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Link Analysis: TrustRank and WebSpam

CS246: Mining Massive Datasets

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Announcements

- **HW 2 and Colab 4 are due today (2/5 at 11:59 pm)**
- **Colab 5 released (due 2/12 at 11:59 pm)**
- HW 1 and Colab 2 grades will be released by next Monday.

PageRank with Random Teleports

- **PageRank equation** [Brin-Page, 98]

$$r_j = \sum_{i \rightarrow j} \beta \frac{r_i}{d_i} + (1 - \beta) \frac{1}{N}$$

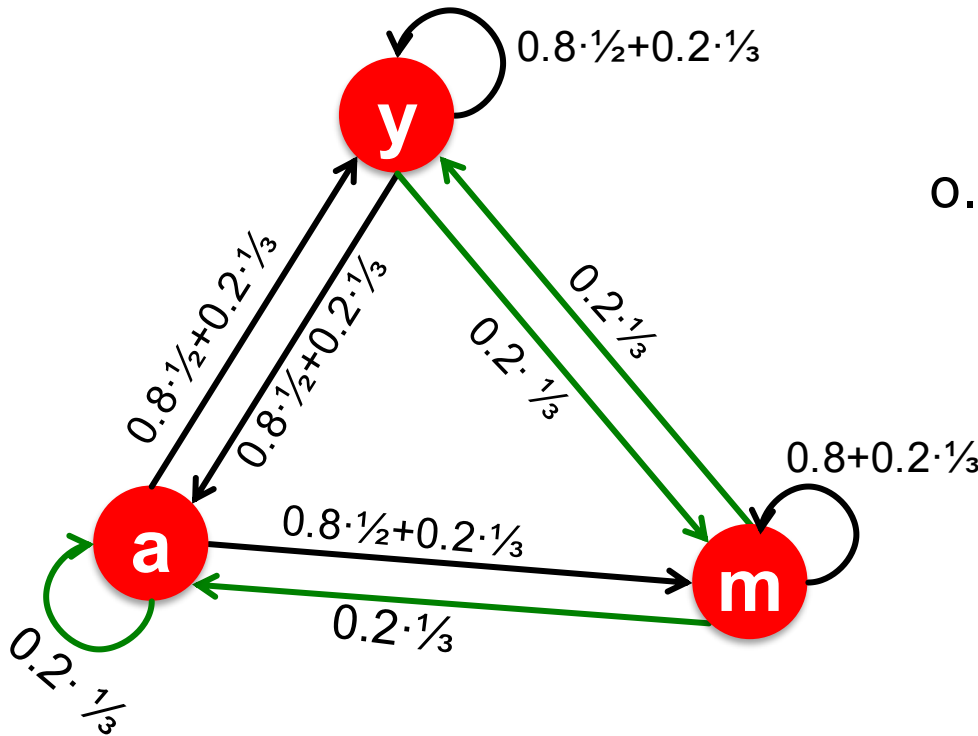
d_i ... out-degree
of node i

- **The Google Matrix A :**

$$A = \beta M + (1 - \beta) \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \frac{1}{N}$$

- **At each step, random surfer has two options:**
 - With probability β , follow a link at random
 - With probability $1-\beta$, jump to some random page

Random Teleports ($\beta = 0.8$)



$$0.8 \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} + 0.2 \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix}$$

y	7/15	7/15	1/15
a	7/15	1/15	1/15
m	1/15	7/15	13/15

y	=	1/3	0.33	0.28	0.26	7/33
a	=	1/3	0.20	0.20	0.18	5/33
m	=	1/3	0.46	0.52	0.56	21/33

Web Search and PageRank

- **Model the web as a graph**
- **Compute the importance of webpages with PageRank**
- **Web-search query**
 - The user types the query “Trojan”
- **Identify relevant webpages**
 - Find webpages relevant to “Trojan”
- **Show them to the user**
 - Webpages with high generic PageRank will be presented first

Some Problems with PageRank

- **Measures generic importance of a page**
 - Will ignore/miss topic-specific authorities
 - **Solution:** Topic-Specific PageRank (**next**)
- **Uses a single measure of importance**
 - Other models of importance
 - **Solution:** Hubs-and-Authorities
- **Susceptible to Link spam**
 - Artificial link topographies created in order to boost page rank
 - **Solution:** TrustRank

Topic-Specific PageRank

Web Search and PageRank

- **Model the web as a graph**
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Topic-Specific PageRank

- **Model the web as a graph**
- **Web-search query**
 - The user types the query “Trojan”
- **Identify relevant webpages**
 - Find webpages relevant to “Trojan”
- **Compute the importance of a webpage according to their relevance to a topic**
- **Show them to the user**
 - Webpages with high topic-specific PageRank will be presented first

Topic-Specific PageRank

- **Instead of generic importance, can we measure importance within a topic?**
- **Goal:** Evaluate Web pages not just according to their importance, but also by how close they are to a particular topic, e.g. “sports” or “history”
- **Allows search queries to be answered based on the interests of a user**
 - **Example:** Query “Trojan” wants different pages depending on whether you are interested in sports, history, or computer security

Topic-Specific Teleportation

- Random walker has a small probability of teleporting at any step
- **Teleport can go to:**
 - **Standard PageRank:** Any page with equal probability
 - To avoid dead-end and spider-trap problems
 - **Topic Specific PageRank:** A topic-specific set of “relevant” pages (**teleport set**)
- **Idea: Bias the random walk**
 - When the walker teleports, they pick a page from a set S
 - S contains only pages that are relevant to the topic
 - For each teleport set S , we get a different vector r_S

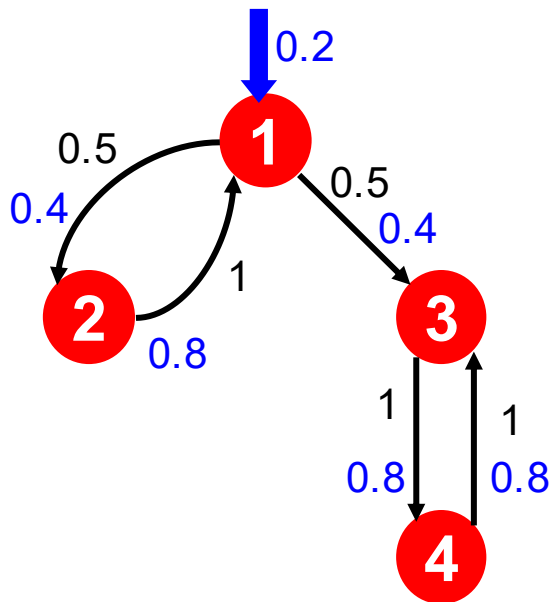
Matrix Formulation

- To make this work all we need is to update the teleportation part of the PageRank formulation:

$$A_{ij} = \begin{cases} \beta M_{ij} + (1 - \beta)/|S| & \text{if } i \in S \\ \beta M_{ij} + 0 & \text{otherwise} \end{cases}$$

- A is a stochastic matrix!
- We weighted all pages in the teleport set S equally
 - Could also assign different weights to pages!
- Compute as for regular PageRank:
 - Multiply by M , then add a vector of $(1 - \beta)/|S|$
 - Maintains sparseness

Example: Topic-Specific PageRank



Suppose $S = \{1\}$, $\beta = 0.8$

Node	Iteration				
	0	1	2	...	stable
1	0.25	0.4	0.28		0.294
2	0.25	0.1	0.16		0.118
3	0.25	0.3	0.32		0.327
4	0.25	0.2	0.24		0.261

$S = \{1\}$, $\beta = 0.9$:
 $r = [0.17, 0.07, 0.40, 0.36]$
 $S = \{1\}$, $\beta = 0.8$:
 $r = [0.29, 0.11, 0.32, 0.26]$
 $S = \{1\}$, $\beta = 0.7$:
 $r = [0.39, 0.14, 0.27, 0.19]$

$S = \{1, 2, 3, 4\}$, $\beta = 0.8$:
 $r = [0.13, 0.10, 0.39, 0.36]$
 $S = \{1, 2, 3\}$, $\beta = 0.8$:
 $r = [0.17, 0.13, 0.38, 0.30]$
 $S = \{1, 2\}$, $\beta = 0.8$:
 $r = [0.26, 0.20, 0.29, 0.23]$
 $S = \{1\}$, $\beta = 0.8$:
 $r = [0.29, 0.11, 0.32, 0.26]$

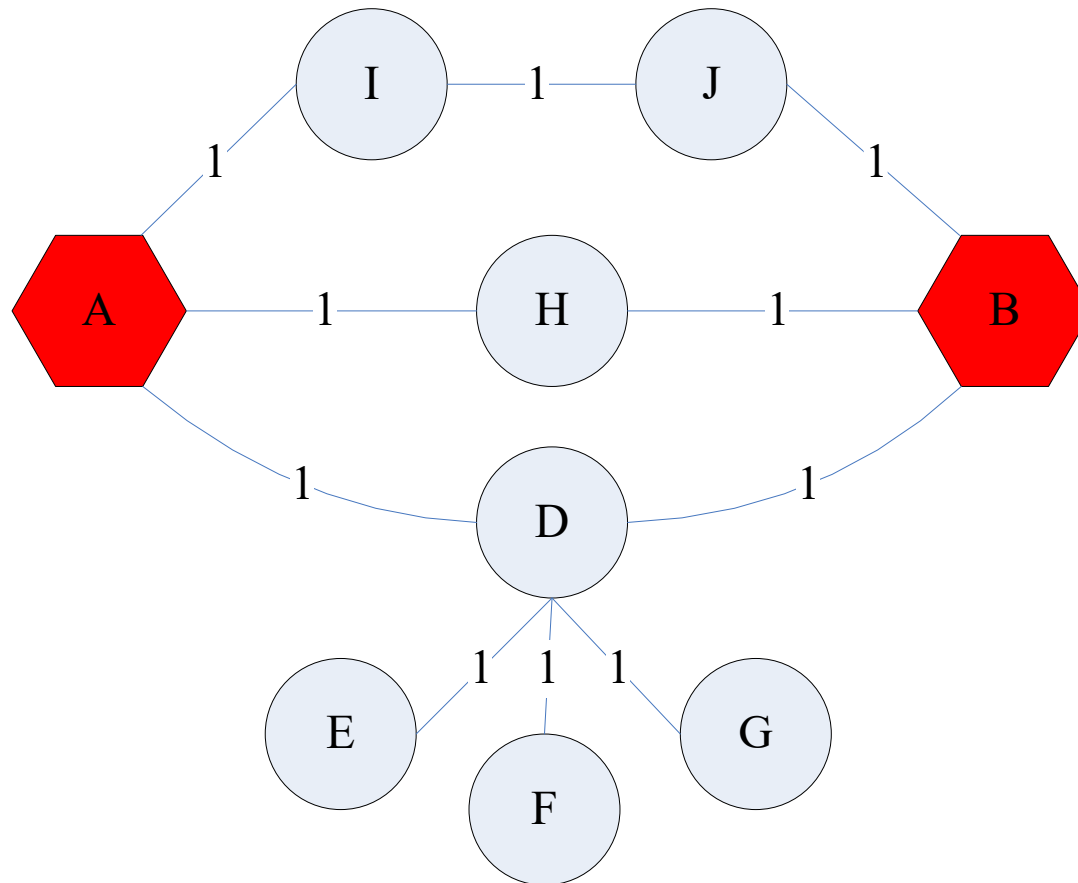
Discovering the Teleport Set S

- **Create different PageRanks for different topics**
 - The 16 DMOZ top-level categories:
 - Arts, Business, Sports,...
- **Which topic ranking to use?**
 - User can pick from a menu
 - Classify query into a topic
 - Can use the **context** of the query
 - E.g., query is launched from a web page talking about a known topic
 - History of queries e.g., “basketball” followed by “Jordan”
 - User context, e.g., user’s bookmarks, ...

Application to Measuring Proximity in Graphs

Random Walk with Restarts: Set S is a single node

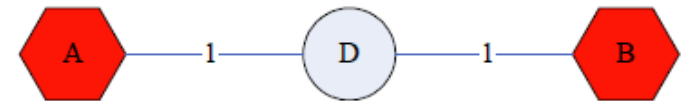
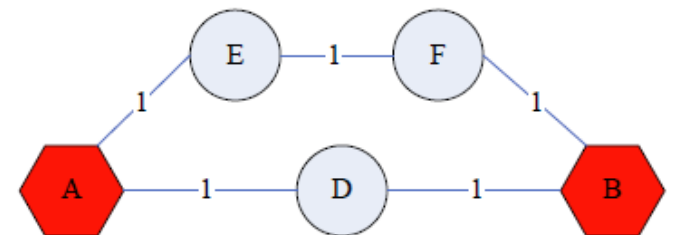
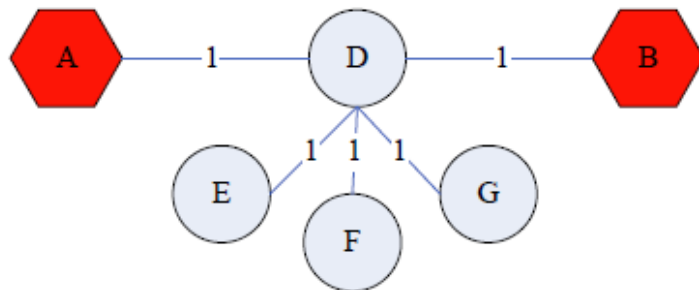
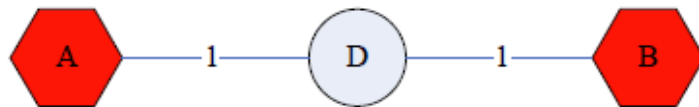
Proximity on Graphs



a.k.a.: Relevance, Closeness, 'Similarity'...

Good proximity measure?

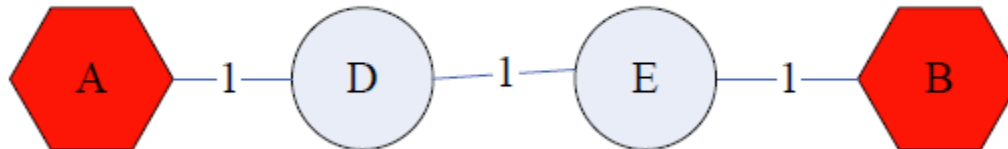
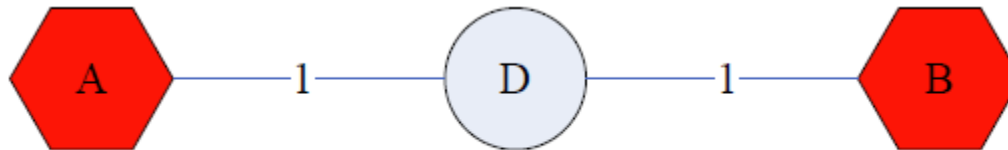
- Shortest path is not good:



- No effect of degree-1 nodes (E, F, G)!
- Multi-faceted relationships

Good proximity measure?

- Network flow is not good:

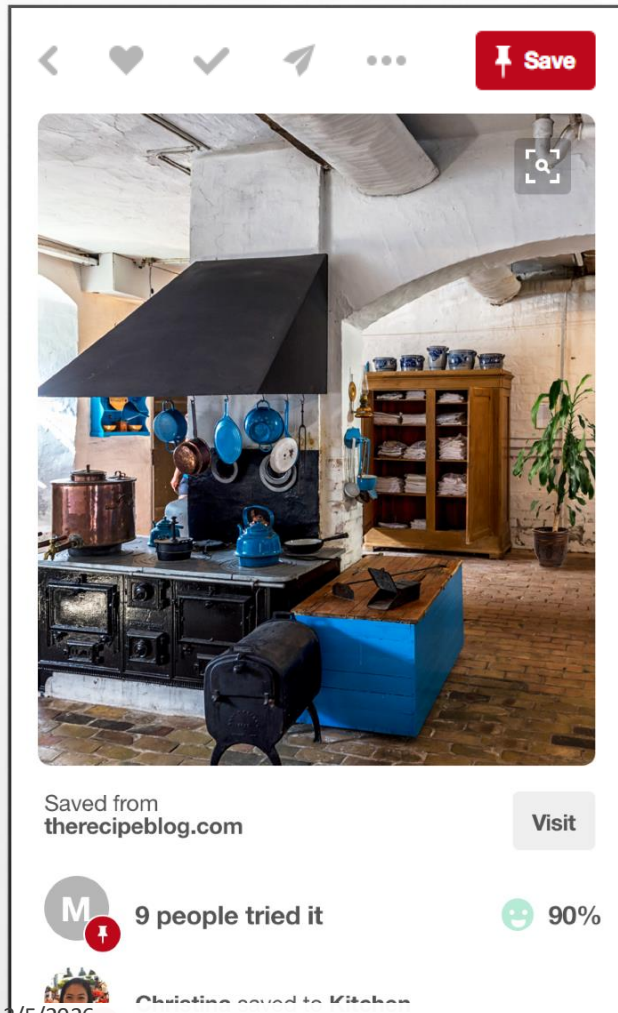


- Does not punish long paths

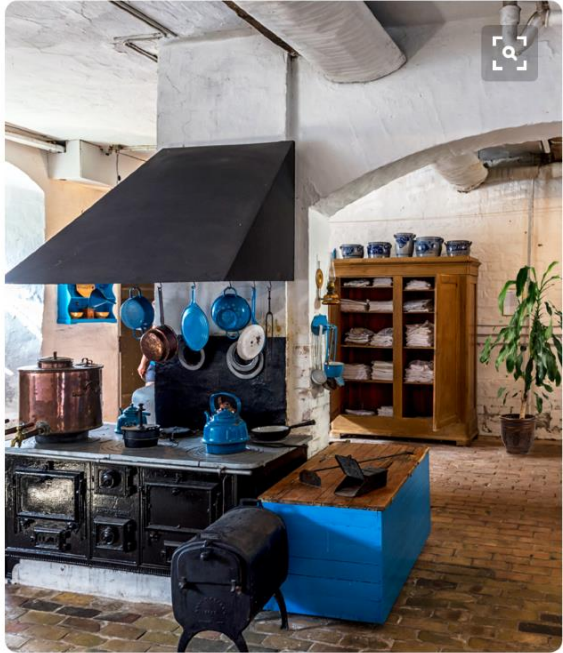
Pixie: Random Walk-based Real-Time Recommender System at Pinterest

https://labs.pinterest.com/user/themes/pin_labs/assets/paper/paper-pixie.pdf

Pinterest




Navigation icons: back, heart, checkmark, share, and menu. A red 'Save' button is visible in the top right corner.



Saved from therecipeblog.com Visit

M 9 people tried it 90%

 Christina moved to Kitchen

1/5/2026



Blue accents
219 Pins



Vintage kitchen
377 Pins



Fireplace
138 Pins

Goal: Radical Personalization

- Recommendations can be radically personalized.
- Adapting in real-time
- **Highly scalable**

From Pins to Pins

Input:



HEALTHY CHOCOLATE STRAWBERRY SHAKE



Chocolate Strawberry Shake

249

This healthier chocolate strawberry shake is like sipping a...

One Lovely Life



Danielle Benzaia
Strawberries

From Pins to Pins

■ Pins to Pins

Input:

Output:



HEALTHY CHOCOLATE STRAWBERRY SHAKE



Chocolate Strawberry Shake † 249

This healthier chocolate strawberry shake is like sipping a...

One Lovely Life

Danielle Benzaia Strawberries



Chocolate Dipped Strawberry Smoothie † 5.3k

Chocolate Dipped Strawberry Smoothie. Just in time for...

Be Whole. Be You. Ed Todd

Ed Todd Drinks- Smoothies



Tropical Orange Smoothie



Easy Breezy Tropical Orange Smoothie † 80.1k

Tropical O...



8 STAPLE SMOOTHIES
(THAT YOU SHOULD KNOW HOW TO MAKE)



8 Staple Smoothies You Should Know How to Make † 5.2k

8 Staple Smoothies That You Should Know



The Perfect Vanilla Pumpkin Smoothie: A Quick &... † 11.4k

The perfect vanilla pumpkin smoothie recipe. Quick, easy and...

BabvSavers

Marybeth @ Bab... Best Comfort Fo...



Spinach-Pear-Celery Smoothie † 60

drink this daily and watch the pounds come off without fuss...

areenreset.com Spring Stutzman R - Drink Up



From Pins to Pins

Input:



HEALTHY CHOCOLATE STRAWBERRY SHAKE



Chocolate Strawberry Shake † 249

This healthier chocolate strawberry shake is like sipping a...

One Lovely Life



Danielle Benzai
Strawberries



HEALTHY CHOCOLATE PEANUT BUTTER CHIP MUFFINS

Healthy Chocolate Peanut Butter Chips Muffins † 119

Healthy Chocolate Peanut Butter Chip Muffins made with greek...

The First Year



Katie - You Brew ...
Healthy Recipes



The Ultimate Healthy Soft & Chewy Chocolate Chip Cookies † 221

The ULTIMATE Healthy Chocolate Chip Cookies -- so buttery...

Amv's Healthy Baking



Robin Guertin
healthy cooking

From Pins to Pins

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 This healthier chocolate strawberry shake is like sipping a...
 One Lovely Life
 Danielle Benzaia Strawberries

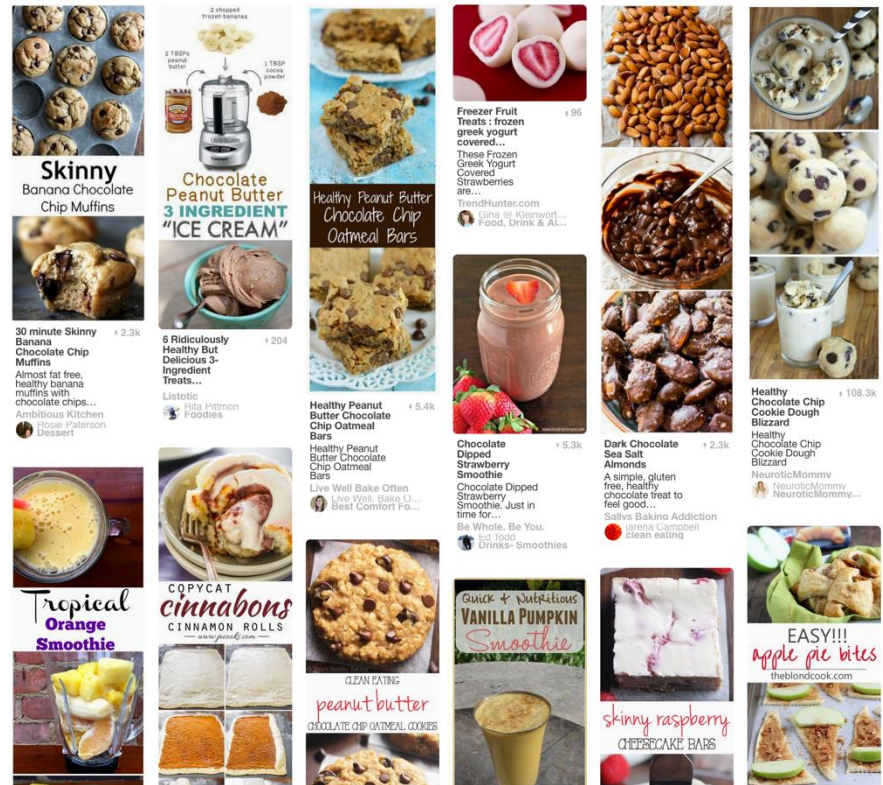


Healthy Chocolate Peanut Butter Chips Muffins † 119
 Healthy Chocolate Peanut Butter Chip Muffins made with greek...
 The First Year
 Katie - You Brew ... Healthy Recipes



The Ultimate Healthy Soft & Chewy Chocolate Chip Cookies † 221
 The ULTIMATE Healthy Chocolate Chip Cookies -- so buttery...
 Amv's Healthy Baking
 Robin Guertin healthy cooking

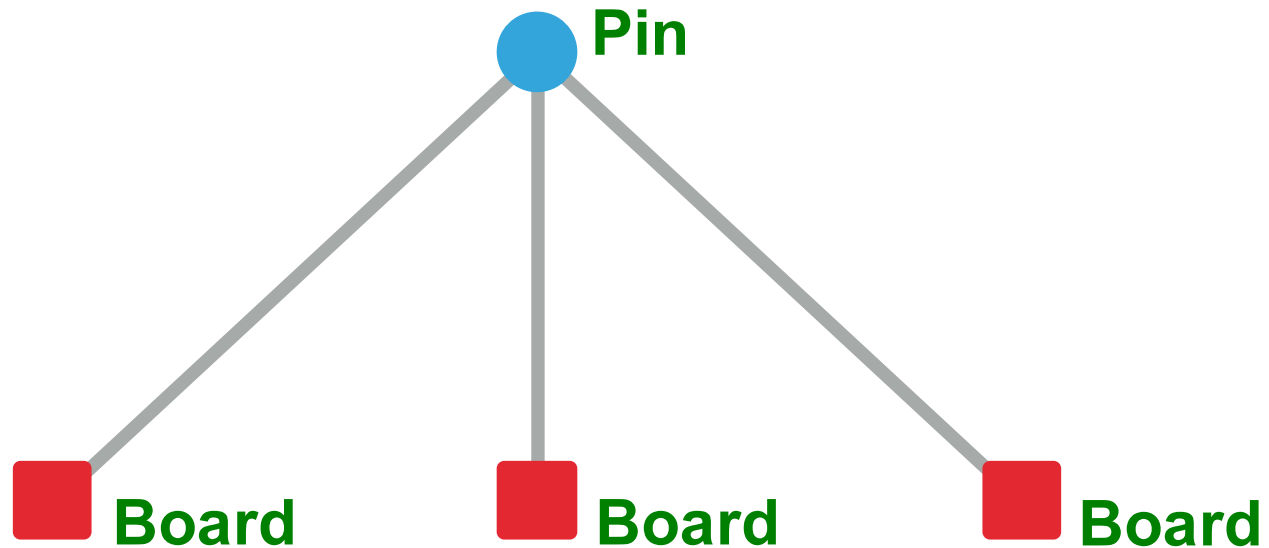
Output:



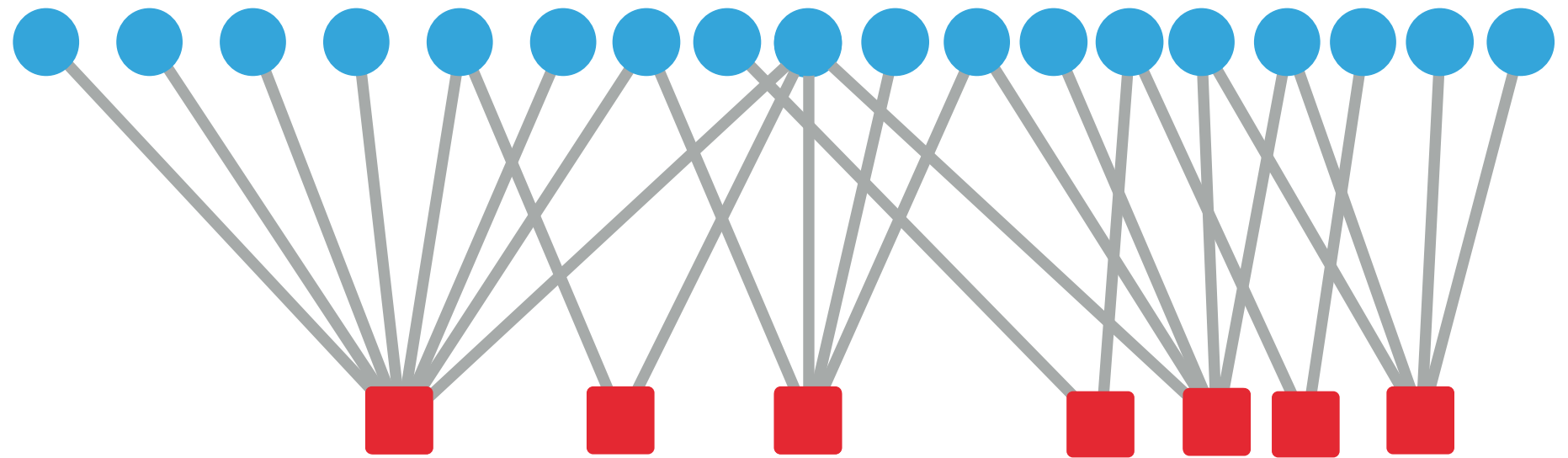
Pinterest is a Giant Bipartite Graph



Bipartite Pin And Board Graph

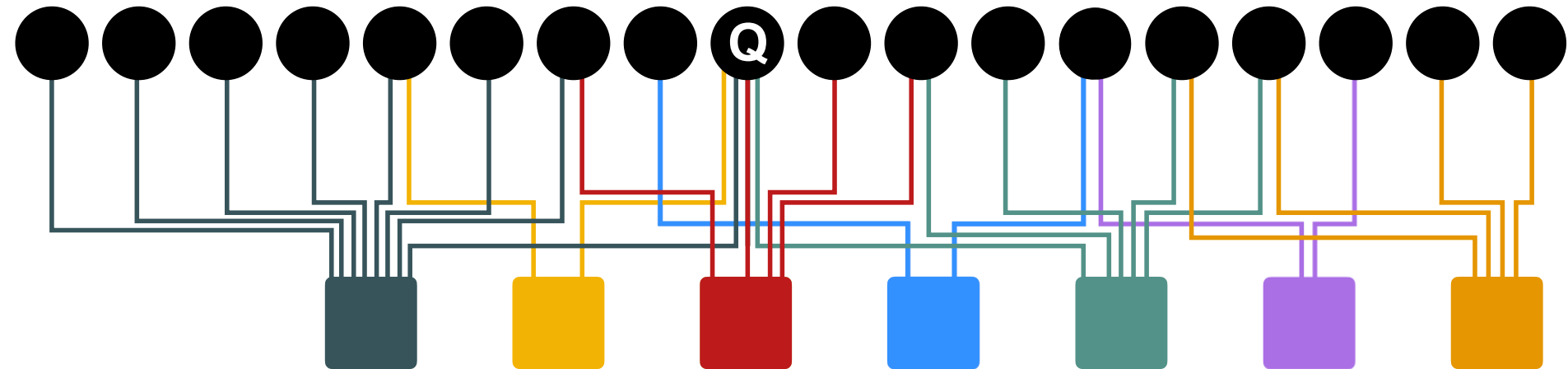


Bipartite Pin And Board Graph



Pixie Random Walks

- **Idea:**
 - Every node has some importance
 - Importance gets evenly split among all edges and pushed to the neighbors
- Given a set of QUERY NODES Q , **simulate a random walk:**

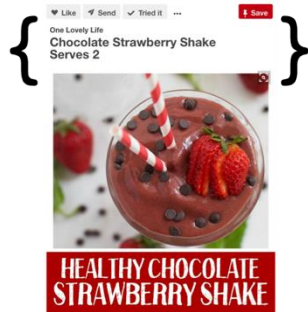


Pixie Random Walk Algorithm

■ Proximity to query node(s) Q :

ALPHA = 0.5

QUERY_NODES =



```
pin_node = QUERY_NODES.sample_by_weight()
```

```
for i in range(N_STEPS):
```

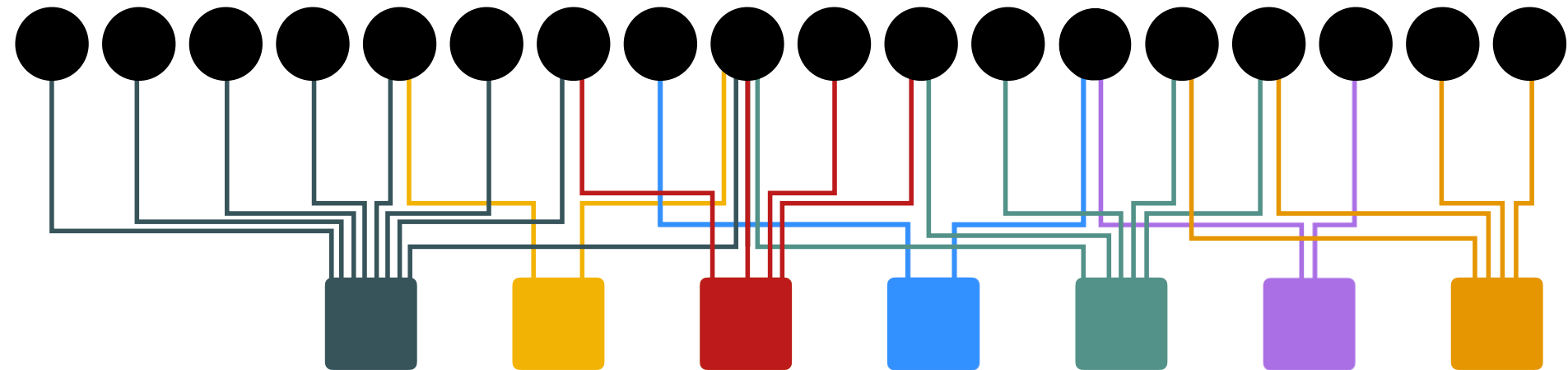
```
    board_node = pin_node.get_random_neighbor()
```

```
    pin_node = board_node.get_random_neighbor()
```

```
    pin_node.visit_count += 1
```

```
    if random() < ALPHA:
```

```
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```

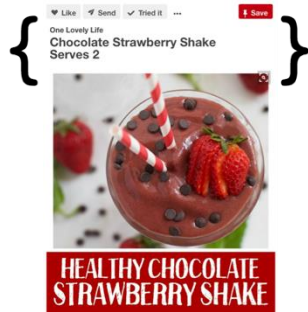


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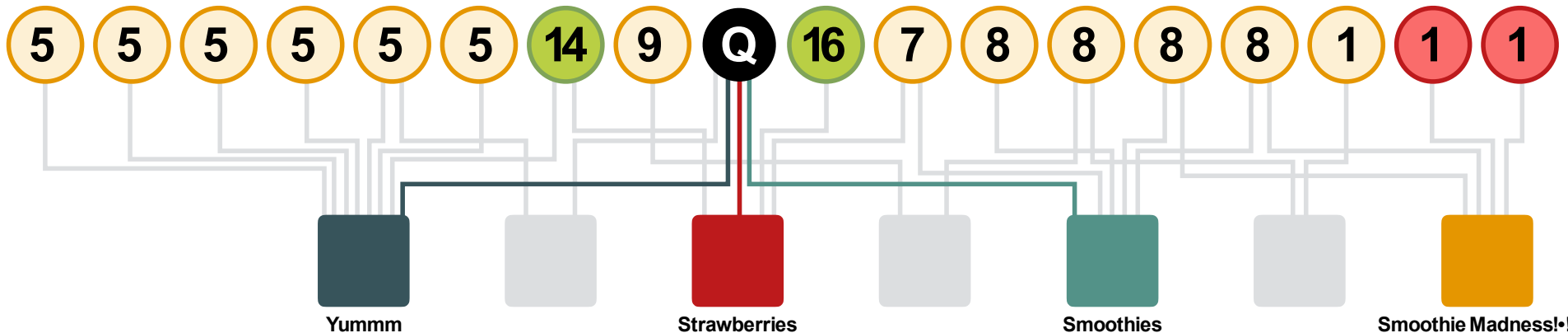
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```

```
    if random() < ALPHA:
```

```
        pin_node = QUERY_NODES.sample_by_weight()
```



Pixie Recommendations

- **Pixie:**

- **Outputs top 1k pins with highest visit count**

Extensions:

- **Weighted edges:** The walk prefers to traverse certain edges:
 - Edges to pins in your local language
 - Personalized edge weights:
 - Pixie for different users and query pins can choose to bias edge selection dynamically based on user and edge features.
 - $\text{Weight} = \text{PersonalizedNeighbor}(E, U)$,
where E is edge and U is the user.

Pixie Recommendations

Extensions:

■ Multiple query pins:

- Each query pin q gets a different importance w_q
- Run PixieRandomWalk for each q in parallel.
- Combine visit counts.
- **Important insight:** The number of steps required to obtain meaningful visit counts depends on the query pin's degree
 - Scale the number of steps allocated to each query pin to be proportional to its degree

Graph Cleaning/Pruning

- **Pinterest graph has 200B edges**
- We don't need all of them!
 - Super popular pins are pinned to millions of boards
 - **Not useful:** When the random walk hits the pin, the signal just disperses. Such pins appear randomly in our recommendations.
- **What we did: Keep only good boards for pins**
 - Compute the similarity between pin's topic vector and each of its boards. Only take boards with high similarity.

Data Type	Number	Size	Memory
Pin Nodes	3 Billion	8 Bytes	24 GiB
Board Nodes	2 Billion	8 Bytes	16 GiB
Undirected Edges	20 Billion	8 Bytes	160 GiB
			208 GiB

Benefits of Pixie

■ Benefits:

- **Blazingly fast:** Given Q , we can output top 1k in 50ms (after doing $\sim 100k$ steps of the random walk)
- Single machine can run 1,500 walks in parallel (1500 recommendation requests per second).
- Fit entire graph in RAM of a single machine (17B edges, 3B nodes)
- Can scale it by just adding more machines

To learn more read: <https://cs.stanford.edu/people/jure/pubs/pixie-www18.pdf>

Recommendations@Twitter

Joint work with many Twitter folks over several years:

<http://www2013.w3c.br/proceedings/p505.pdf>

<https://www.vldb.org/pvldb/vol9/p1281-sharma.pdf>

Recommendations@Twitter

Who to follow

Ramnath Balasubramanian and 3 others follow



Jiasong Sun
@jiasong_sun

Software Engineer @twitter

Follow

Gilad Mishne and 5 others follow



David Burkett
@david_burkett

Doesn't usually write well in the short form, but is glad that other people do.

Follow

David Gleich and 2 others follow



Nelly Litvak
@nellylitvak

Professor in Applied Mathematics at University of Twente and Eindhoven University of Technology| complex networks| novelty in education| non-fiction author

Follow

Show more >



662 961 6,219



Elon Musk liked
DirtyTesla 🚗 ⚡️ Starlink Plz 🚗 @Dirt... · 8h ...
If you experience any kind of traffic like this, you need Autopilot. It makes the experience relaxing instead of stressful.



Elon Musk and 2 others

58 61 1,317



Mekka 🇳🇬 🇳🇬 🇳🇬 *My Mask Protects You*
Okereke liked
Andrea Pitzer @andrapitzer · 3h ...
I'm skeptical of all politicians, because it's so much easier to say things than to do them. But it's such a relief that we now have a president who isn't actively using every public appearance to foment hatred and intolerance. It may be a low bar, but it still feels like a gift.

6 20 240

Show this thread



Serena Williams ✓

@serenawilliams



Following

Suggested



Venus Williams ✓
@Venuseswilliams

Tennis player, big sister, grown up girl. Double Tap! ❤️ Be Well ❤️ #CoachVenus @elevenbyvenus workouts @ link in bio

Follow



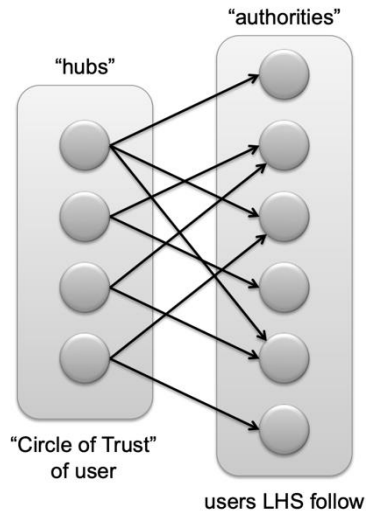
Rafa Nadal ✓
@RafaelNadal

Tennis player

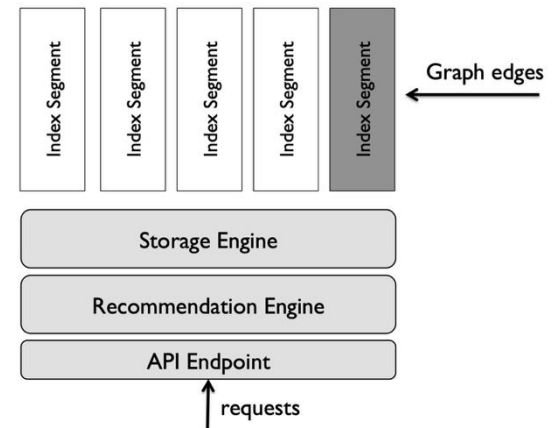
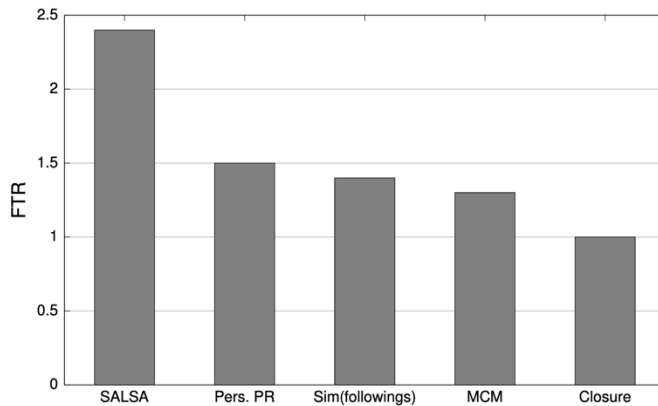
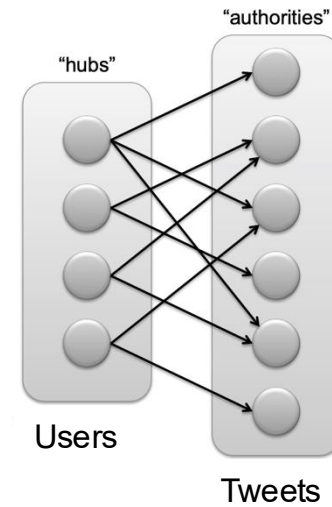
Follow

SALSA for Recommendations

User Recs



Content Recs



TrustRank: Combating Spam on the Web

What is Web Spam?

- **Spamming:**
 - Any deliberate action to boost a web page's position in search engine results, incommensurate with the page's real value
- **Spam:**
 - Web pages that are the result of spamming
- This is a very broad definition
 - **SEO** industry might disagree!
 - SEO = search engine optimization
- Approximately **10-15%** of web pages are spam

Web Search

- **Early search engines:**
 - Crawl the Web
 - Index pages by the words they contained
 - Respond to search queries (lists of words) with the pages containing those words
- **Early page ranking:**
 - Attempt to order pages matching a search query by “importance”
 - **First search engines considered:**
 - (1) Number of times query words appeared
 - (2) Prominence of word position, e.g. title, header

First Spammers

- As people began to use search engines to find things on the Web, those with commercial interests tried to **exploit search engines** to bring people to their own site – whether they wanted to be there or not
- **Example:**
 - Shirt-seller might pretend to be about “movies”
- **Techniques for achieving high relevance/importance for a web page**

First Spammers: Term Spam

- **How do you make your page appear to be about movies?**
 - **(1)** Add the word movie 1,000 times to your page
 - Set text color to the background color, so only search engines would see it
 - **(2)** Or, run the query “movie” on your target search engine
 - See what page came on top of result ranking
 - Copy it into your page, make it “invisible”
- **These and similar techniques are term spam**

Google's Solution to Term Spam

- **Believe what people say about you, rather than what you say about yourself**
 - Use words in the anchor text (words that appear underlined to represent the link) and its surrounding text
- **PageRank as a tool to measure the “importance” of Web pages**

Why Does It Work?

- **Our hypothetical shirt-seller loses**
 - Saying they are about movies doesn't help, because others don't say they are about movies
 - Their page isn't very important, so it won't be ranked high for shirts or movies
- **Example:**
 - Shirt-seller creates 1,000 pages, each links to theirs with "movie" in the anchor text
 - These pages have no links in, so they get low PageRank
 - So the shirt-seller can't beat truly important movie pages, like IMDB

Why Does It NOT Work?



Web

Results 1 - 10 of about 969,000 for [miserable failure](#). (0.06 seconds)

[Biography of President George W. Bush](#)

Biography of the president from the official White House web site.

www.whitehouse.gov/president/gwbbio.html - 29k - [Cached](#) - [Similar pages](#)

[Past Presidents](#) - [Kids Only](#) - [Current News](#) - [President](#)

[More results from www.whitehouse.gov »](#)

[Welcome to MichaelMoore.com!](#)

Official site of the gadfly of corporations, creator of the film Roger and Me and the television show The Awful Truth. Includes mailing list, message board, ...

www.michaelmoore.com/ - 35k - Sep 1, 2005 - [Cached](#) - [Similar pages](#)

[BBC NEWS | Americas | 'Miserable failure' links to Bush](#)

Web users manipulate a popular search engine so an unflattering description leads to the president's page.

news.bbc.co.uk/2/hi/americas/3298443.stm - 31k - [Cached](#) - [Similar pages](#)

[Google's \(and Inktomi's\) Miserable Failure](#)

A search for **miserable failure** on Google brings up the official George W.

Bush biography from the US White House web site. Dismissed by Google as not a ...

searchenginewatch.com/sereport/article.php/3296101 - 45k - Sep 1, 2005 - [Cached](#) - [Similar pages](#)



SPAM FARMING

Google vs. Spammers: Round 2!

- Once Google became the dominant search engine, spammers began to work out ways to fool Google
- **Spam farms** were developed to concentrate PageRank on a single page
- **Link spam:**
 - Create link structures that boost PageRank of a particular page



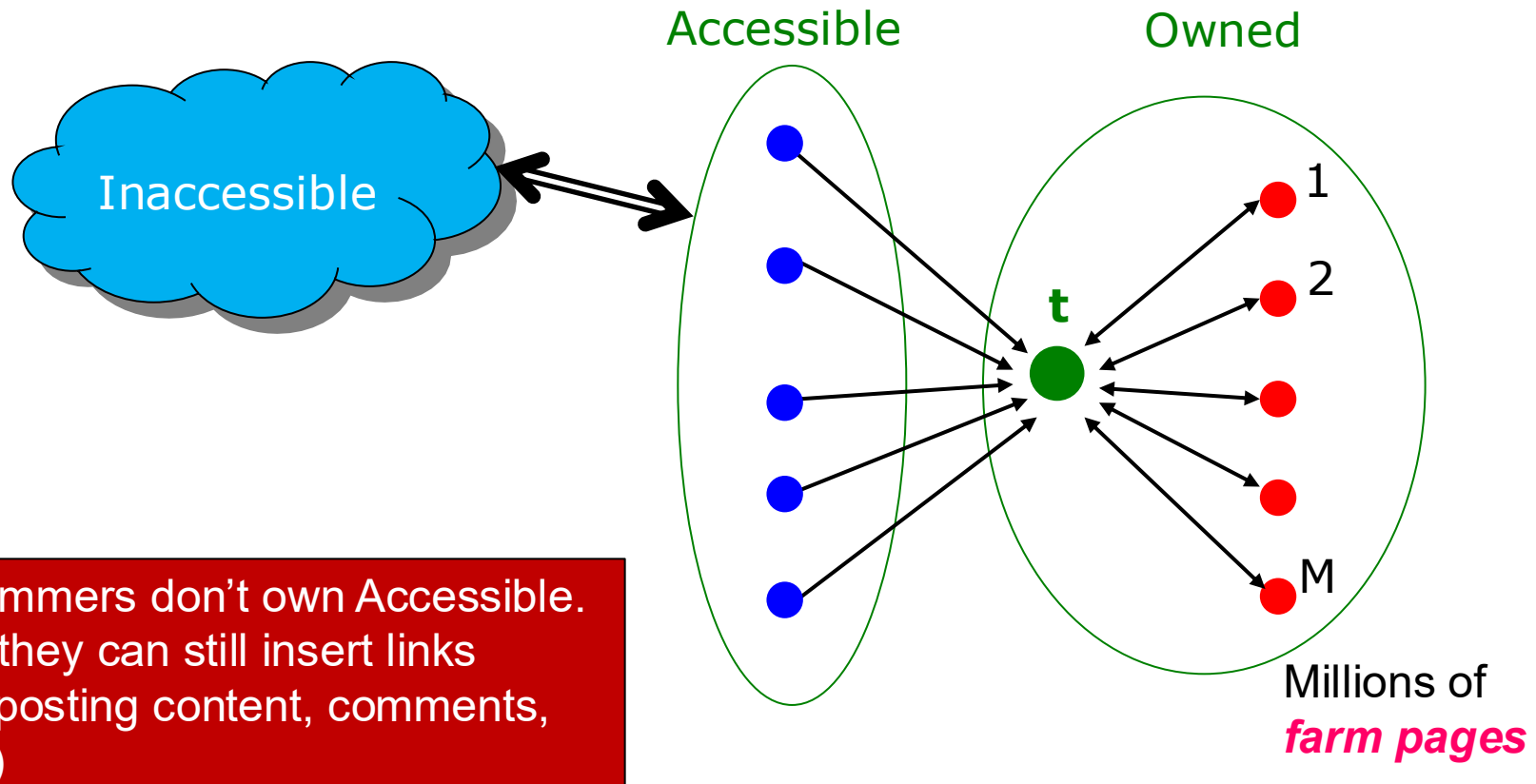
Link Spamming

- **Three kinds of web pages from a spammer's point of view**
 - **Inaccessible pages**
 - **Accessible pages**
 - e.g., blog comments pages
 - spammer can post links to his pages
 - **Owned pages**
 - Completely controlled by spammer
 - May span multiple domain names

Link Farms

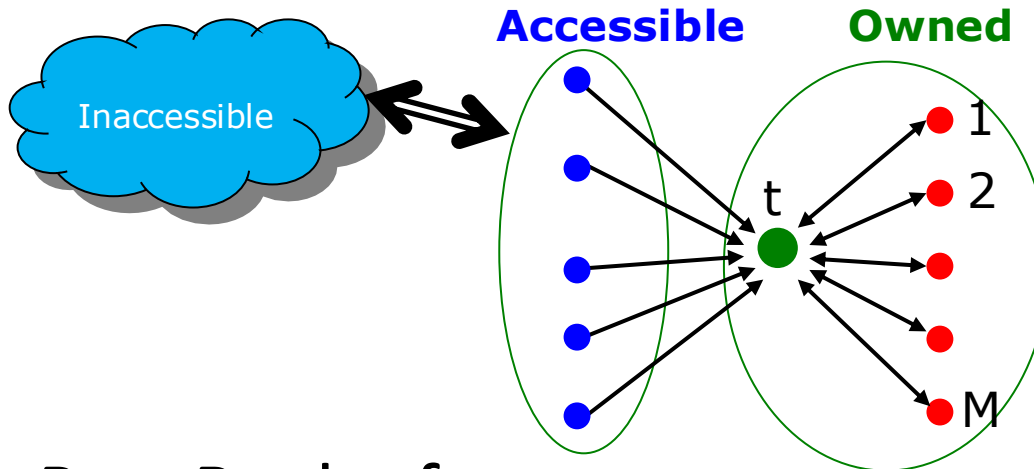
- **Spammer's goal:**
 - Maximize the PageRank of target page t
- **Technique:**
 - Get as many links from accessible pages as possible to target page t
 - Construct “link farm” to get PageRank multiplier effect

Link Farms



One of the most common and effective organizations for a link farm

Analysis



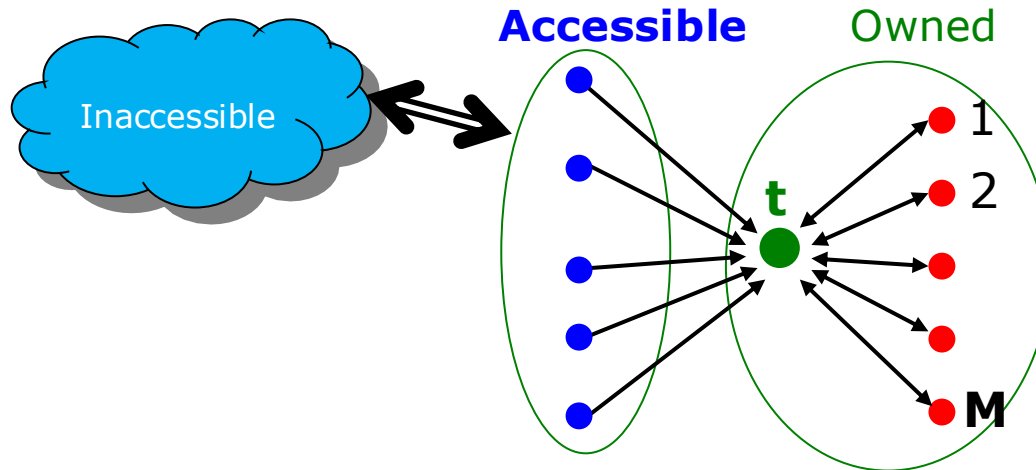
N...# pages on the web
M...# of pages spammer owns

- y : PageRank of target page t
- x : PageRank contributed by accessible pages
- Rank of each “owned” page = $\frac{\beta y}{M} + \frac{1-\beta}{N}$
- $$y = x + \beta M \left[\frac{\beta y}{M} + \frac{1-\beta}{N} \right] + \frac{1-\beta}{N}$$

$$= x + \beta^2 y + \frac{\beta(1-\beta)M}{N} + \frac{1-\beta}{N}$$
- $$y = \frac{x}{1-\beta^2} + c \frac{M}{N} \quad \text{where } c = \frac{\beta}{1+\beta}$$

Very small; ignore
Now we solve for y

Analysis



N...# pages on the web
M...# of pages spammer
owns

- $y = \frac{x}{1-\beta^2} + c \frac{M}{N}$ where $c = \frac{\beta}{1+\beta}$
- For $\beta = 0.85$, $1/(1-\beta^2) = 3.6$
- Multiplier effect for acquired PageRank
- By making M large, we can make y as large as we want

TrustRank: Combating Spam on the Web

Combating Spam

Two ways to Combat link spam:

- **Detection and blacklisting of structures that look like spam farms**
 - Leads to another war – hiding and detecting spam farms
- **TrustRank** = topic-specific PageRank with a teleport set of **trusted pages**
 - **Example:** .edu domains, .gov domains
 - similar domains for non-US websites

TrustRank: Idea

- **TrustRank is Topic-Specific PageRank**
 - **Topic** = the set of **trustworthy** pages
 - It is rare for a “good” page to point to a “bad” (spam) page
- **To develop a suitable teleport set:**
 1. Sample a set of **seed pages** from the web
 2. Have an **oracle (human)** to identify the good pages and the spam pages in the seed set
 - **Expensive task**, so we must make seed set as small as possible

Trust Propagation

- Call the subset of seed pages that are identified as **good** the **trusted pages**
- Perform a topic-sensitive PageRank with **teleport set = trusted pages**
 - **Propagate trust through links:**
 - Each page gets a trust value between **0** and **1**
- **Solution 1: Use a threshold value and mark all pages below the trust threshold as spam**

Why is it a good idea?

- **Trust attenuation:**

- The degree of trust conferred by a trusted page decreases with the distance in the graph

- **Trust splitting:**

- The larger the number of out-links from a page, the less scrutiny the page author gives each out-link
- Trust is **split** across out-links

Picking the Seed Set

- **Two conflicting considerations:**
 - Human has to inspect each seed page, so seed set must be as small as possible
 - Must ensure every **good page** gets adequate trust rank, so need to make all good pages reachable from seed set by short paths

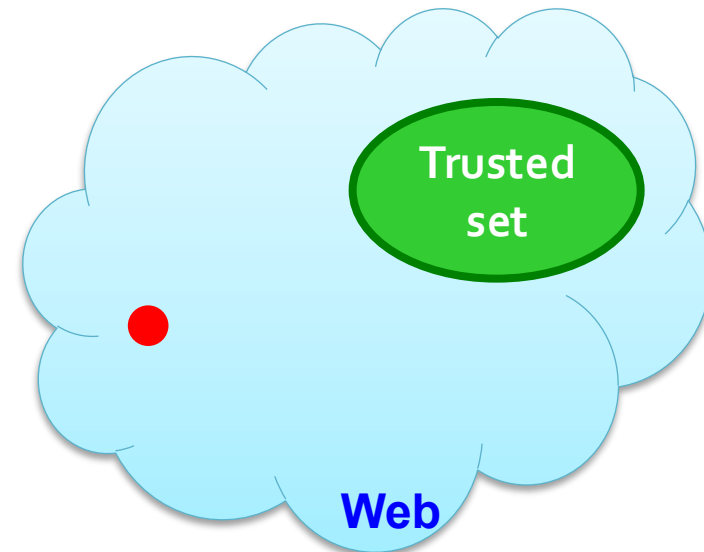
Approaches to Picking Seed Set

- Suppose we want to pick a seed set of k pages
- **How to do that?**
- **(1) PageRank:**
 - Pick the top k pages by PageRank
 - Theory is that bad pages can't get really high ranks
- **(2) Use trusted domains** whose membership is controlled, like .edu, .mil, .gov

Spam Mass

Spam Mass

- In the **TrustRank** model, we start with good pages and propagate trust
- **Complementary view:**
What fraction of a page's PageRank comes from **spam** pages?
- In practice, we don't know all the spam pages, so we need to estimate



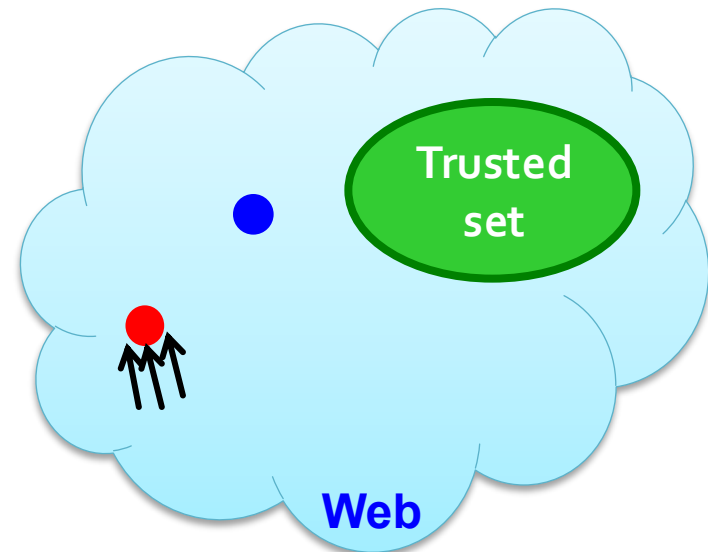
Spam Mass Estimation

Solution 2:

- r_p = PageRank of page p
- r_p^+ = PageRank of p with teleport into **trusted** pages only
- **Then:** What fraction of a page's PageRank comes from spam pages?

$$r_p^- = r_p - r_p^+$$

- **Spam mass of p** = $\frac{r_p^-}{r_p}$
 - Pages with high spam mass are spam



Summary of Today's lecture

- Topic specific PageRank
 - Custom teleportation vector
- Random Walk with Restarts
 - Recommendations
- Spam farming
- TrustRank and Spam Mass estimation

Extras

Pixie Recommendations

Extensions:

■ Multiple query pins:

- Each query pin q gets a different importance w_q
- Run PixieRandomWalk for each q in parallel.
- Combine visit counts.
- **Important insight:** The number of steps required to obtain meaningful visit counts depends on the query pin's degree
 - Scale the number of steps allocated to each query pin to be proportional to its degree

Pixie Recommendations

Extensions:

■ Multi-hit Booster:

- For multi-pin queries we prefer recommendations related to multiple query pins q .
 - Candidates with high visit counts from multiple query pins are more relevant to the query than candidates having equally high total visit count but all coming from a single query pin.
- **Solution:** When combining visit counts use:

$$V[p] = \left(\sum_{q \in Q} \sqrt{V_q[p]} \right)^2$$

Note that when a candidate pin p is visited by walks from only a single query pin q then the count is unchanged. However, if the candidate pin is visited from multiple query pins, then the count is boosted.

Pixie Recommendations

Extensions:

■ Early stopping:

- Insight: We only care about top-1k most visited pins.
- So, we don't need to walk a fixed big number of steps
- We just walk until 1k-th most visited pin has at least 20 visits.

Graph Cleaning/Pruning

- **Pinterest graph has 200B edges**
- We don't need all of them!
 - Super popular pins are pinned to millions of boards
 - **Not useful:** When the random walk hits the pin, the signal just disperses. Such pins appear randomly in our recommendations.
- **What we did: Keep only good boards for pins**
 - Compute the similarity between pin's topic vector and each of its boards. Only take boards with high similarity.

Data Type	Number	Size	Memory
Pin Nodes	3 Billion	8 Bytes	24 GiB
Board Nodes	2 Billion	8 Bytes	16 GiB
Undirected Edges	20 Billion	8 Bytes	160 GiB
			208 GiB

Trust Propagation: Simple Model

- **Set trust of each trusted page to 1**
- Suppose trust of page p is t_p
 - Page p has a set of out-links o_p
- For each $q \in o_p$, p **confers the trust** to q
 - $\beta t_p / |o_p|$ for $0 < \beta < 1$
- **Trust is additive**
 - Trust of p is the sum of the trust conferred on p by all its in-linked pages
- **Note similarity to Topic-Specific PageRank**
 - Within a scaling factor, **TrustRank = PageRank** with trusted pages as teleport set