Web's version of …



(… even if the page is linked in a negative way.)

Link Analysis

So if we just count links to a page we can determine its importance and we are done?

Link Spamming

Claritin Clomid Combivent Confido Copegus Cordarone Coreg Coumadin Cozaar Crestor Cyklokapron Cymbalta Cystone Cytotec Danazol Deltasone Depakote Desyrel Detrol Diabecon Diakof Diarex Didronel Differin Dilantin Diovan Dostinex Elavil Elimite Emsam Endep Eurax Evecare Evista Exelon Famvir Feldene Femara Femcare Flomax Flonase Flovent Fosamax Gasex Geodon Geriforte Herbolax High Love Himcocid Himcolin Himcospaz Himplasia Hoodia Hytrin Hyzaar Imdur Imitrex Inderal Ismo Isoptin Isordil Kamagra Karela Keftab Koflet Kytril Lamictal Lamisil Lanoxin Lariam Lasix Lasuna Leukeran Levaquin Levlen Levothroid Lincocin Lioresal Lisinopril Liv.52 Lopid Lopressor Loprox Lotensin Lotrisone Loxitane Lozol Lukol Lynoral Maxaquin Menosan Mentat Mentax Mevacor Mexitil Miacalcin Micardis Mobic Monoket Motrin Myambutol Mycelex-G Mysoline Naprosyn Neurontin Nicotinell Nimotop Nirdosh Nizoral Nolvadex Nonoxinol Noroxin Omnicef Ophthacare Oxytrol Pamelor Parlodel Paxil Penisole Phentrimine Pilex Plan B Plavix Plendil Pletal Prandin Pravachol Prednisone Premarin Prevacid Prilosec Prinivil Procardia Prograf Prometrium Propecia Proscar Protonix Proventil Prozac Purim Purinethol Quibron-T Relafen Renalka Reosto Requip Retin-A Revia Rhinocort Rimonabant Risperdal Rocaltrol Rogaine Rumalaya Sarafem Septilin **Serevent** **Serophene** **Seroquel** Shallaki Shoot Sinequan Singulair Snoroff Sorbitrate Speman Starlix StretchNil Stromectol Styplon Sumycin Superman Sustiva Synthroid Tenormin Topamax Trandate Tricor Trimox Triphala Tulasi Urispas V-Gel Vantin Vasodilan Vasotec Ventolin Viramune Vytorin Xeloda Xenacore Zanaflex Zantac Zebeta Zelnorm Zerit Yerba Diet Wellbutrin SR Women Attracting Pheromones Women's Intimacy Enhancer Women's Intimacy Enhancer Cream Virility Gum Vitamin A & D Viagra + Cialis Viagra + Cialis + Levitra Viagra Jelly Viagra Soft + Cialis Soft Viagra Soft Tabs Ultimate Male Enhancer Toprol XL Touch-Up Kit Tentex Royal Tentex Forte Tiberius Erectus Zero Nicotine 2 Complete Professional Whitening Kits 2 Sets Of Moldable Mouth Trays 36 Beauty Acne-n-Pimple Cream ActoPlus Met Superloss Multi SleepWell (Herbal XANAX) Shuddha Guggulu Rythmol SR Rumalaya Forte Pulmicort Inhaler Professional Plasma Tooth Whitening Kit Premium Diet Patch Penis Growth Oil Penis Growth Pack Penis Growth Patch Penis Growth Pills Orgasm Enhancer Norpace CR Mental Booster Men Attracting Pheromones Menopause Gum Male Enhancement Oil Male Enhancement Patch Male Enhancement Pills Male Sexual Tonic InnoPran XL Hoodia Weight Loss Gum Hoodia Weight Loss Patch Human Growth Hormone Agent Glucotrol XL Green Tea Grifulvin V Gyne-Lotrimin Hair Loss Cream Herbal Maxx Herbal Phentermine Flagyl ER Female Sexual Tonic Female Viagra Epivir-HBV Diet Maxx Deluxe Handheld Plasma Whitening Tool Deluxe Whitening System With Plasma Lamp Coral Calcium Cialis Jelly Cialis Soft Tabs Calcium Carbonate Bust Enhancer Beconase AQ Anatrim Diet Pills Advair Diskus Advanced Gain Pro Breast Augmentation Breast Enhancement Breast Enhancement Gel Breast Enhancement Gum Breast Intense Buy Trazodone Buy Celebrex Buy Alprazolam Buy Tramadol Buy Fioricet Buy Soma Buy Cialis Buy Carisoprodol Buy Levitra Buy Ultram Buy Ambien Buy Viagra Buy Xanax Buy Phentermine Buy Valium Buy Diazepam Generic Celebrex Generic Alprazolam Generic Tramadol Generic Fioricet Generic Soma Generic Cialis Generic Carisoprodol Generic Levitra Generic Ultram Generic Ambien

Link Importance

So which should count for more?
A link from http://en.wikipedia.org/wiki/Barack_Obama?
Or a link from http://blackmagicspecialist.net.in?

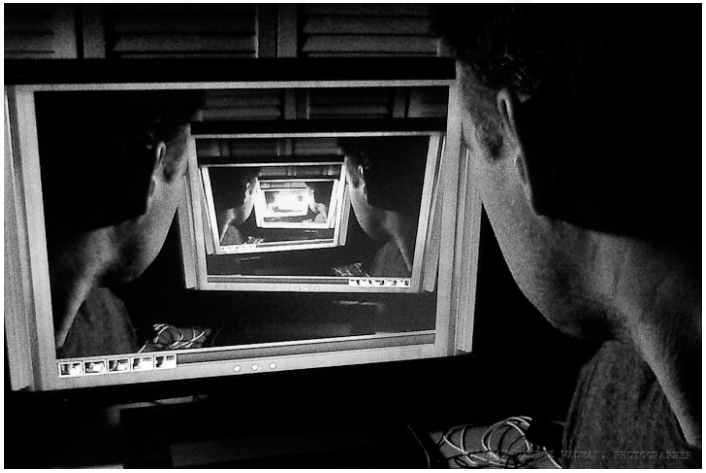
PageRank

PageRank: Central Assumption

A page with lots of inlinks from important pages with few outlinks is more important

PageRank: Recursive Definition

A page with lots of inlinks from important pages with few outlinks is more important



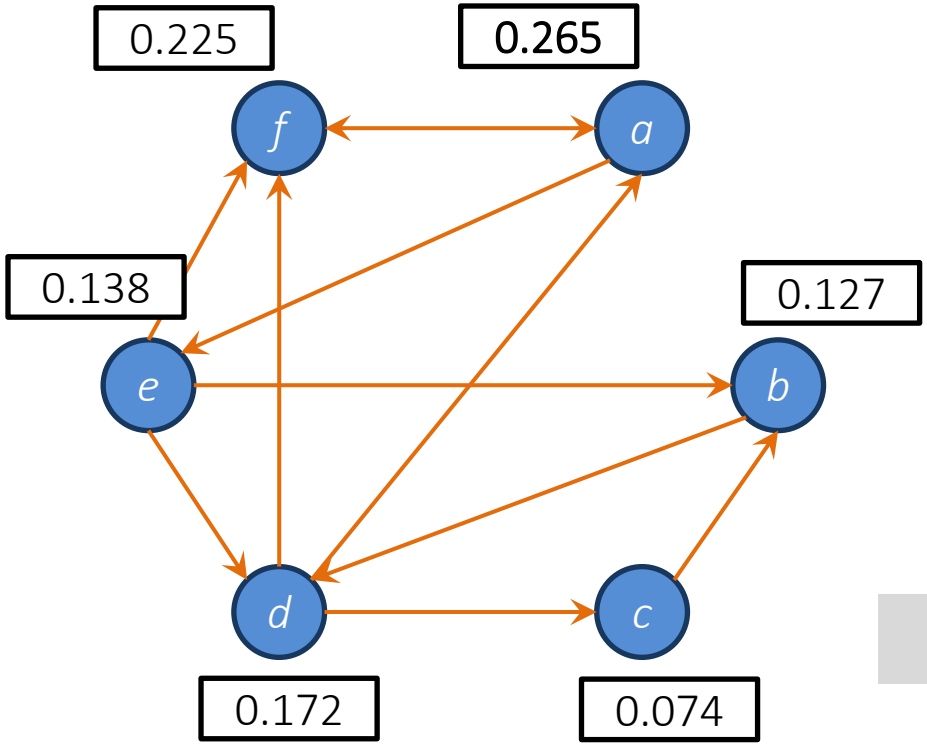
PageRank Model

- The Web: a directed graph

$$G = (V, E)$$

Vertices (*pages*)

Edges (*links*)



Which vertex is most important?

$$V = \{a, b, c, d, e, f\}$$

$$E = \{(a, e), (a, f), (b, d), (c, b), (d, a), (d, c), (d, f), (e, b), (e, d), (e, f), (f, a)\}$$

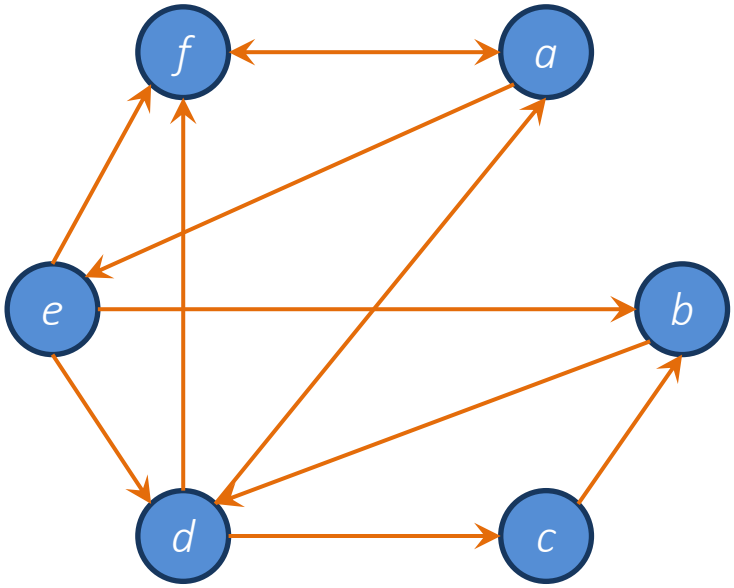
PageRank Model

- The Web: a directed graph

$$G = (V, E)$$

Vertices (*pages*)

Edges (*links*)



$$\text{out}(v) \coloneqq \{v' \in V \mid (v, v') \in E\}$$

$$\text{in}(v) \coloneqq \{v' \in V \mid (v', v) \in E\}$$

$$\text{rank}_0(v) \coloneqq \frac{1}{|V|}$$

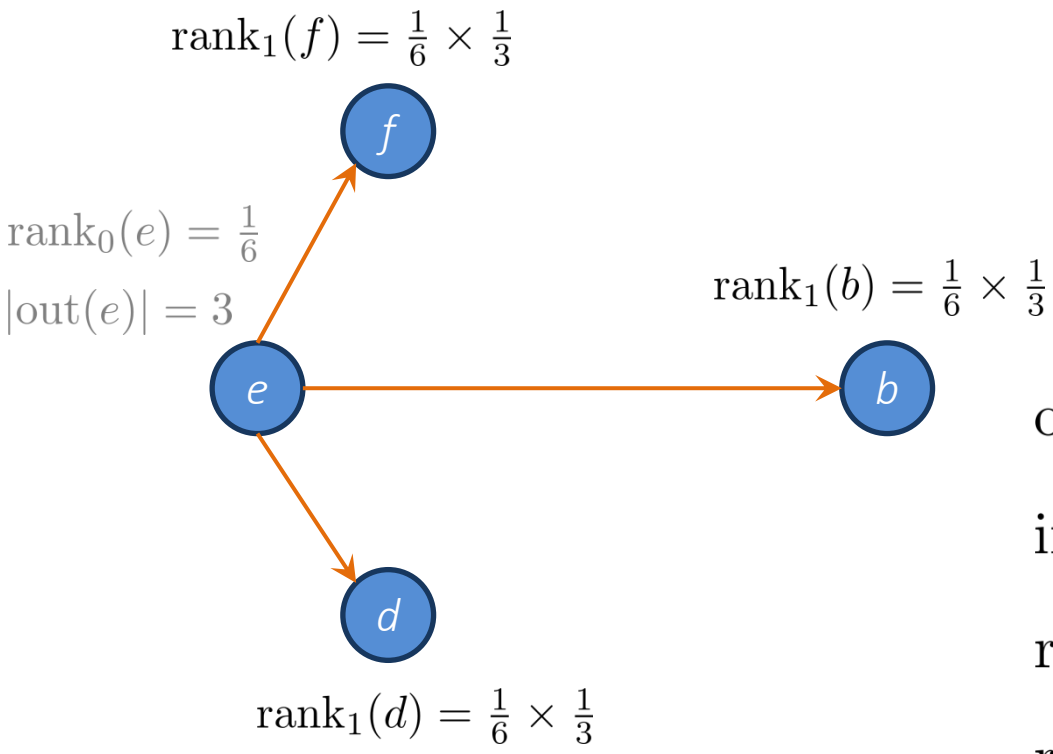
$$\text{rank}_i(v) \coloneqq \sum_{v' \in \text{in}(v)} \frac{\text{rank}_{i-1}(v')}{|\text{out}(v')|}$$

PageRank Model

$G = (V, E)$

Vertices (*pages*)

Edges (*links*)



$$\text{out}(v) \coloneqq \{v' \in V \mid (v, v') \in E\}$$

$$\text{in}(v) \coloneqq \{v' \in V \mid (v', v) \in E\}$$

$$\text{rank}_0(v) \coloneqq \frac{1}{|V|}$$

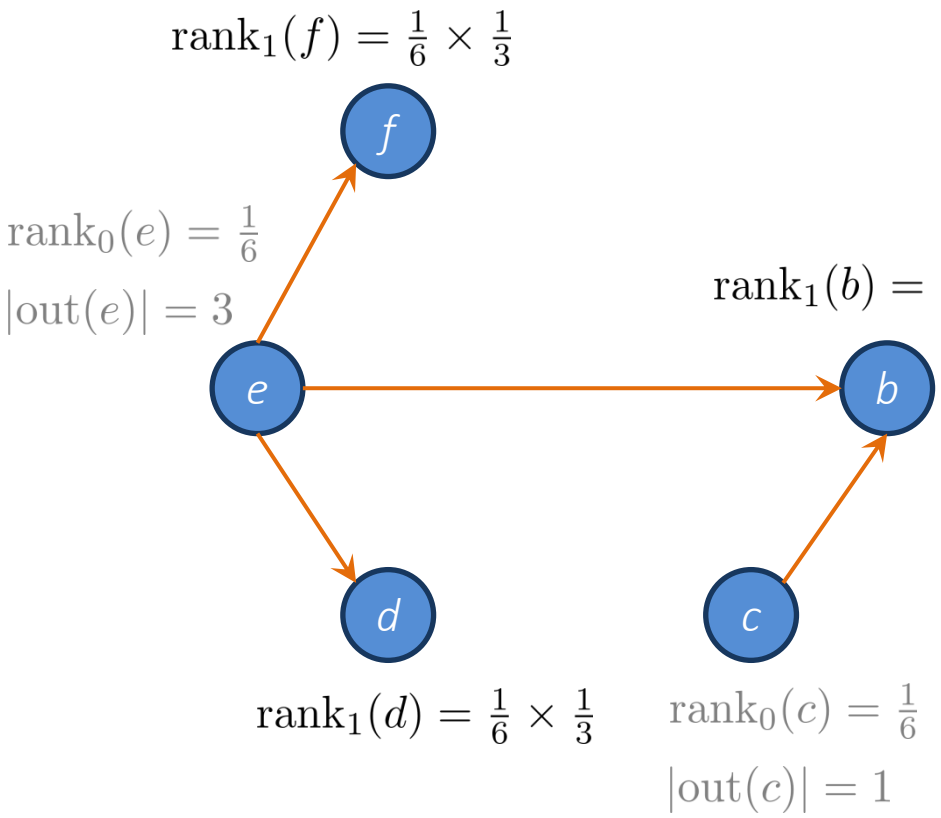
$$\text{rank}_i(v) \coloneqq \sum_{v' \in \text{in}(v)} \frac{\text{rank}_{i-1}(v')}{|\text{out}(v')|}$$

PageRank Model

$G = (V, E)$

Vertices (*pages*)

Edges (*links*)



$$\text{out}(v) \coloneqq \{v' \in V \mid (v, v') \in E\}$$

$$\text{in}(v) \coloneqq \{v' \in V \mid (v', v) \in E\}$$

$$\text{rank}_0(v) \coloneqq \frac{1}{|V|}$$

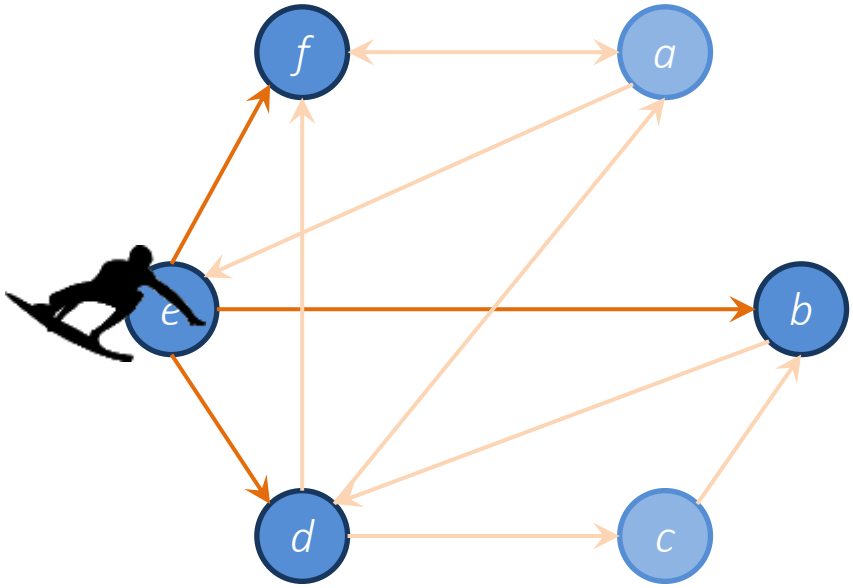
$$\text{rank}_i(v) \coloneqq \sum_{v' \in \text{in}(v)} \frac{\text{rank}_{i-1}(v')}{|\text{out}(v')|}$$

• • •

PageRank: Random Surfer Model

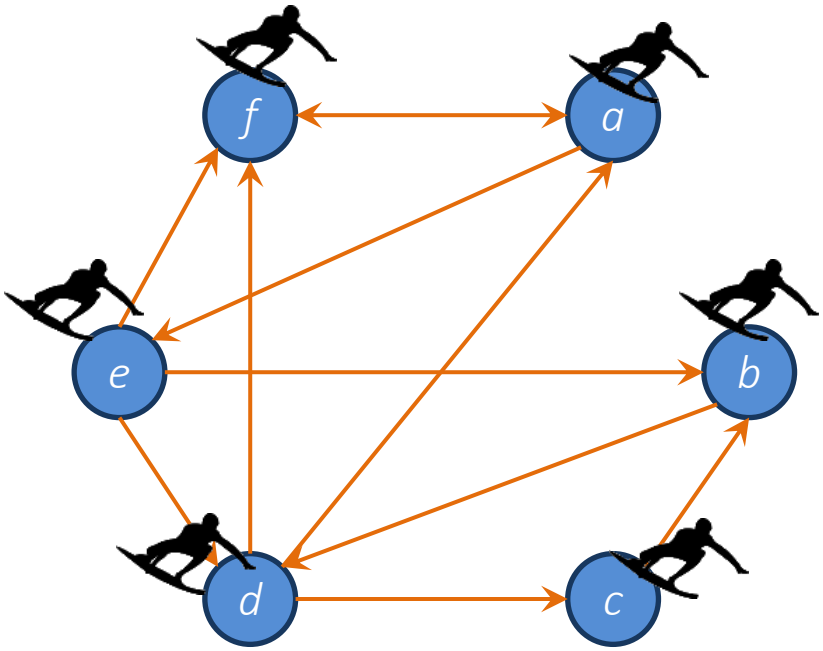
= someone surfing the web, clicking links randomly

- What is the probability of being at page *x* after *n* hops?



PageRank: Random Surfer Model

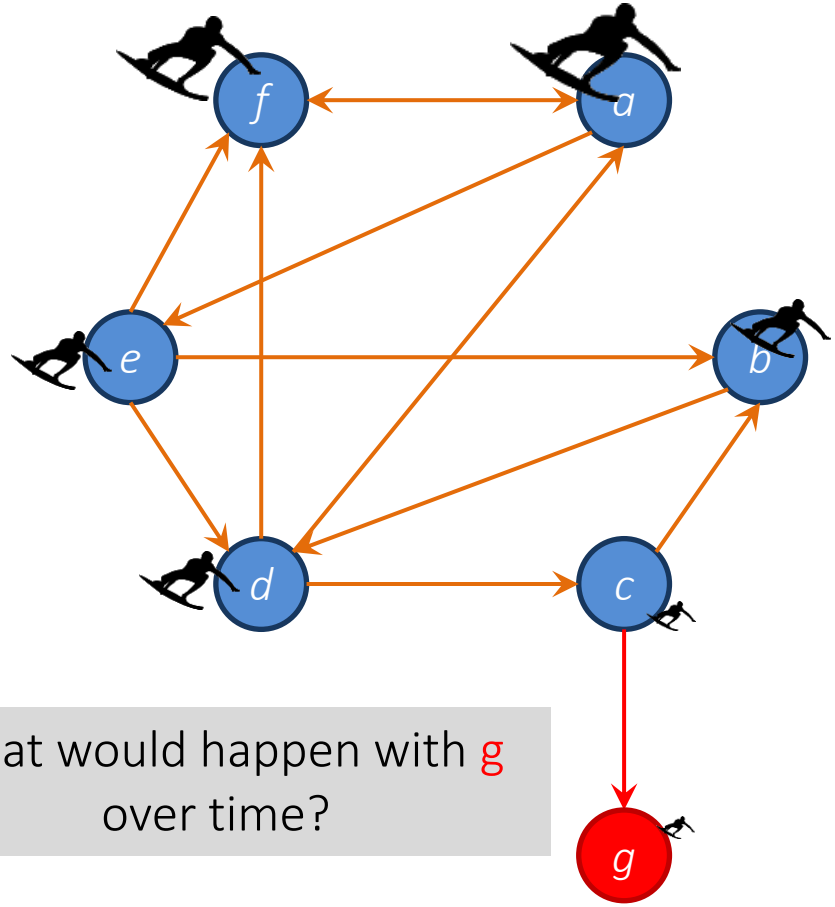
= someone surfing the web, clicking links randomly



- What is the probability of being at page *x* after *n* hops?
- *Initial state:* surfer equally likely to start at any node

PageRank: Random Surfer Model

= someone surfing the web, clicking links randomly

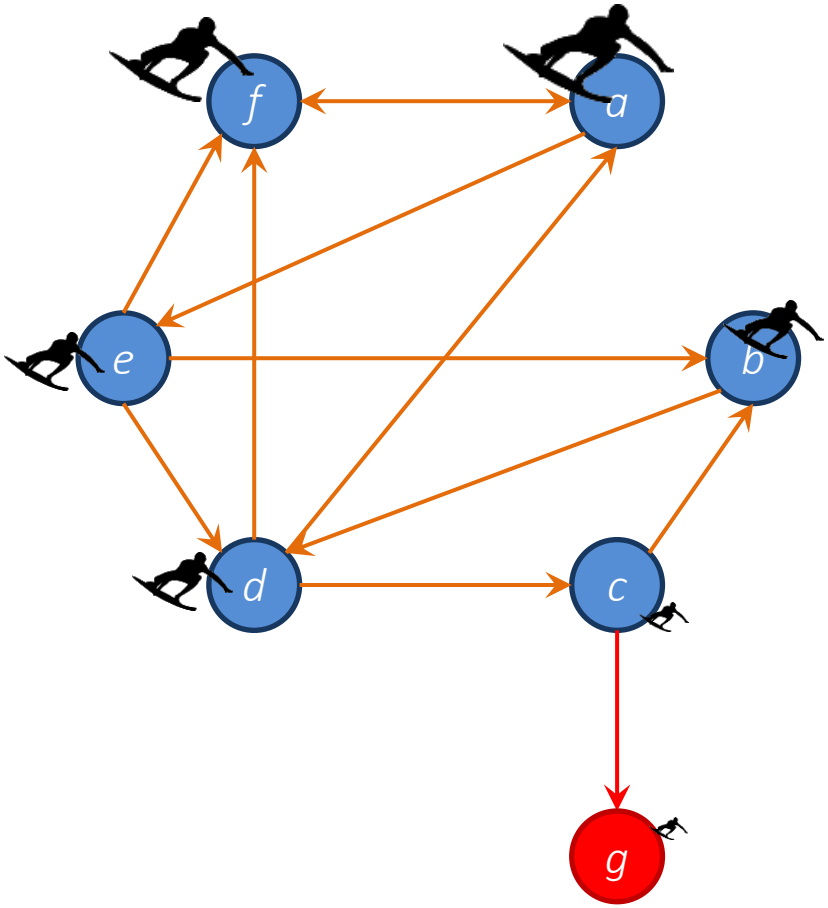


- What is the probability of being at page *x* after *n* hops?
- *Initial state:* surfer equally likely to start at any node
- PageRank applied iteratively for each hop: score indicates probability of being at that page after that many hops

What would happen with g over time?

PageRank: Random Surfer Model

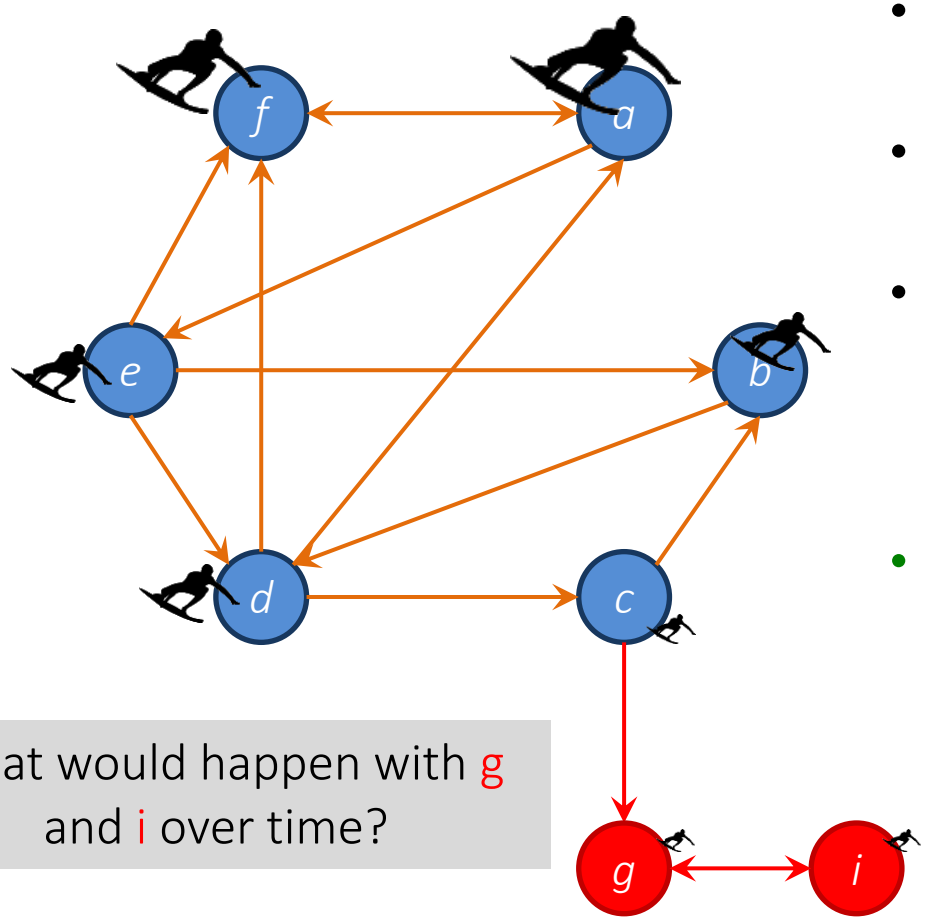
= someone surfing the web, clicking links randomly



- What is the probability of being at page *x* after *n* hops?
- *Initial state:* surfer equally likely to start at any node
- PageRank applied iteratively for each hop: score indicates probability of being at that page after that many hops
- If the surfer reaches a page without links, the surfer randomly jumps to another page

PageRank: Random Surfer Model

= someone surfing the web, clicking links randomly

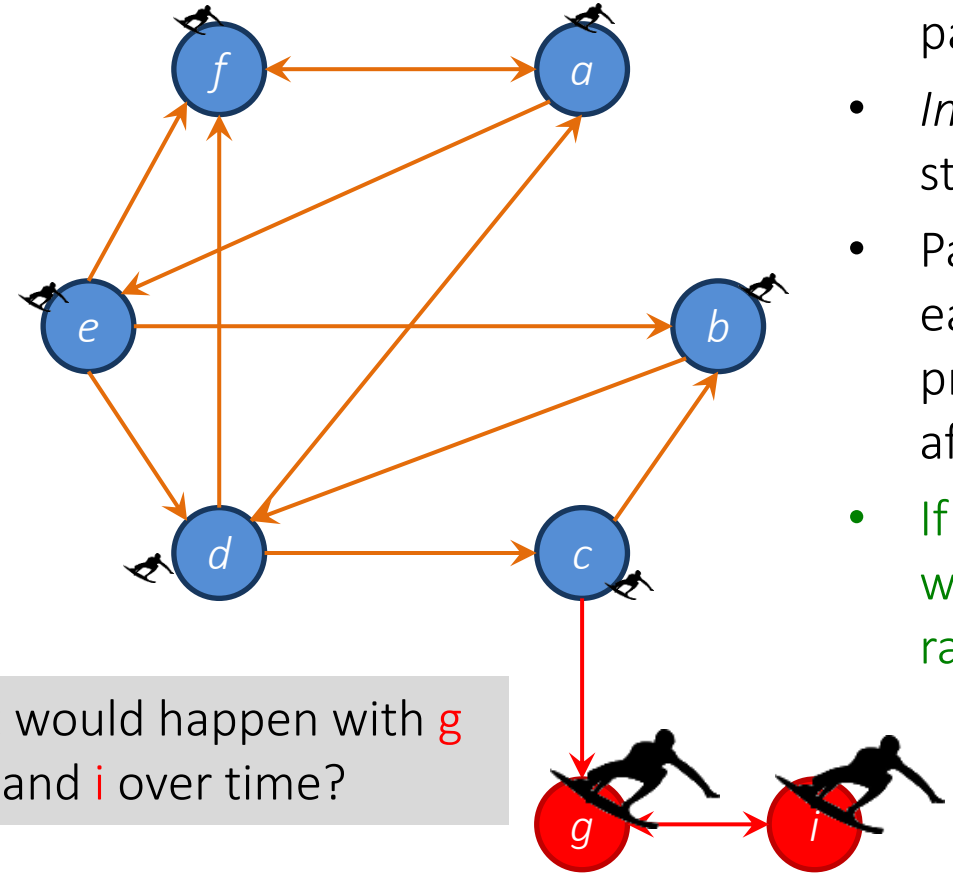


- What is the probability of being at page *x* after *n* hops?
- *Initial state:* surfer equally likely to start at any node
- PageRank applied iteratively for each hop: score indicates probability of being at that page after that many hops
- If the surfer reaches a page without links, the surfer randomly jumps to another page

What would happen with g and i over time?

PageRank: Random Surfer Model

= someone surfing the web, clicking links randomly

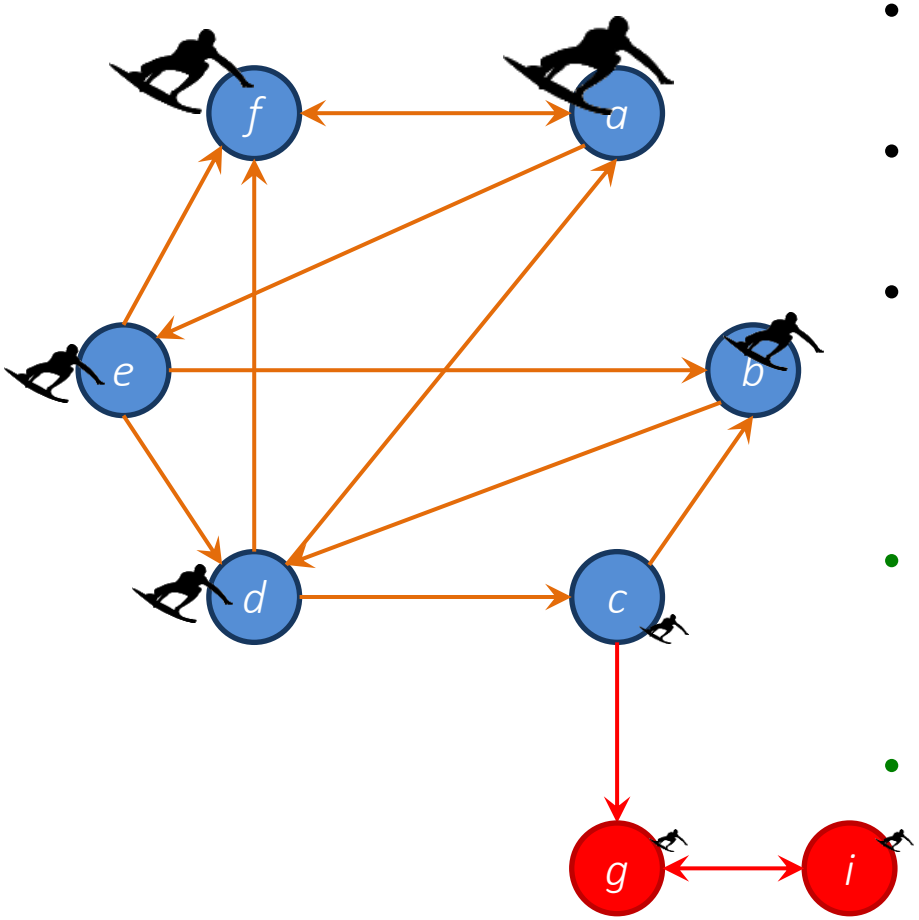


- What is the probability of being at page *x* after *n* hops?
- *Initial state:* surfer equally likely to start at any node
- PageRank applied iteratively for each hop: score indicates probability of being at that page after than many hops
- If the surfer reaches a page without out-links, the surfer randomly jumps to another page

What would happen with g and i over time?

PageRank: Random Surfer Model

= someone surfing the web, clicking links randomly



- What is the probability of being at page *x* after *n* hops?
- *Initial state:* surfer equally likely to start at any node
- PageRank applied iteratively for each hop: score indicates probability of being at that page after than many hops
- If the surfer reaches a page without out-links, the surfer randomly jumps to another page
- The surfer will jump to a random page at any time with a probability 1 – *d … this avoids traps and ensures convergence!*

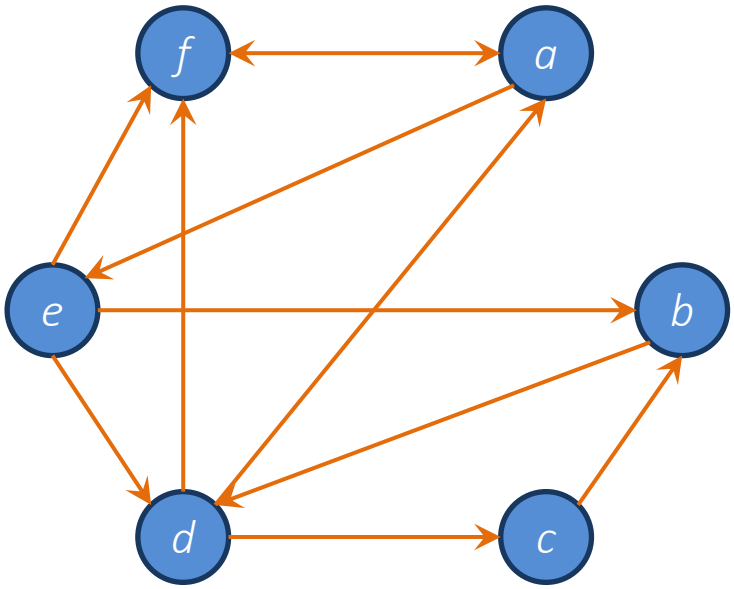
PageRank Model: Final Version

- The Web: a directed graph

$$G = (V, E)$$

Vertices (*pages*)

Edges (*links*)



$$\text{out}(v) \coloneqq \{v' \in V \mid (v, v') \in E\}$$

$$\text{in}(v) \coloneqq \{v' \in V \mid (v', v) \in E\}$$

$$\text{rank}_0(v) \coloneqq \frac{1}{|V|}$$

$$V' \coloneqq \{v \in V : |\text{out}(v)| = 0\}$$

$$V'' \coloneqq \{v \in V : |\text{out}(v)| \neq 0\}$$

d is the follow-a-link probability

typically $(d = 0.85)$

$$\text{rank}_i(v) \coloneqq d \times \sum_{u \in \text{in}(v)} \frac{\text{rank}_{i-1}(u)}{|\text{out}(u)|} + \sum_{v' \in V'} \frac{\text{rank}_{i-1}(v')}{|V|} + (1-d) \times \sum_{v'' \in V''} \frac{\text{rank}_{i-1}(v'')}{|V|}$$

PageRank: Benefits

- ✓ More robust than a simple link count
- ✓ Fewer ties than link counting
- ✓ Scalable to approximate (for sparse graphs)
- ✓ Convergence guaranteed

Two Sides to Ranking: Importance

Google

PageRank

>

Computing PageRank at scale

Graph Parallel Frameworks: Pregel

Pregel: A System for Large-Scale Graph Processing

Grzegorz Malewicz, Matthew H. Austern, Aart J. C. Bik, James C. Dehnert, Ilan Horn,
Naty Leiser, and Grzegorz Czajkowski
Google, Inc.
{malewicz,austern,ajcbik,dehnert,ilan,naty,gczaj}@google.com

ABSTRACT

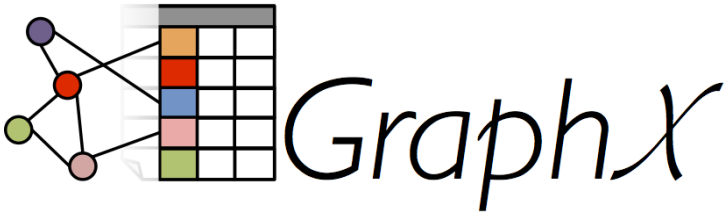
Many practical computing problems concern large graphs. Standard examples include the Web graph and various social networks. The scale of these graphs—in some cases billions of vertices, trillions of edges—poses challenges to their efficient processing. In this paper we present a computational model suitable for this task. Programs are expressed as a sequence of iterations, in each of which a vertex can receive messages sent in the previous iteration, send messages to other vertices, and modify its own state and that of its outgoing edges or mutate graph topology. This vertex-centric approach is flexible enough to express a broad set of algorithms. The model has been designed for efficient, scalable and fault-tolerant implementation on clusters of thousands of commodity computers, and its implied synchronicity makes reasoning about programs easier. Distribution-related details are hidden behind an abstract API. The result is a framework for processing large graphs that is expressive and easy to program.

disease outbreaks, or citation relationships among published scientific work—have been processed for decades. Frequently applied algorithms include shortest paths computations, different flavors of clustering, and variations on the page rank theme. There are many other graph computing problems of practical value, *e.g.*, minimum cut and connected components.

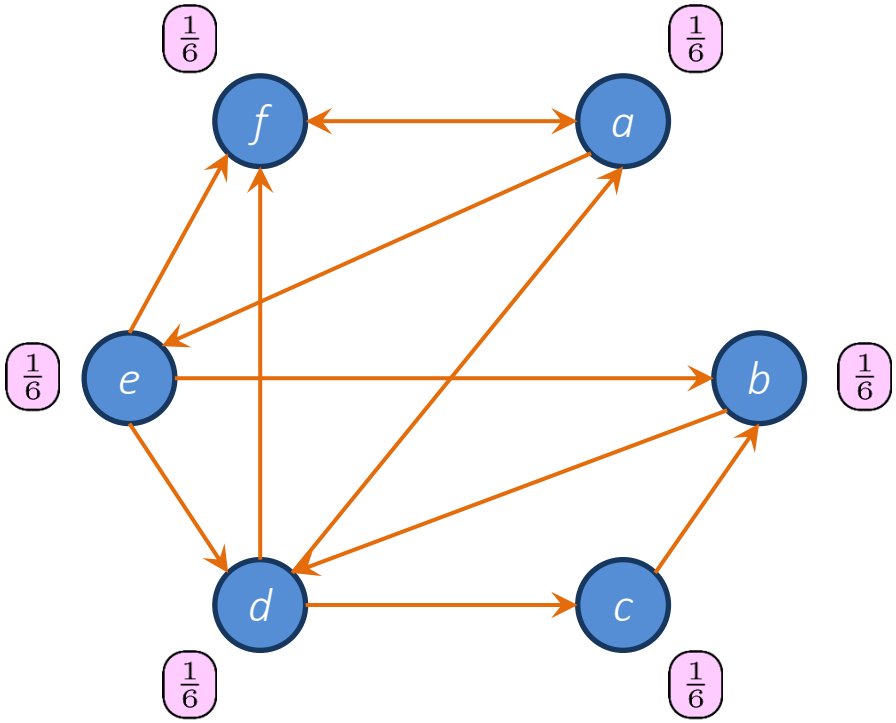
Efficient processing of large graphs is challenging. Graph algorithms often exhibit poor locality of memory access, very little work per vertex, and a changing degree of parallelism over the course of execution [31, 39]. Distribution over many machines exacerbates the locality issue, and increases the probability that a machine will fail during computation. Despite the ubiquity of large graphs and their commercial importance, we know of no scalable general-purpose system for implementing arbitrary graph algorithms over arbitrary graph representations in a large-scale distributed environment.

Implementing an algorithm to process a large graph typically means choosing among the following options:

Graph Parallel Frameworks: Open Source

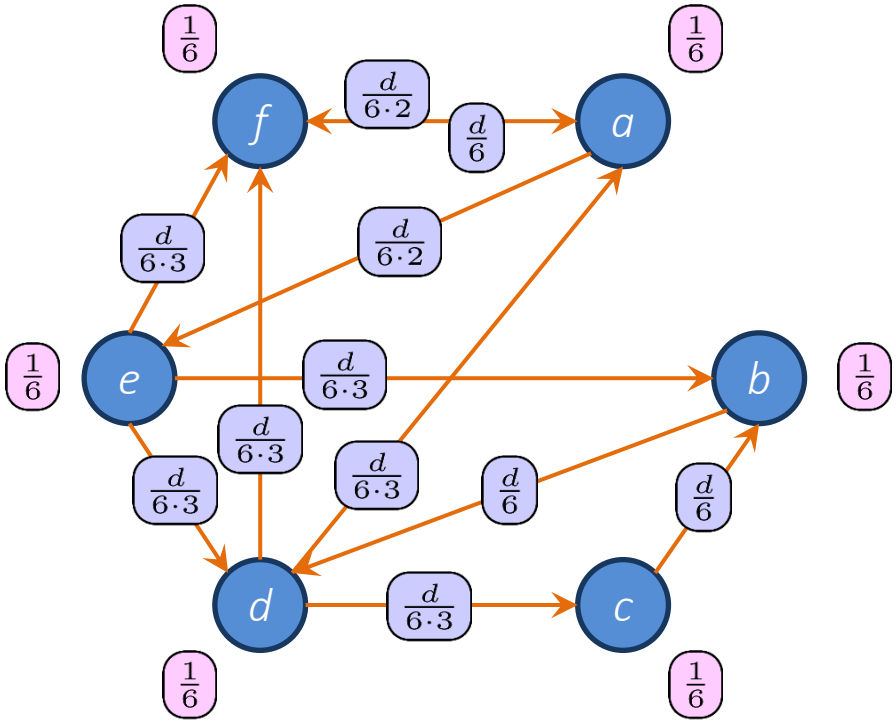


Vertex-Centric Computation



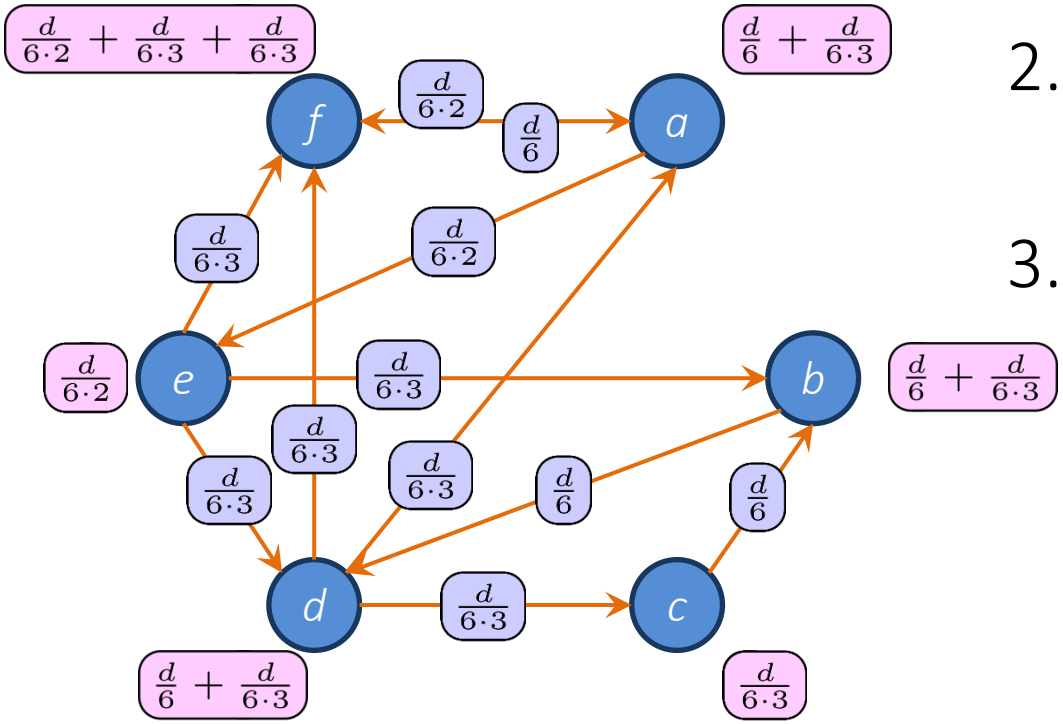
1. Nodes assigned state

Vertex-Centric Computation



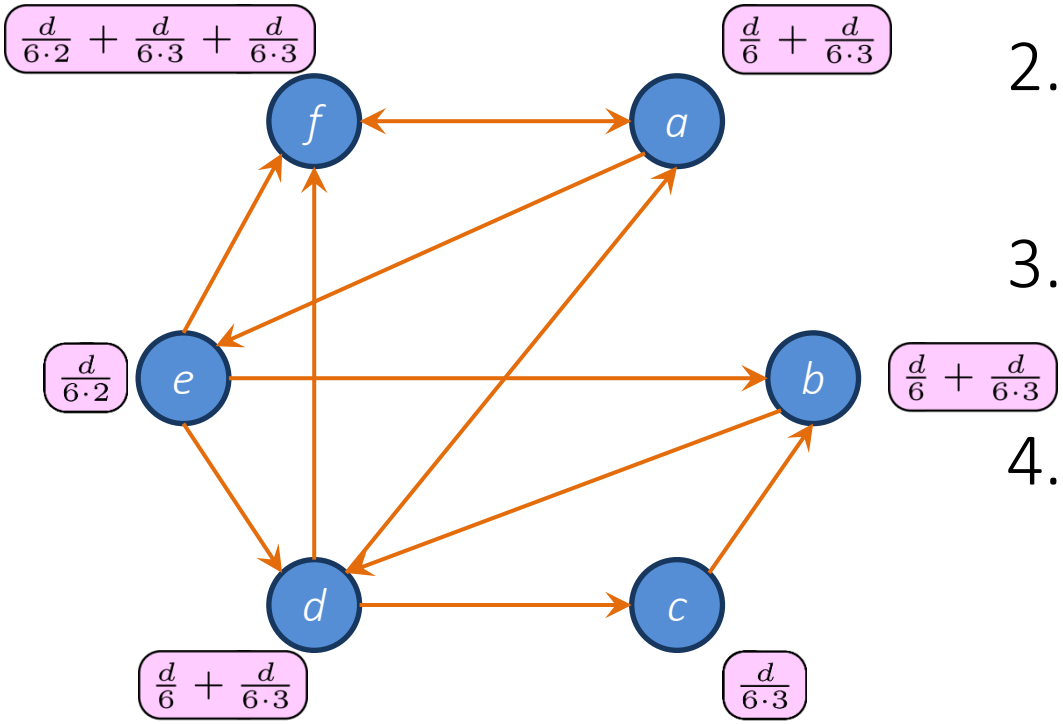
1. Nodes assigned state
2. Nodes pass messages (typically along edges)

Vertex-Centric Computation



1. Nodes assigned state
2. Nodes pass messages (typically along edges)
3. Nodes aggregate messages received

Vertex-Centric Computation



1. Nodes assigned state
2. Nodes pass messages (typically along edges)
3. Nodes aggregate messages received
4. GOTO 2. until some termination criteria are reached

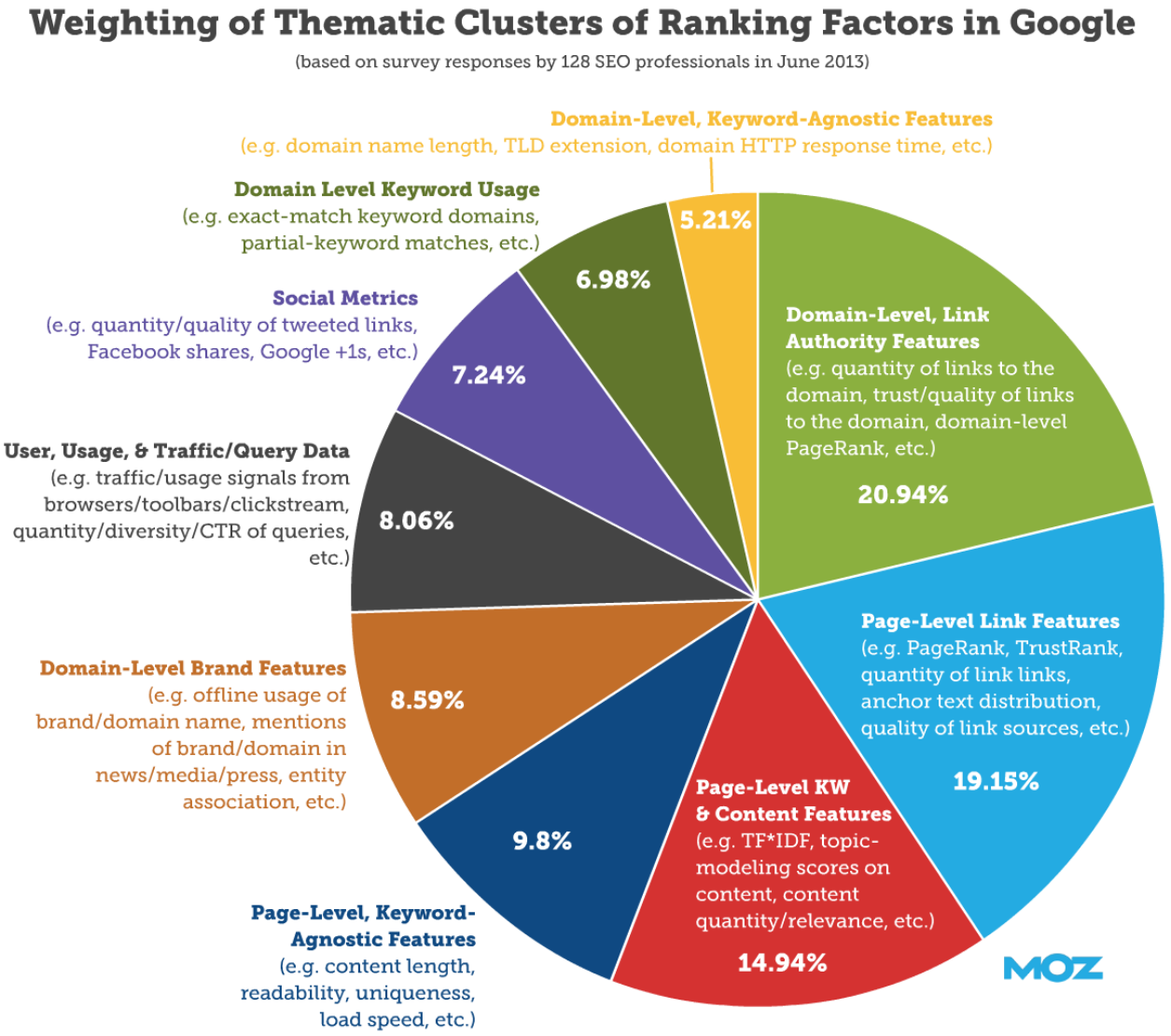
Vertex-Centric Computation: Other Features

- Message passing and aggregation done in parallel
- Optional message passing to non-neighbours
- Optional global “aggregation” phase
- Optional changes to the graph topology

How does google really rank?

An educated guess

How Modern Google ranks results (maybe)



According to survey of SEO experts, not people in Google

How Modern Google ranks results (maybe)

Why so secretive?

According to survey of SEO experts, not people in Google

Ranking: Science or Art?

Questions?