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# Link Analysis: TrustRank and WebSpam

CS246: Mining Massive Datasets

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<http://cs246.stanford.edu>



# PageRank with Random Teleports

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

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

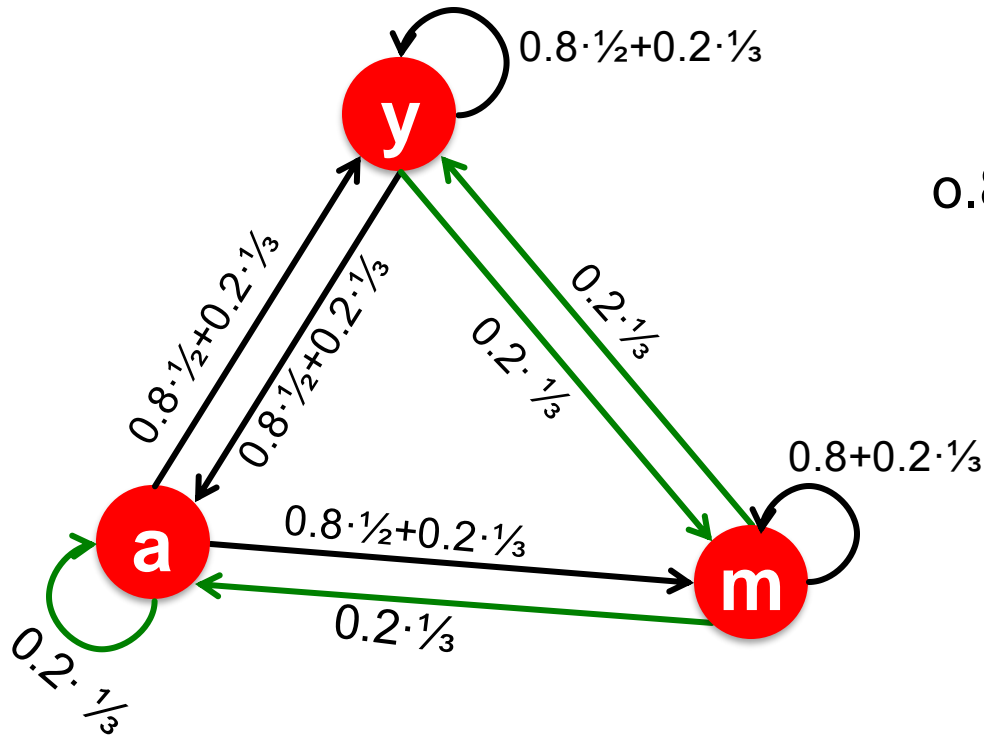
$d_i$  ... out-degree  
of node  $i$

- **The Google Matrix  $A$ :**

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

- **At each step, random surfer has two options:**
  - With probability  $\beta$ , 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

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  - The user types the query “Trojan”
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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 generic 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  $r_S$

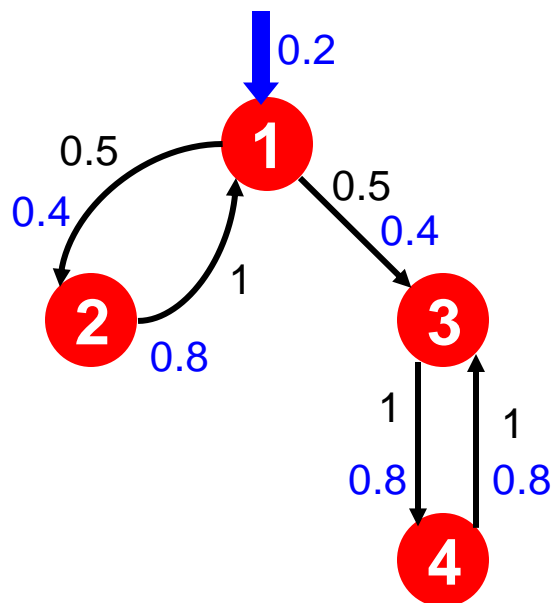
# Matrix Formulation

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

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

- $A$  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  $(\mathbf{1} - \beta)/|S|$
  - 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

$S = \{1\}$ ,  $\beta = 0.9$ :

$r = [0.17, 0.07, 0.40, 0.36]$

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

$r = [0.29, 0.11, 0.32, 0.26]$

$S = \{1\}$ ,  $\beta = 0.7$ :

$r = [0.39, 0.14, 0.27, 0.19]$

$S = \{1, 2, 3, 4\}$ ,  $\beta = 0.8$ :

$r = [0.13, 0.10, 0.39, 0.36]$

$S = \{1, 2, 3\}$ ,  $\beta = 0.8$ :

$r = [0.17, 0.13, 0.38, 0.30]$

$S = \{1, 2\}$ ,  $\beta = 0.8$ :

$r = [0.26, 0.20, 0.29, 0.23]$

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

$r = [0.29, 0.11, 0.32, 0.26]$

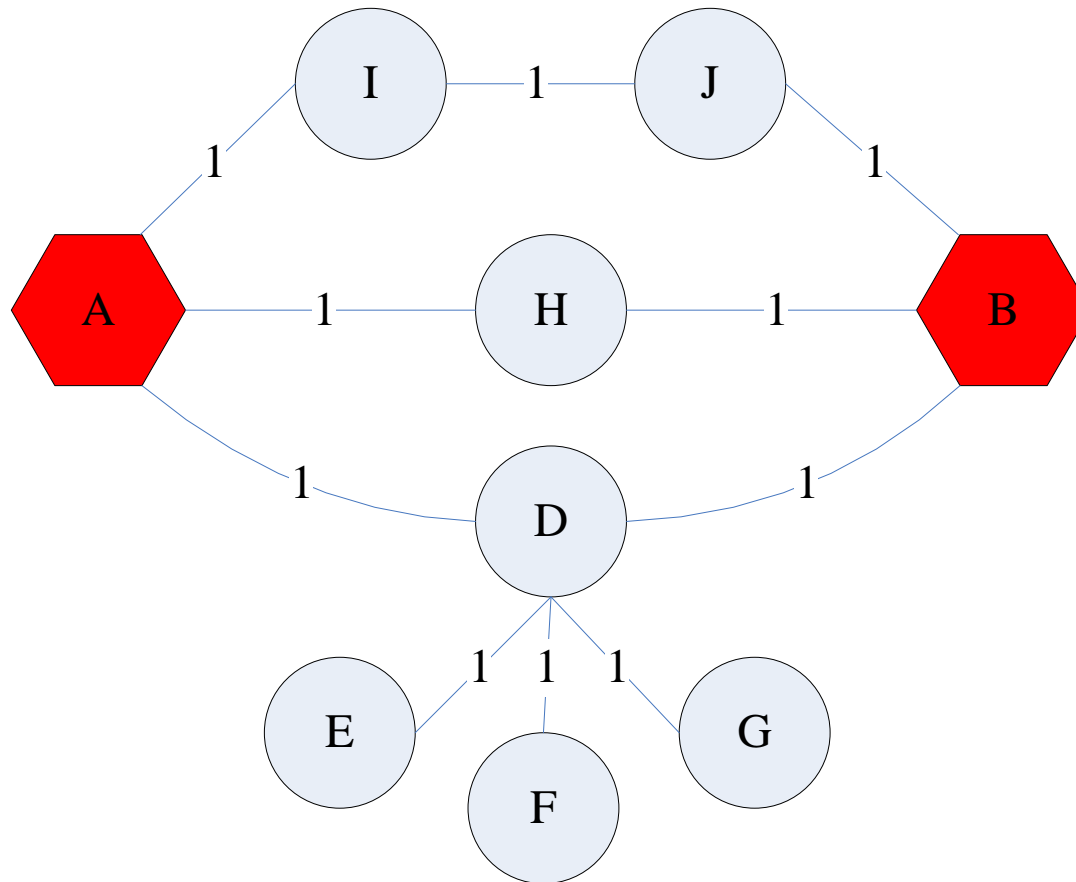
# Discovering the Teleport Set $S$

- **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

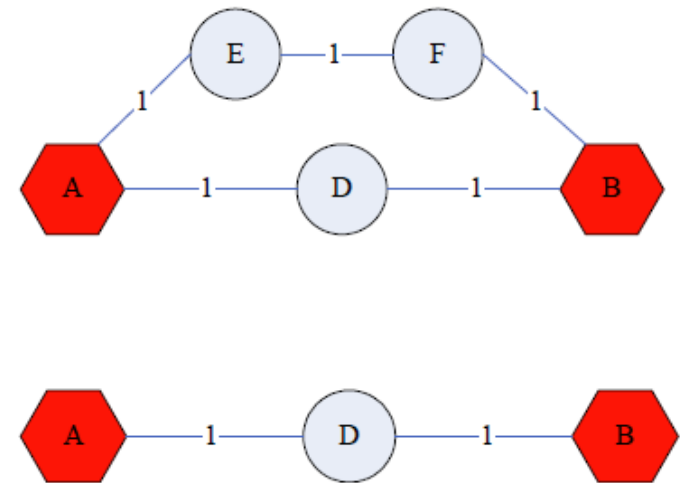
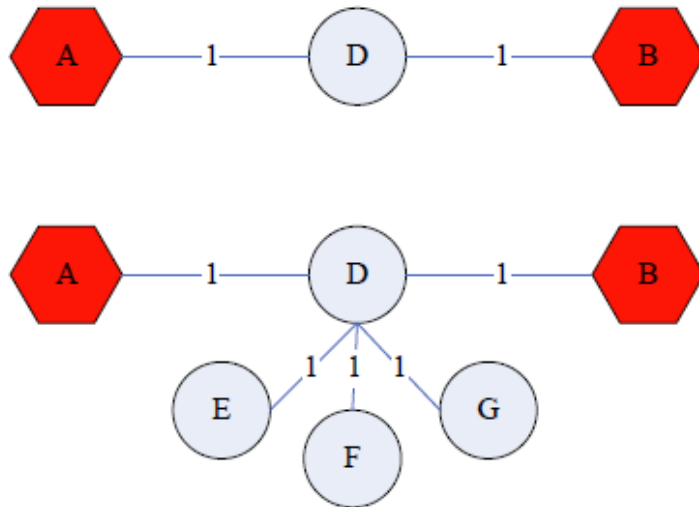
# Proximity on Graphs



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

# Good proximity measure?

- **Shortest path is not good:**

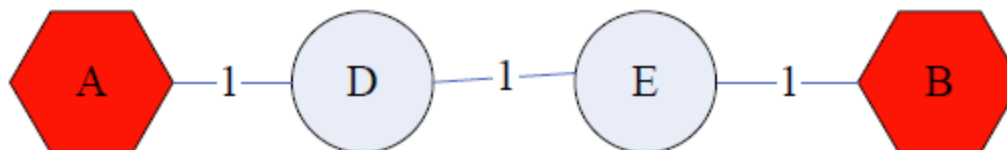
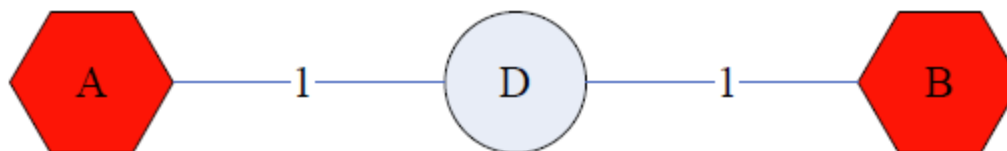


- **No effect of degree-1 nodes (E, F, G)!**
- **Multi-faceted relationships**



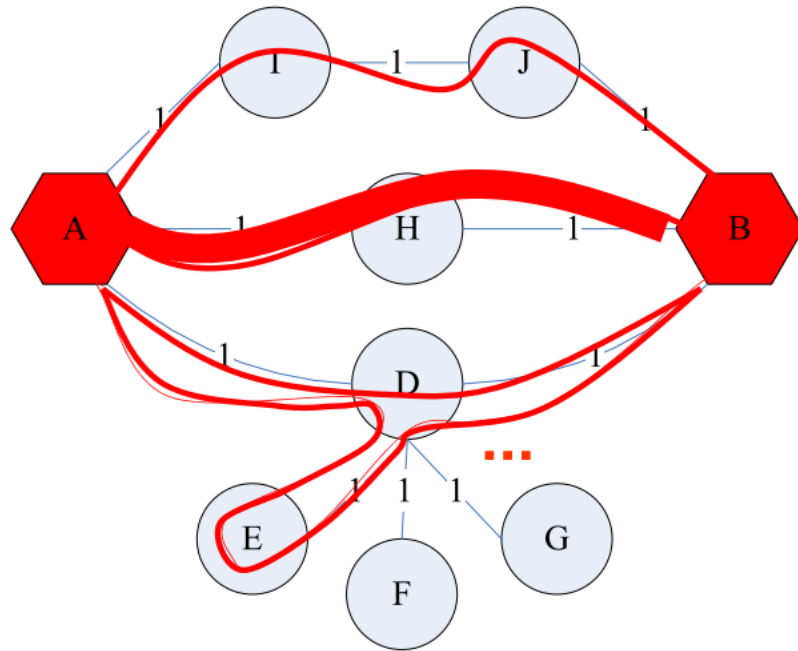
# Good proximity measure?

- Network flow is not good:



- Does not punish long paths

# What is a good notion of proximity?



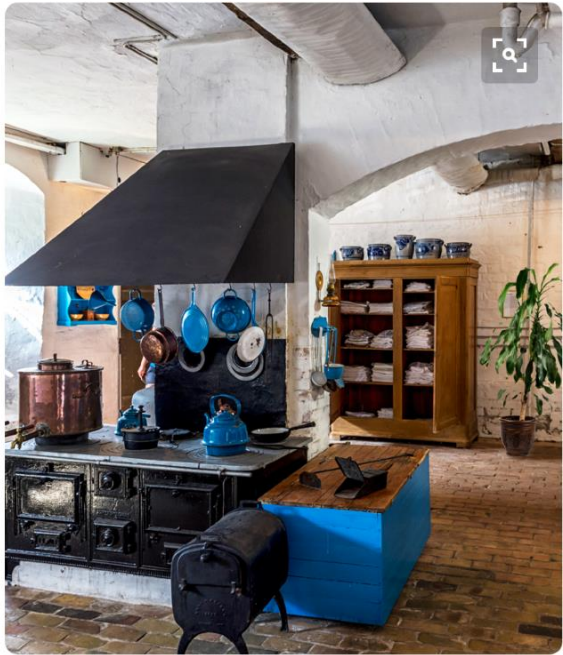
- **Need a method that considers:**
  - Multiple connections
  - Multiple paths
  - Degree of the node

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

[https://labs.pinterest.com/user/themes/pin\\_labs/assets/paper/paper-pixie.pdf](https://labs.pinterest.com/user/themes/pin_labs/assets/paper/paper-pixie.pdf)

# Pinterest

< ♥ ✓ ✈ ... **Save**



Saved from [therecipeblog.com](http://therecipeblog.com) **Visit**

**M** 9 people tried it **90%**

**Christina saved to Kitchen**



## 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 Berzai's Strawberries



**Chocolate Dipped Strawberry Smoothie** † 5.3k

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

Be Whole. Be You.

Ed Todd's Drinks- Smoothies



**Tropical Orange Smoothie**



**Easy Breezy Tropical Orange Smoothie** † 80.1k



**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

**Quick & Nutritious VANILLA PUMPKIN Smoothie**



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

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

BabySavers  
 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's 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 Benzaia  
Strawberries



**HEALTHY CHOCOLATE PEANUT BUTTER CHIP MUFFINS**  
Healthy Chocolate Peanut Butter Chip 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

## Input:



**HEALTHY CHOCOLATE STRAWBERRY SHAKE**



**Chocolate Strawberry Shake** † 249

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

One Lovely Life



Danielle Benzaia  
Strawberries



**HEALTHY CHOCOLATE PEANUT BUTTER CHIP MUFFINS**

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

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## Output:



**Skinny Banana Chocolate Chip Muffins** † 2.3k



**Chocolate Peanut Butter 3 INGREDIENT "ICE CREAM"** † 204

6 Ridiculously Healthy But Delicious 3-Ingredient Treats...

Listotic  
Vita Hibison  
Foodsies



**Tropical Orange Smoothie**



**COPYCAT CINNAMON ROLLS**



**Healthy Peanut Butter Chocolate Chip Oatmeal Bars** † 5.4k



**Chocolate Dipped Strawberry Smoothie** † 5.3k

Live Well, Bake Often  
Best Comfort Fo...

Be Whole, Be You.  
Ed. Jodie  
Drinks+Smoothies



**CLEAN EATING PEANUT BUTTER CHOCOLATE CHIP OATMEAL COOKIES**



**QUICK + NUTRITIOUS VANILLA PUMPKIN SMOOTHIE**



**Healthy Chocolate Chip Cookie Dough Blizzard** † 108.3k



**Healthy Chocolate Chip Cookie Dough Blizzard**

NeuroticMommy  
NeuroticMommy...

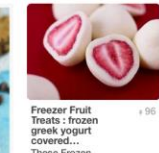
NeuroticMommy  
NeuroticMommy...



**Healthy Chocolate Chip Cookie Dough Blizzard**



**Healthy Chocolate Chip Cookie Dough Blizzard**



**Healthy Chocolate Chip Cookie Dough Blizzard** † 108.3k



**Healthy Chocolate Chip Cookie Dough Blizzard**

NeuroticMommy  
NeuroticMommy...

NeuroticMommy  
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**Healthy Chocolate Chip Cookie Dough Blizzard**



**Healthy Chocolate Chip Cookie Dough Blizzard**



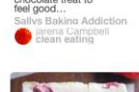
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**Healthy Chocolate Chip Cookie Dough Blizzard**

NeuroticMommy  
NeuroticMommy...

NeuroticMommy  
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**Healthy Chocolate Chip Cookie Dough Blizzard**



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NeuroticMommy  
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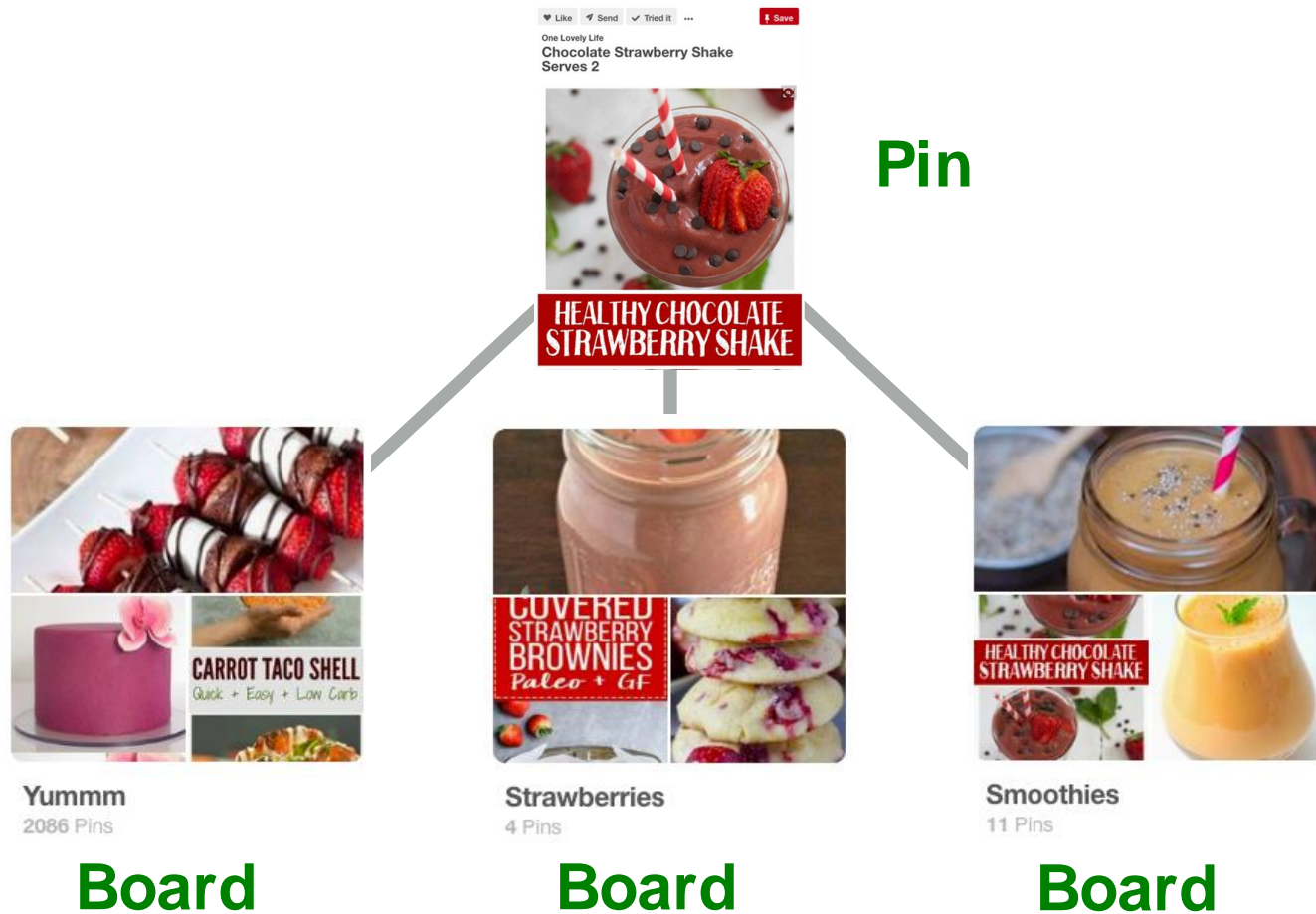


**Healthy Chocolate Chip Cookie Dough Blizzard**

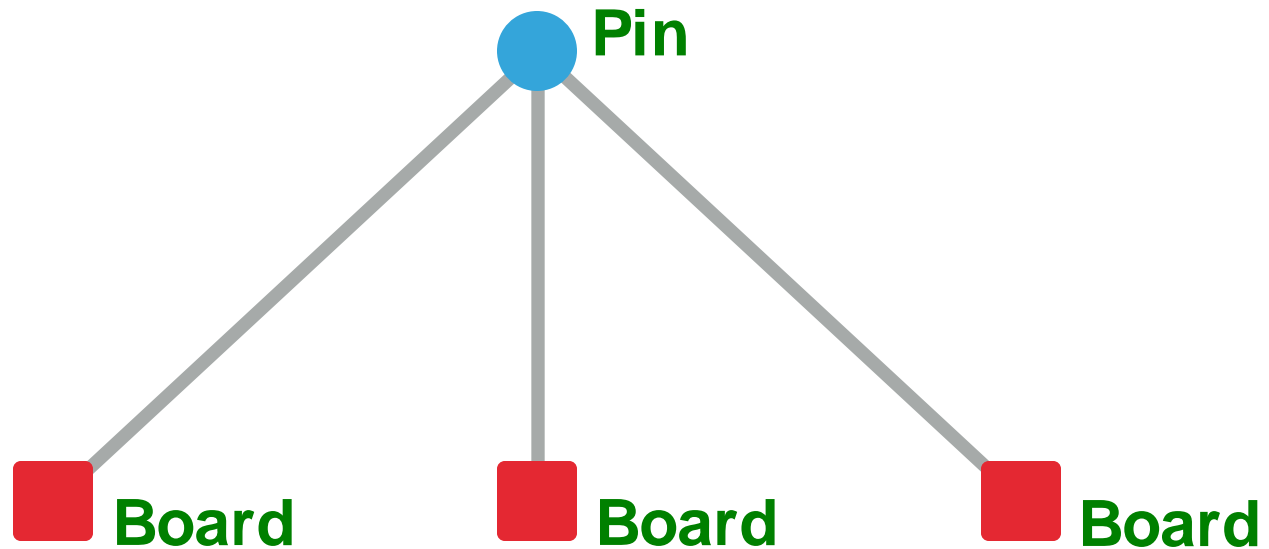


**Healthy Chocolate Chip Cookie Dough Blizzard**

# Pinterest is a Giant Bipartite Graph

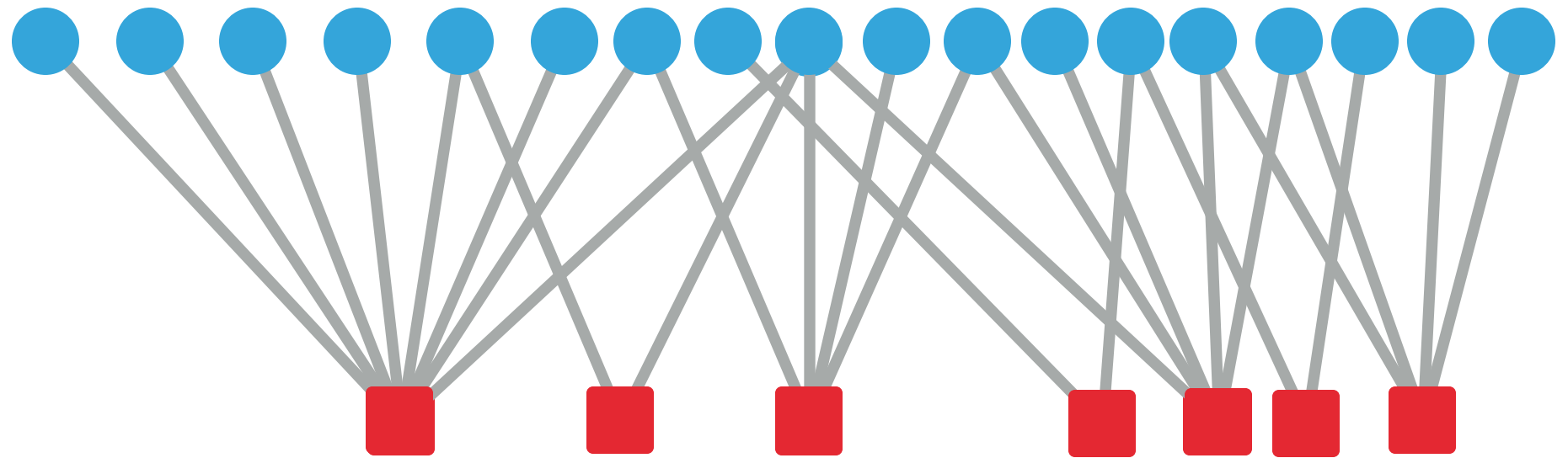


# Bipartite Pin And Board Graph



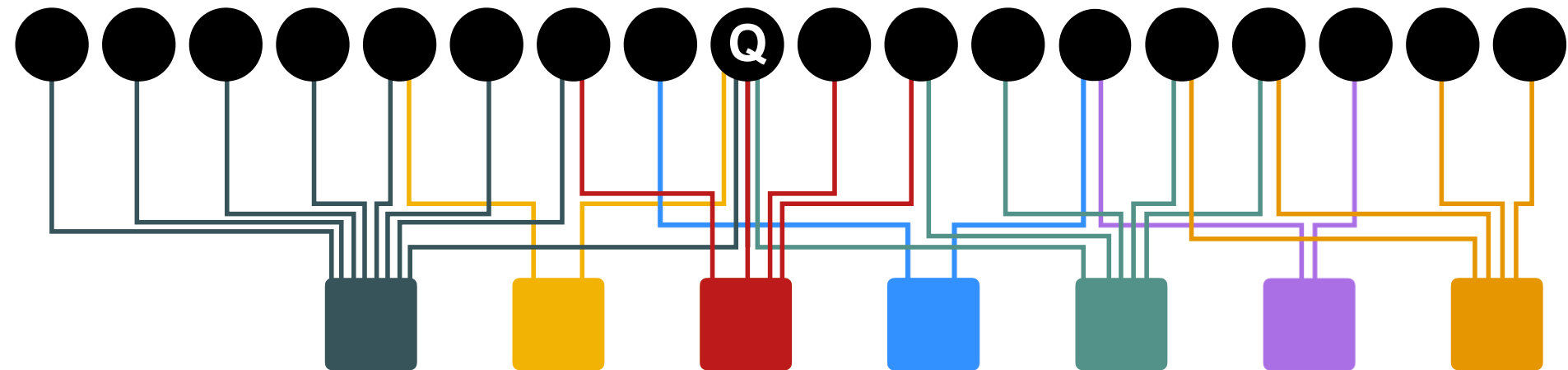


# Bipartite Pin And Board Graph



# 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:**

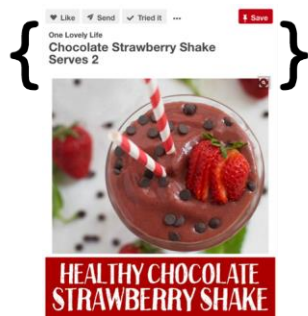


# Pixie Random Walk Algorithm

## ■ Proximity to query node(s) $Q$ :

ALPHA = 0.5

QUERY\_NODES =



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

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

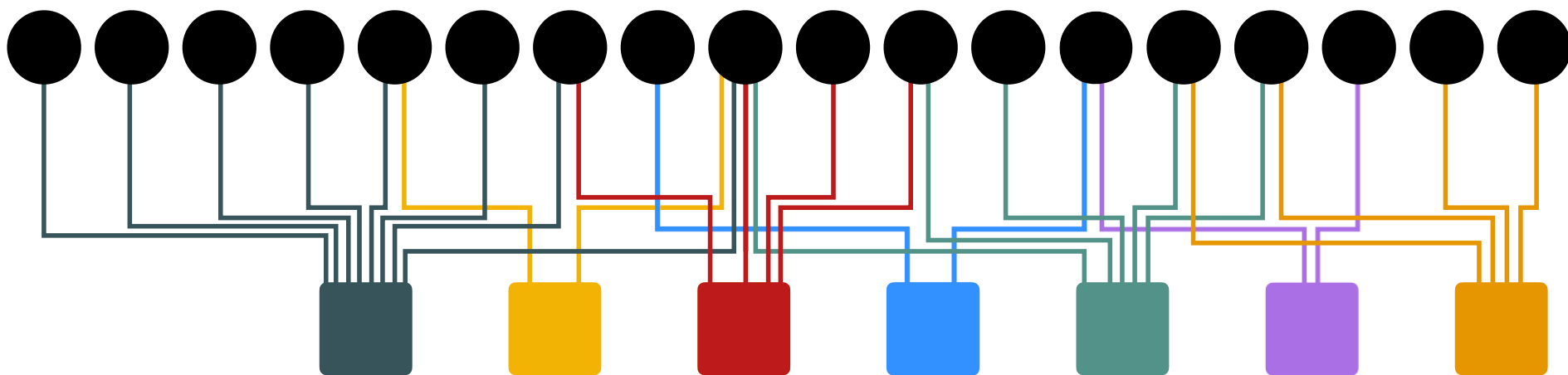
```
    board_node = pin_node.get_random_neighbor()
```

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

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

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

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

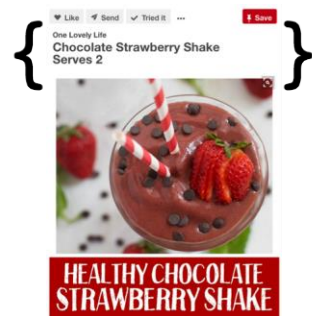


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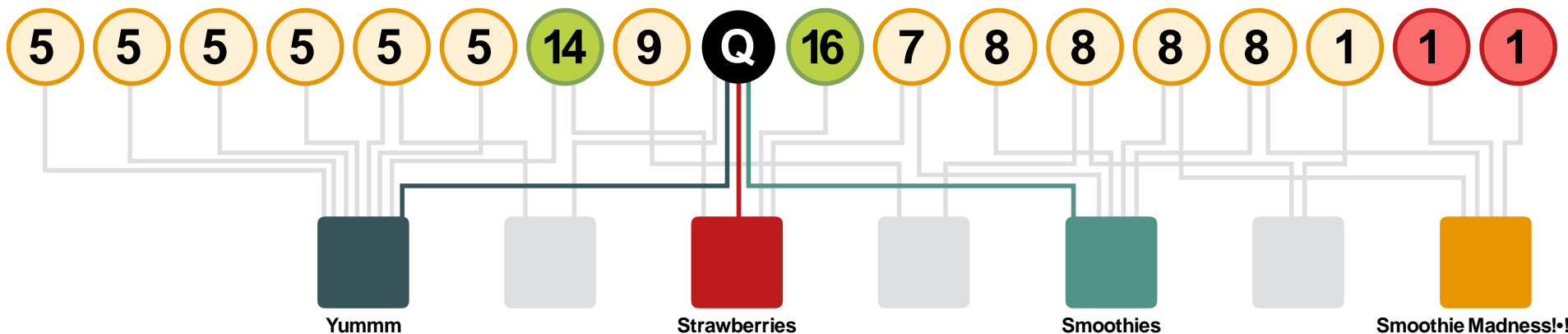
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```
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```

```
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```





# 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

# 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

# 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

Follow

Software Engineer @twitter

Gilad Mishne and 5 others follow



**David Burkett**  
@david\_burkett

Follow

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

David Gleich and 2 others follow



**Nelly Litvak**  
@nellylitvak

Follow

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

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

Follow

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

**Rafa Nadal** ✓  
@RafaelNadal

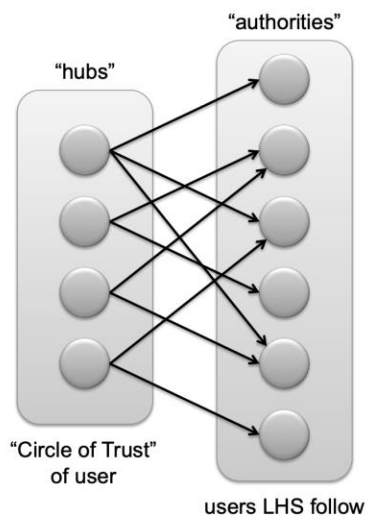
Follow

Tennis player

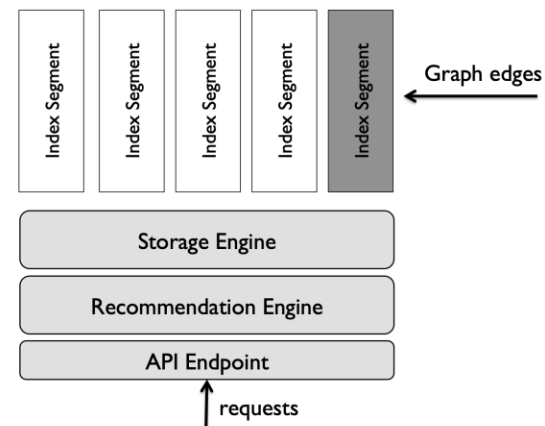
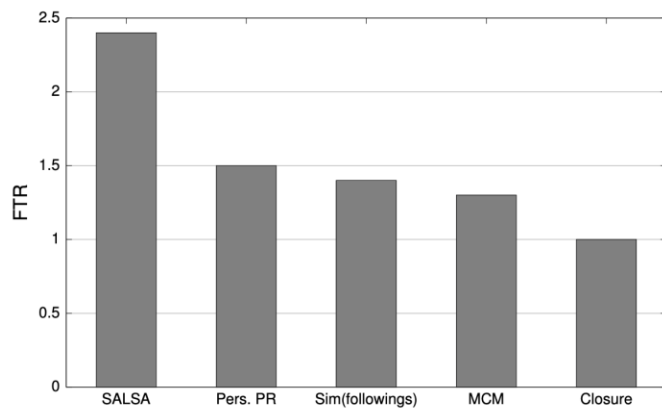
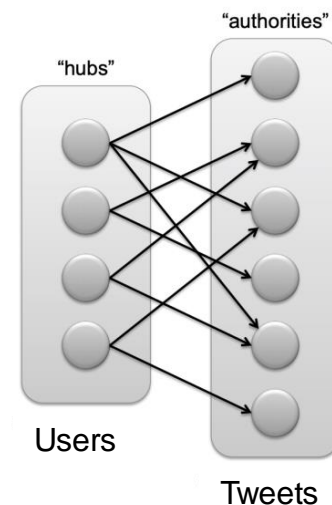


# SALSA for Recommendations

## 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](http://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/](http://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](http://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](http://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



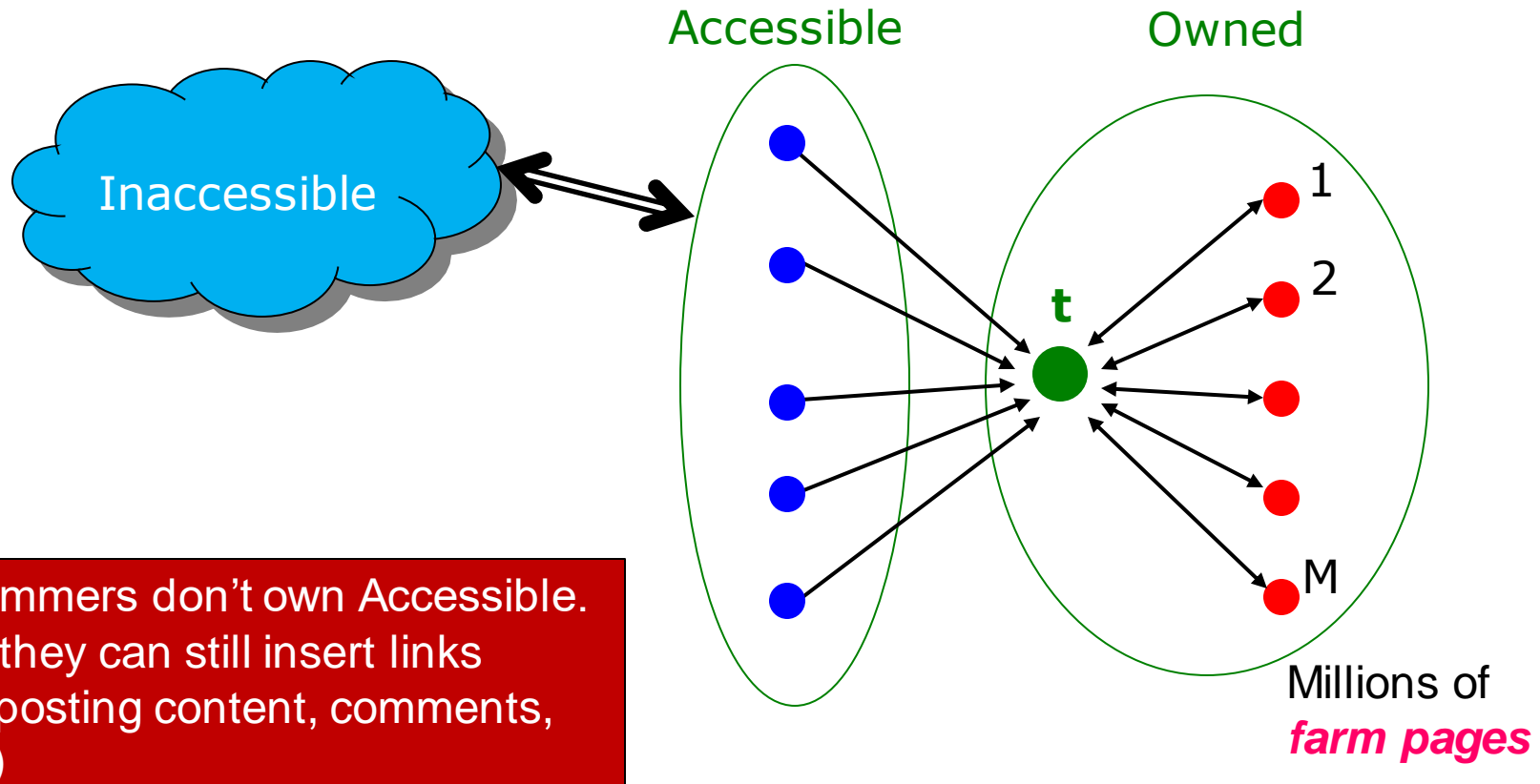
# Link Spamming

- **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

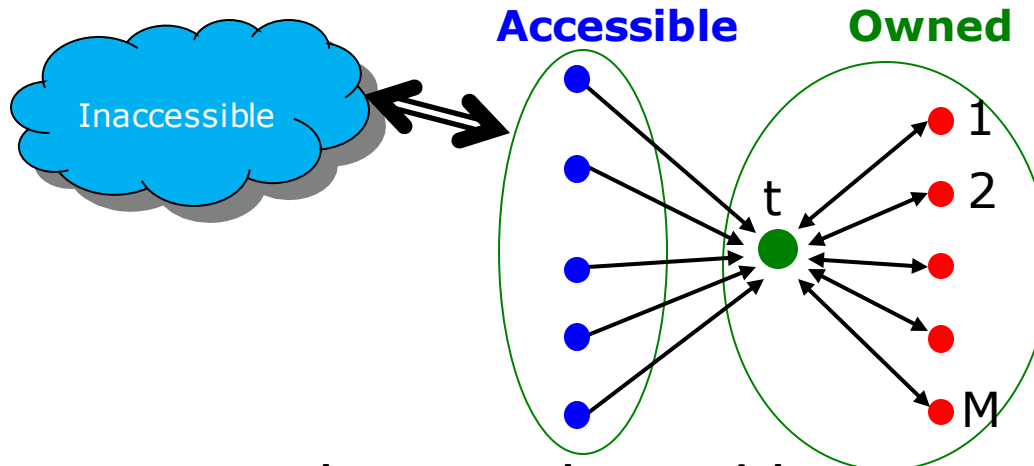
- **Spammer's goal:**
  - Maximize the PageRank of target page  $t$
- **Technique:**
  - Get as many links from accessible pages as possible to target page  $t$
  - Construct “link farm” to get PageRank multiplier effect

# 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

- $x$ : PageRank contributed by accessible pages
- $y$ : PageRank of target page  $t$

- Rank of each “owned” page =  $\frac{\beta y}{M} + \frac{1-\beta}{N}$

- $$y = x + \beta M \left[ \frac{\beta y}{M} + \frac{1-\beta}{N} \right] + \frac{1-\beta}{N}$$

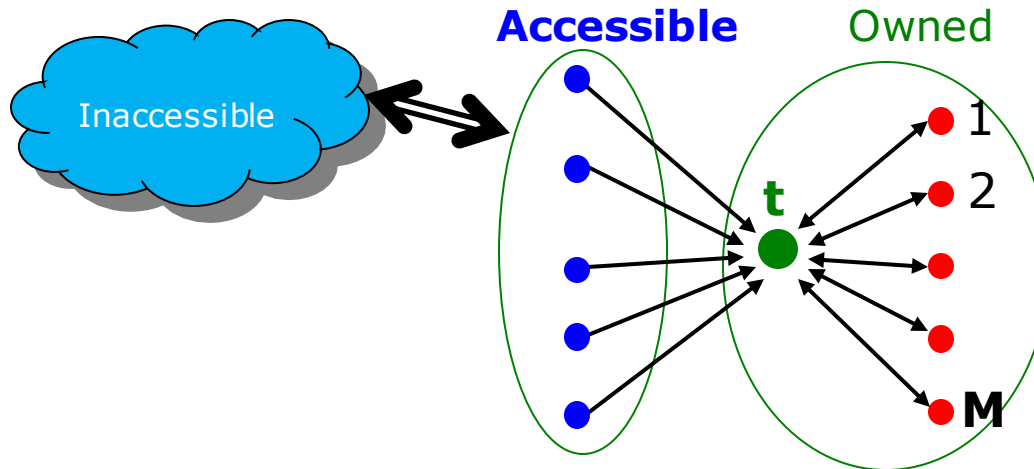
$$= x + \beta^2 y + \frac{\beta(1-\beta)M}{N} + \frac{1-\beta}{N}$$

Very small; ignore  
 Now we solve for  $y$

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



# 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**

# 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

# 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

# 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:**

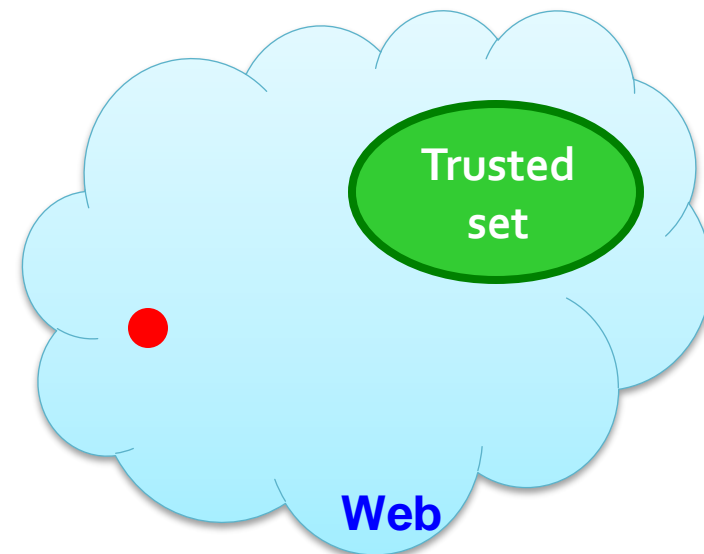
- The larger the number of out-links from a page, the less scrutiny the page author gives each out-link
- Trust is **split** across out-links

# 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



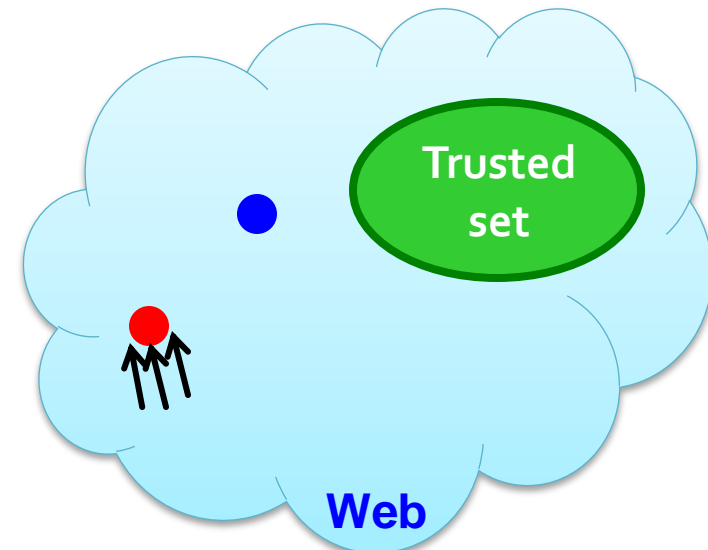
# Spam Mass Estimation

## 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

# 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