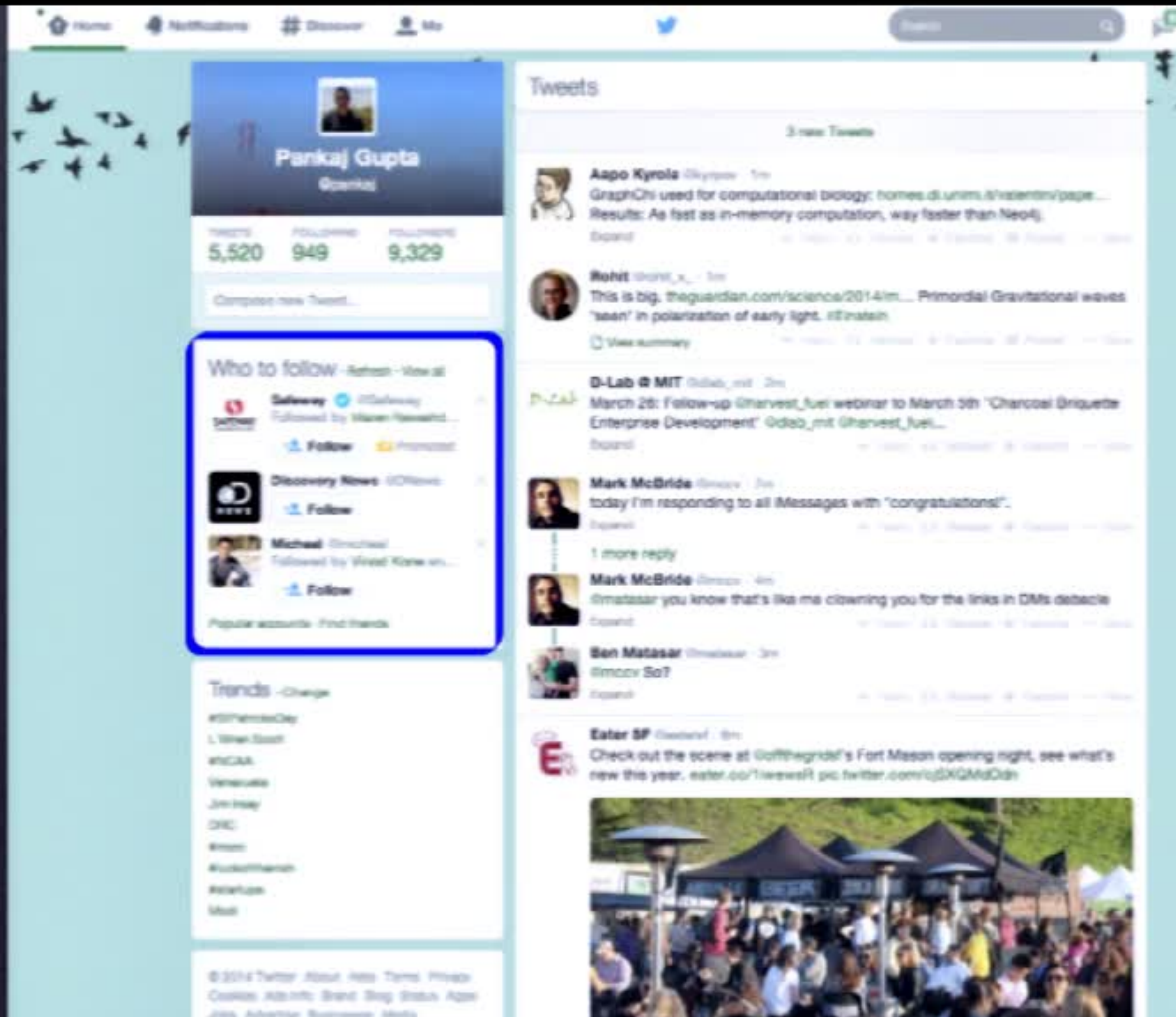
Efficient Algorithms for Personalization in Social Networks

Ashish Goel

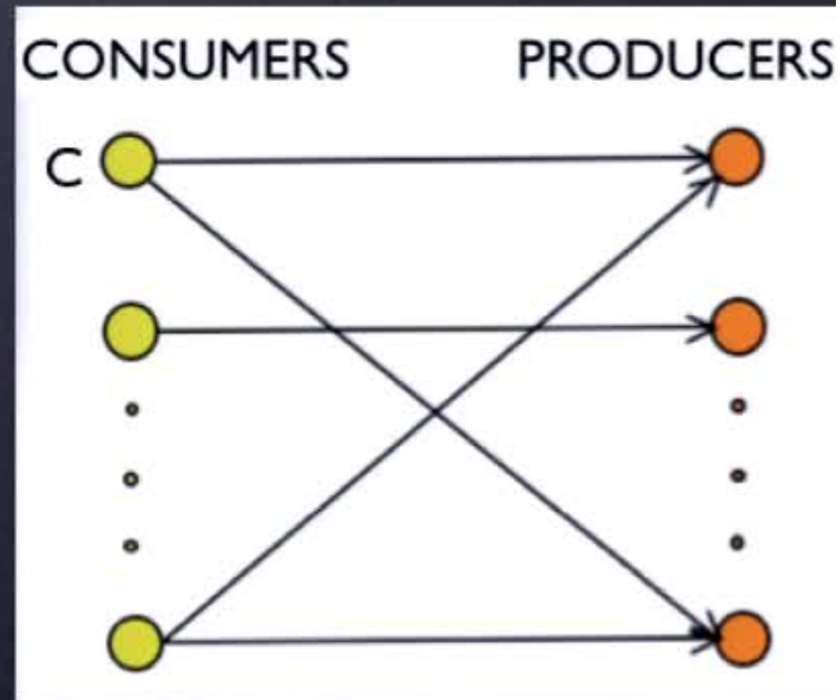

Pankaj Gupta
5,520
949
9,329
Who to follow
Tweets
Aapo Kyrola
GraphChi used for computational biology:
Results: As fast as in-memory computation, way faster than Neo4j.
Rohit
This is big. theguardian.com/science/2014/m... Primordial Gravitational waves "seen" in polarization of early light.
D-Lab @ MIT
March 26: Follow-up @harvest_fuel webinar to March 5th "Charcoal Briquette Enterprise Development" @dlab_mit @harvest_fuel...
Mark McBride
today I'm responding to all iMessages with "congratulations!".
1 more reply
Mark McBride
@matasar you know that's like me clowning you for the links in DMs debacle
Ben Matasar
@mccv So?
Eater SF
Check out the scene at @offthegrid's Fort Mason opening night, see what's new this year.
Safeway
Discovery News
Michael
Follow
Trends

Collaborative Filtering

To get recommendations for C, compute similarity scores for all consumers, and relevance scores for all producers, with respect to C

1. Start with sim(C) = 1

2. Propagate similarity scores along graph edges to compute relevance scores, and vice-versa



Many propagation methods; Often, a linear system of equations

Collaborative Filter: Love or Money

How should we do this propagation? Two extremes:

LOVE: All the similarity score of a consumer X gets transferred to each producer that X follows, and the same in the reverse direction

- Analogous to Singular Value Decompositions in the dense graph limit (HITS)

MONEY: If X follows d producers, then a fraction 1/d of the similarity score of X gets transferred to each producer that X follows (SALSA)

Personalized PageRank

Given a consumer C, perform a random walk on the Follow graph. If the walk is at node v, then the walk:

- Jumps back to node C with probability α
- Follows a random edge out of v with probability $1 - \alpha$

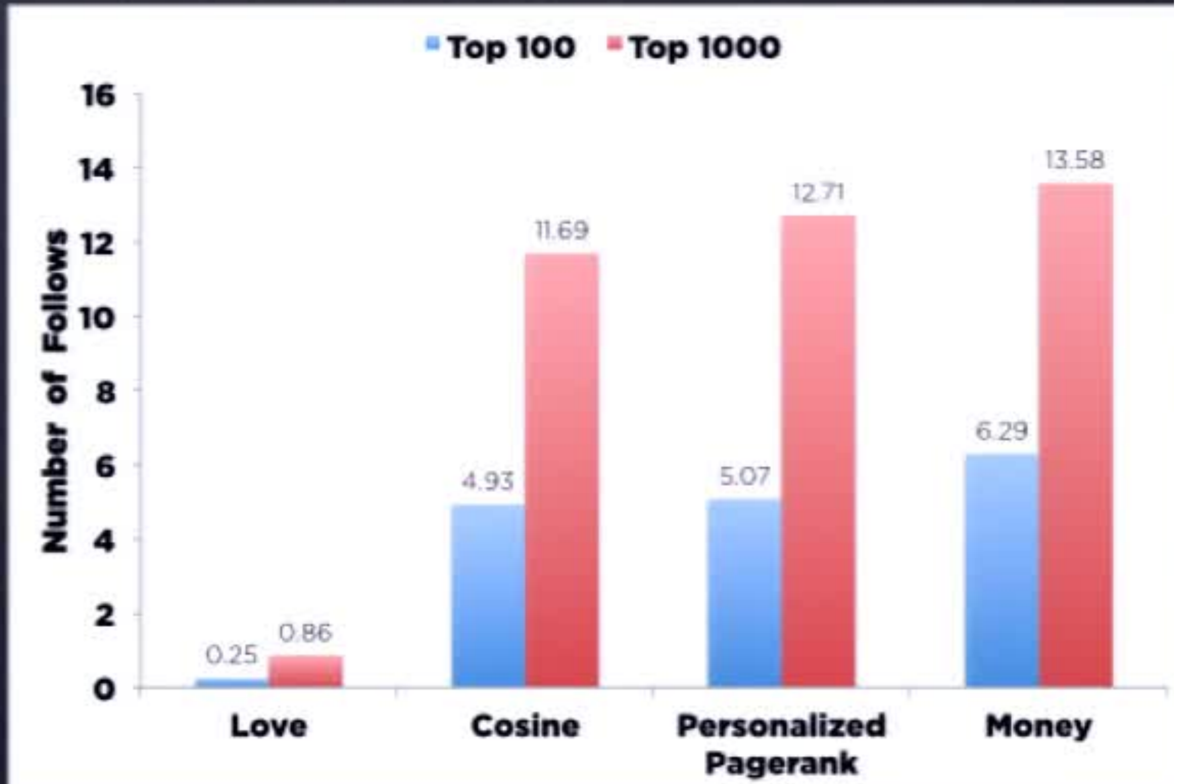
The Personalized PageRank of node Y is the weight of Y in the stationary distribution of this random walk

SALSA/Money is just Personalized PageRank run on the undirected consumer-producer graph

A Dark Test

Run various algorithms to predict follows, but don't display the results. Instead, just observe how many of the top predictions get followed organically

[Bahmani, Chowdhury, Goel; 2010]



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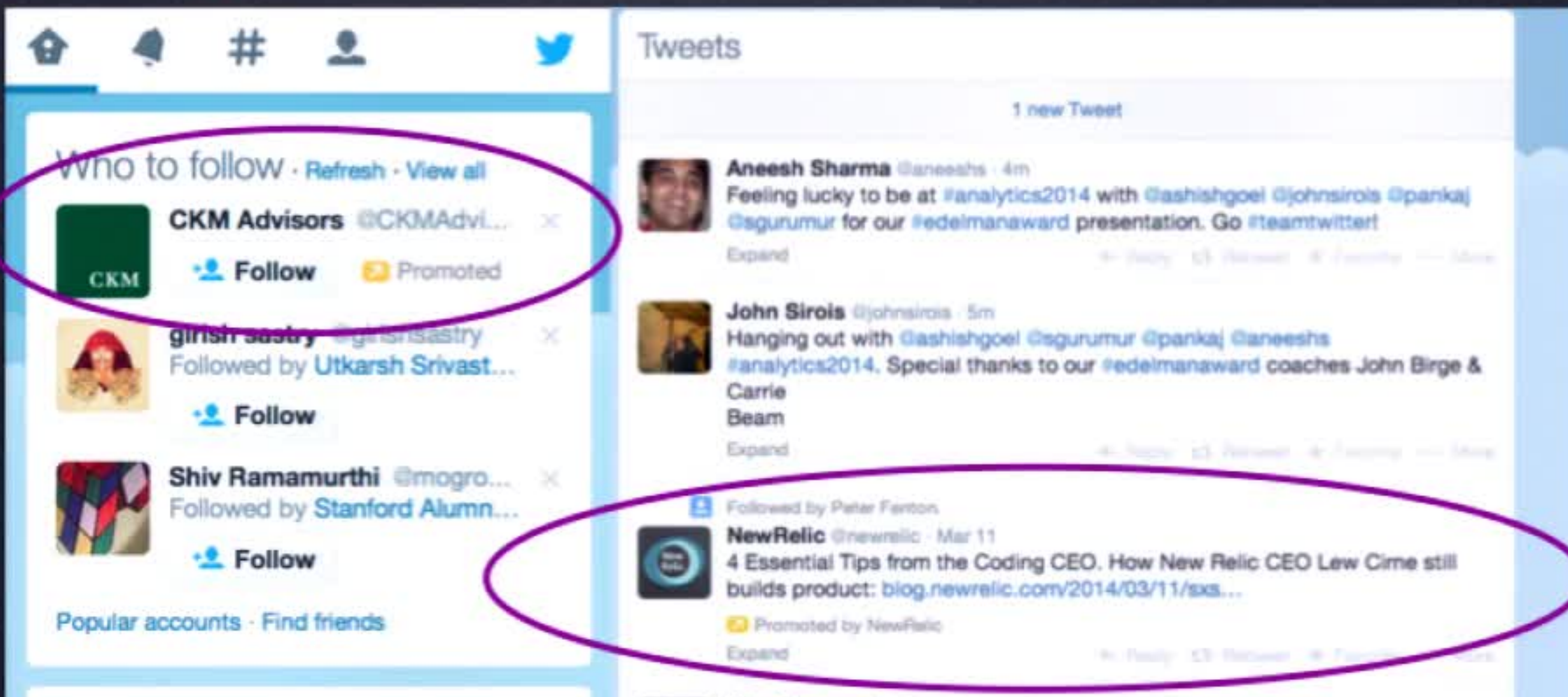
Strategic Impact

Creates billions of new follows every year

- More than 1/8 of new follows are directly via the Who-to-Follow module
- More than 15% of active users (> 36 Million users) make at least one follow every month via this module

Promoted Tweets and Promoted Accounts



Impact on Revenue

"The Who-To-Follow system was crucial, in a fundamental way, for the Promoted Accounts product, and the Promoted Tweets product also initially used the Who-To-Follow system's targeting"

– Alex Roetter (VP of Engineering, Revenue)

Need for Efficient Algorithms

1. Fast Cosine Similarity
2. Fast Incremental PageRank
3. Fast Personalized PageRank
4. Computing via Intersections

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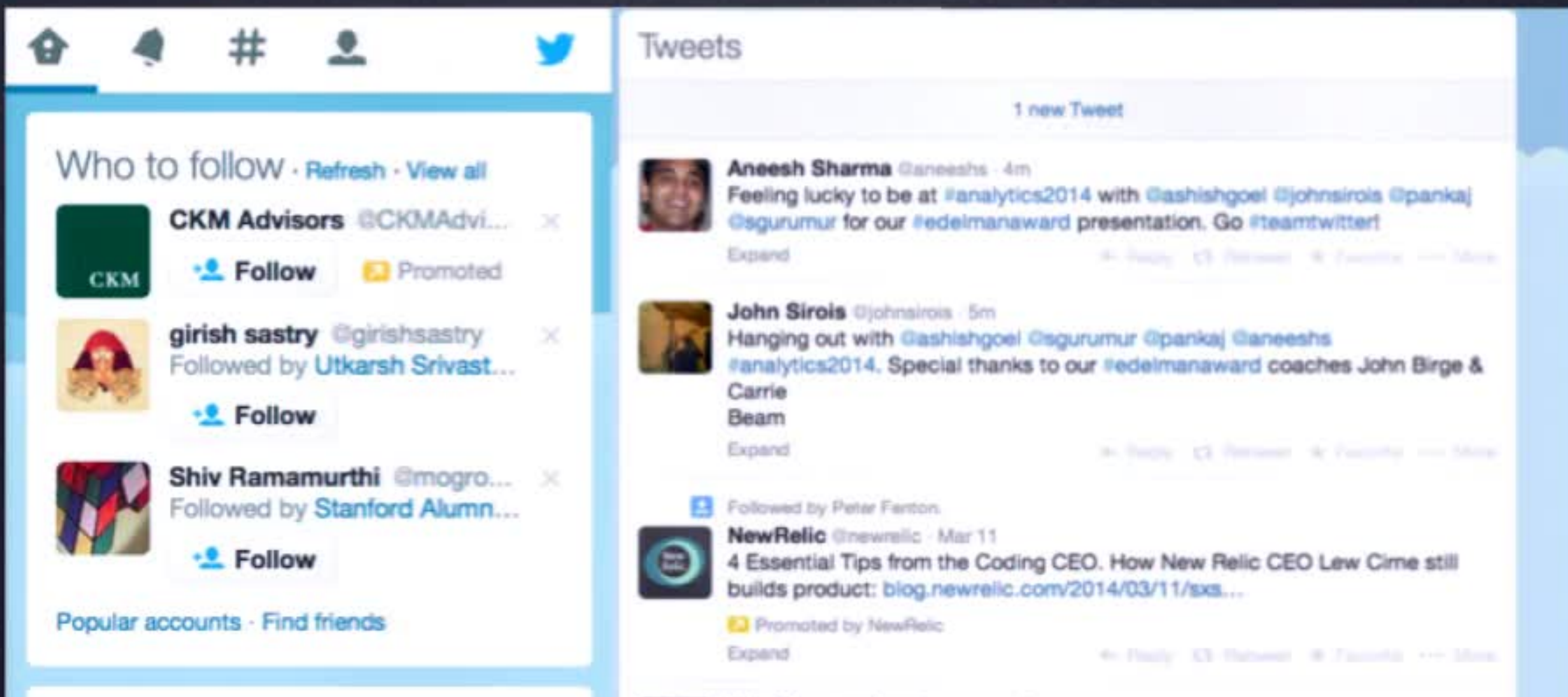

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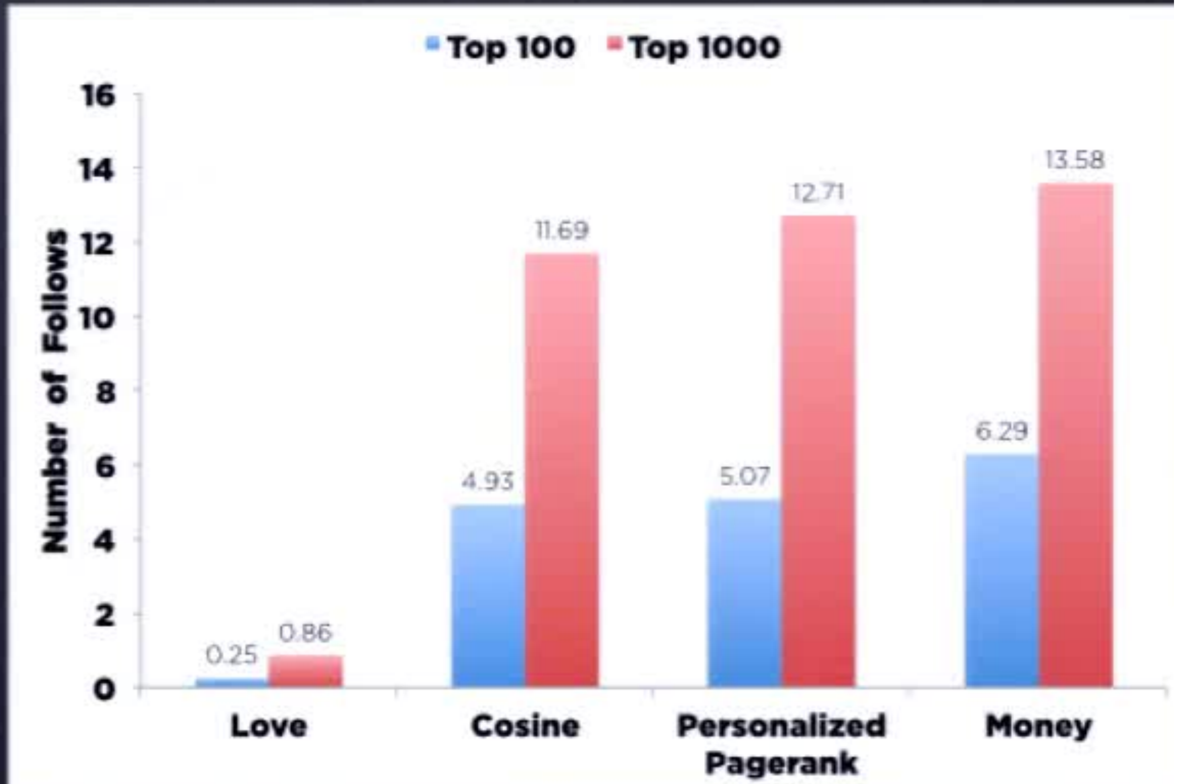

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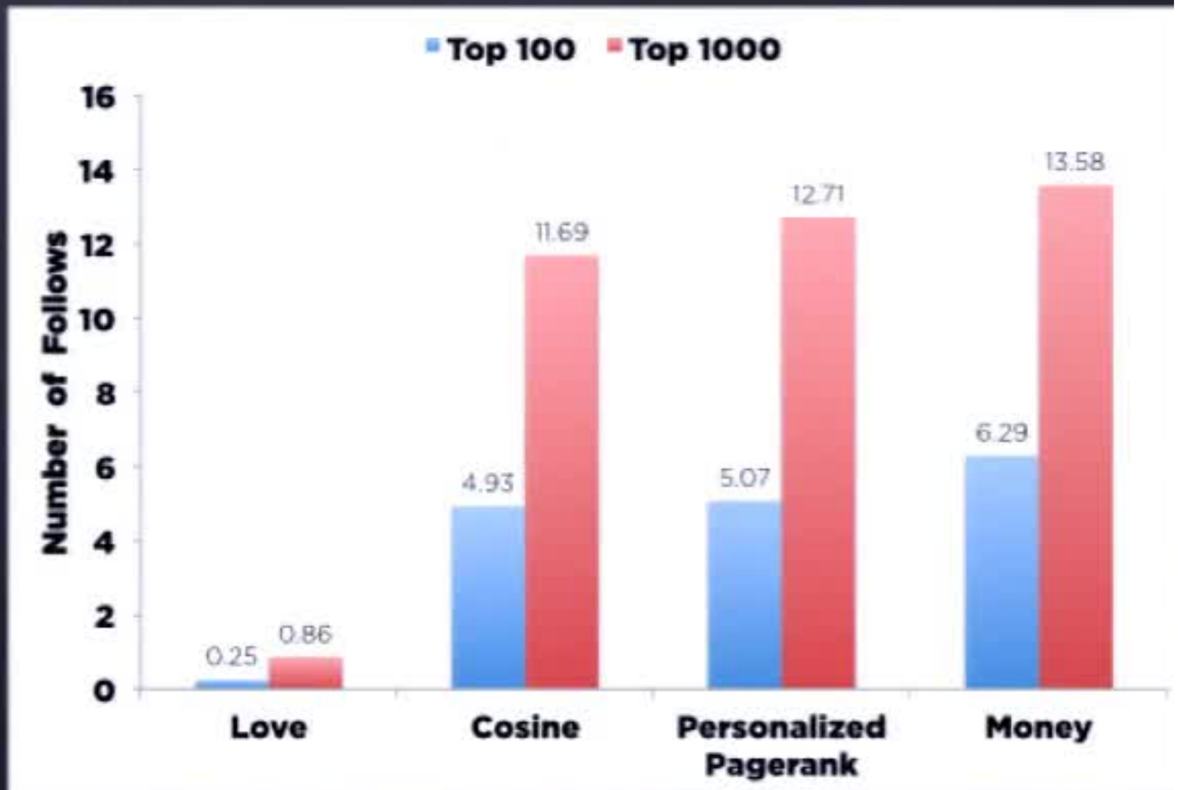

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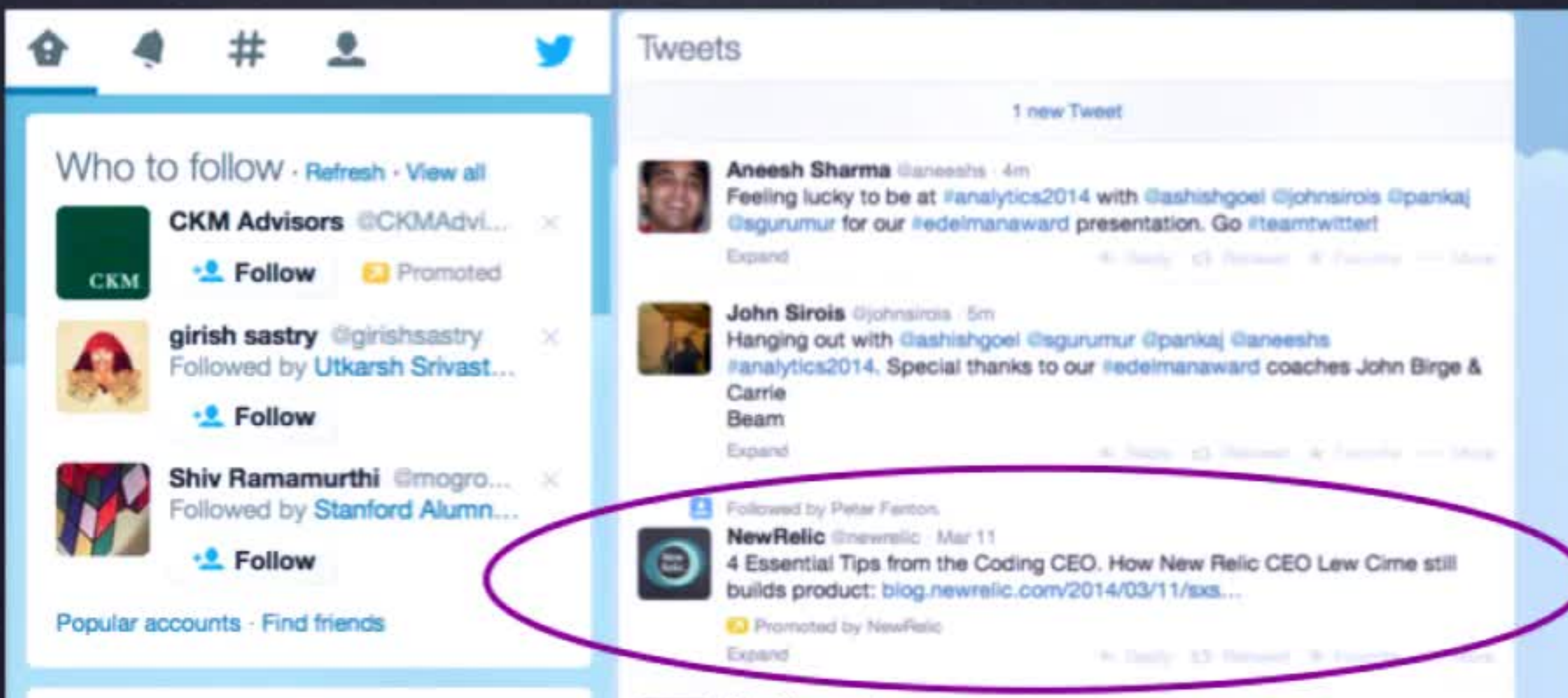

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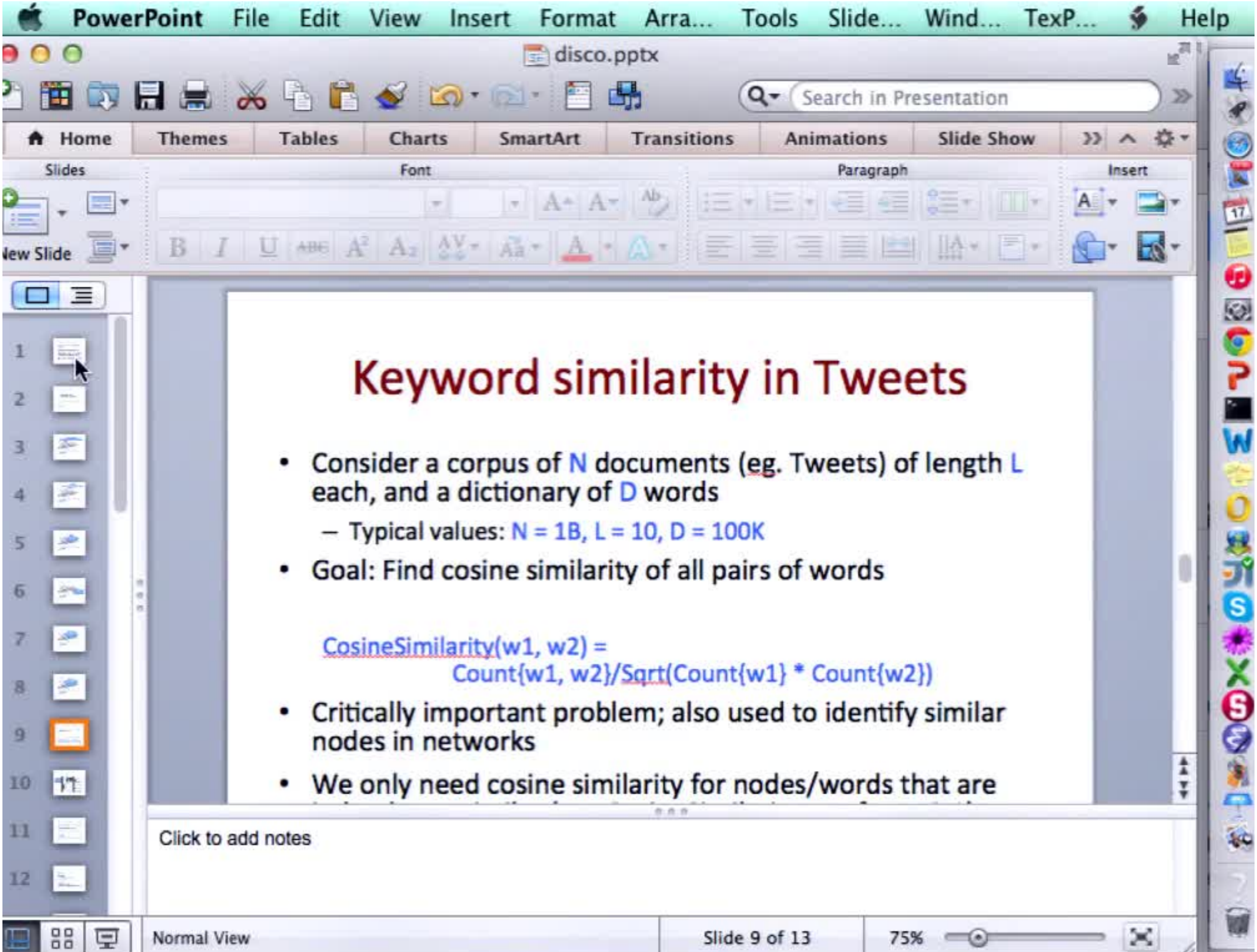
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Goal: Find cosine similarity of all pairs of words
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We only need cosine similarity for nodes/words that are
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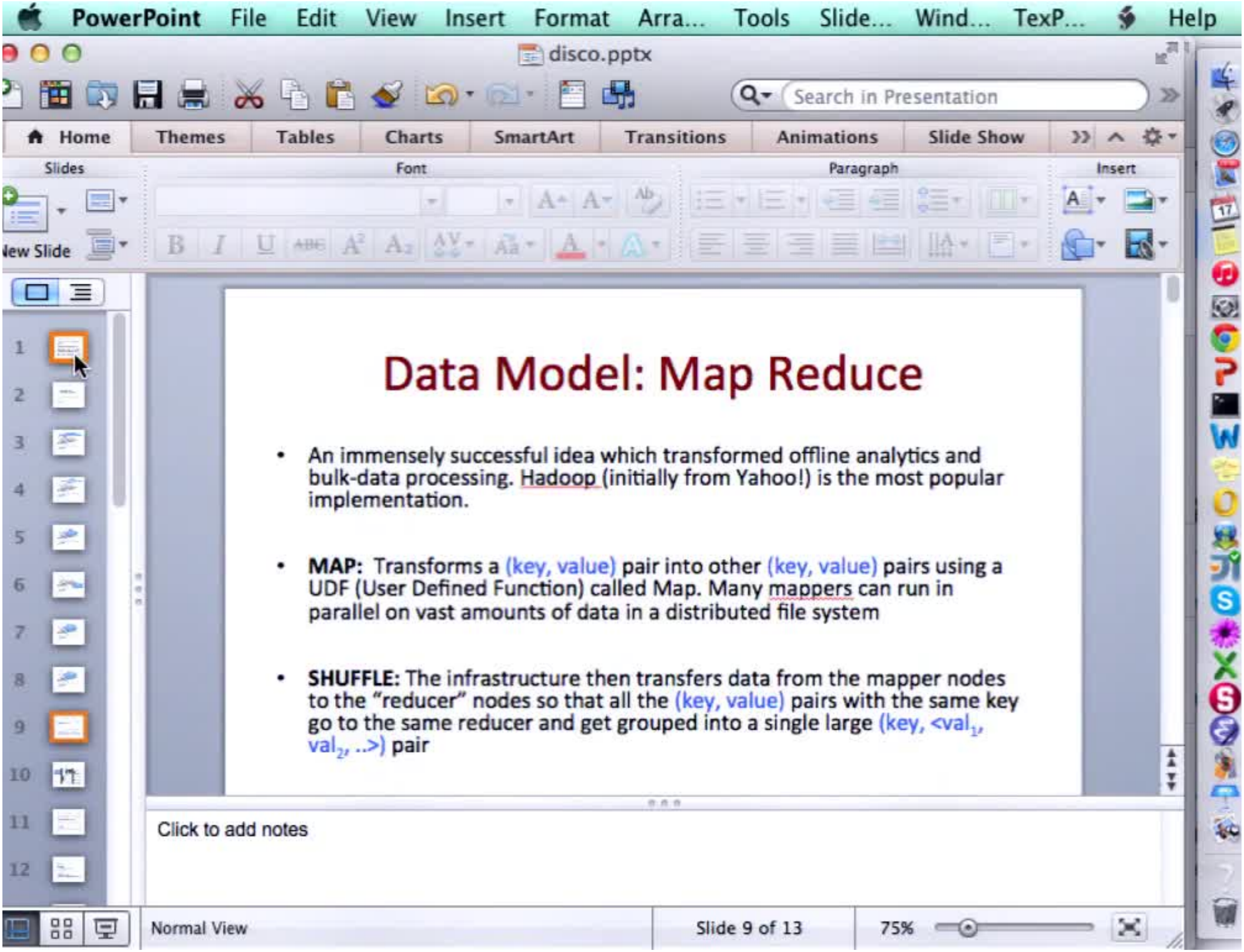
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Data Model: Map Reduce
• An immensely successful idea which transformed offline analytics and bulk-data processing. Hadoop (initially from Yahoo!) is the most popular implementation.
• MAP: Transforms a (key, value) pair into other (key, value) pairs using a UDF (User Defined Function) called Map. Many mappers can run in parallel on vast amounts of data in a distributed file system
• SHUFFLE: The infrastructure then transfers data from the mapper nodes to the "reducer" nodes so that all the (key, value) pairs with the same key go to the same reducer and get grouped into a single large (key, <val$_1$, val$_2$, ..>) pair
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- **REDUCE:** A UDF that processes this grouped (key, $\langle val_1, val_2, .. \rangle$) pair for a single key. Many reducers can run in parallel.

Complexity Measures

- Key-Complexity:
  - The maximum size of a key-value pair
  - The amount of time taken to process each key
  - The memory required to process each key
- Sequential Complexity:
  - The total time needed by all the mappers and reducers together
  - The total output produced by all the mappers and reducers together
- Number of MapReduce phases

[Goel, Munagala; 2012]

THE AMOUNT OF WORK DONE PER COMPUTER IF WE HAD INFINITELY MANY COMPUTERS

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[Goel, Munagala; 2012]

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OFTEN, IMPORTANT ONLY FOR REDUCERS

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THE AMOUNT OF WORK DONE ON A SINGLE COMPUTER

[Goel, Munagala; 2012]

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SHUFFLE SIZE

[Goel, Munagala; 2012]

Complexity Measures

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THE AMOUNT OF WORK DONE TO AGGREGATE ALL THE VALUES FOR A SINGLE KEY (SORTING) IS NOT A COMPLEXITY MEASURE

[Goel, Munagala; 2012]

Keyword similarity in Tweets

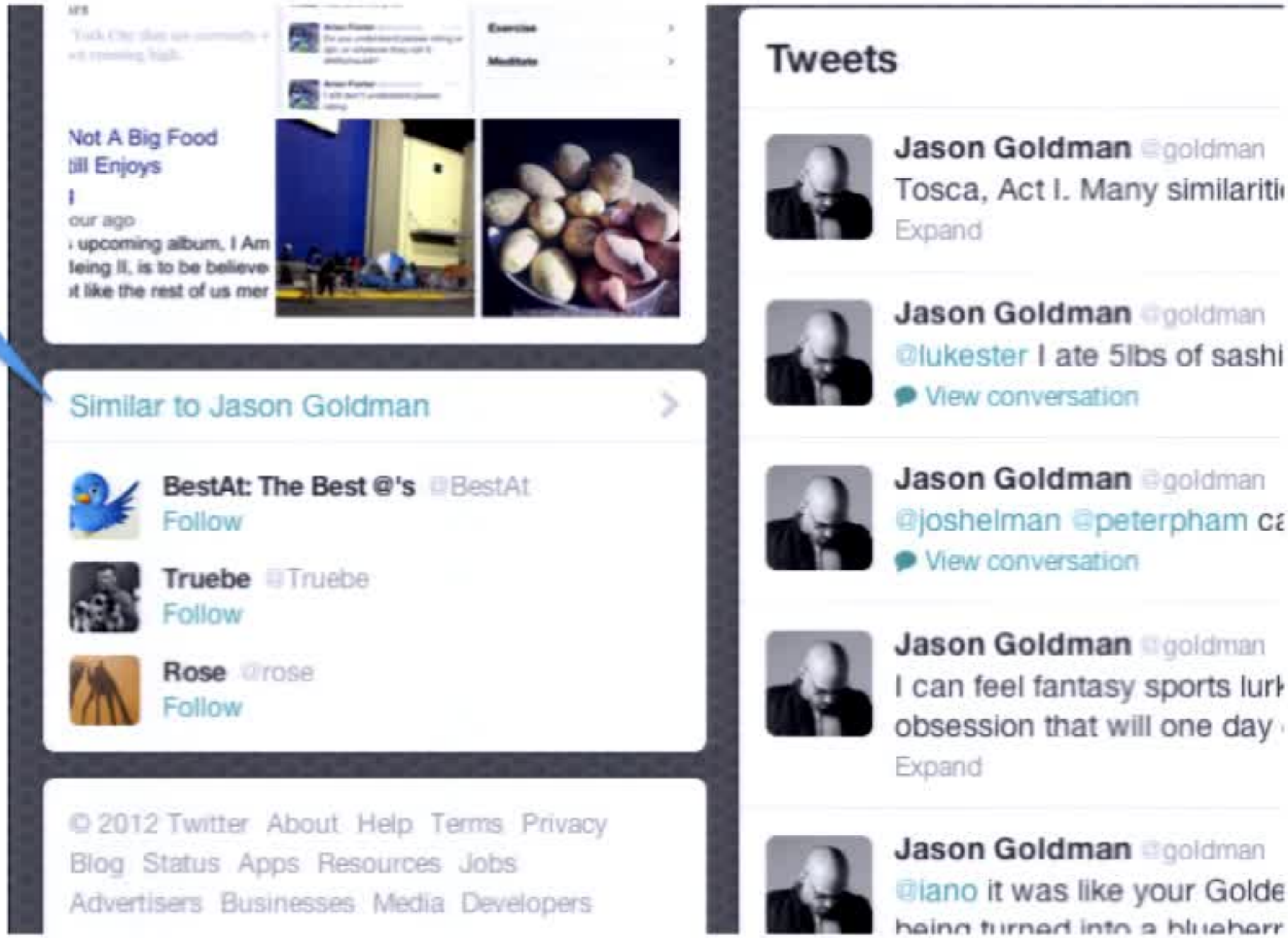
- Consider a corpus of N documents (eg. Tweets) of length L each, and a dictionary of D words
  - Typical values: N = 1B, L = 10, D = 100K
- Goal: Find cosine similarity of all pairs of words

CosineSimilarity(w1, w2) =
Count{w1, w2}/Sqrt(Count{w1} * Count{w2})

- Critically important problem; also used to identify similar nodes in networks
- We only need cosine similarity for nodes/words that are indeed very similar (say CosineSimilarity > ε, for ε=0.1)

Example Application

USER-USER SIMILARITY



Cosine Similarity [Brute Force]

- Assumption: The tweet corpus is annotated with word counts, so every occurrence of every word is tagged with the frequency of that word as well
  - Need this for other reasons anyway (eg. trends, search)
- Count all co-occurrences between all words
  - MAP(tweet): for every pair of words w1, w2 in the tweet, EMIT({w1, w2}, 1)
  - REDUCE({w1, w2}, <1, 1, ...>): If the size of the value vector(i.e. number of 1's) is larger than ε Sqrt(Count{w1} * Count{w2}) then EMIT({w1, w2})
- Sequential complexity: Requires shuffling N*L*L data across in Hadoop, ≈ 100 Billion records
- Reduce-key complexity: Could be as large as N, or with combining, K (the number of mappers)
- Observation: most of the data shuffled by brute force algorithm was being wasted

Cosine Similarity [Random Sampling]

CosineSimilarity(w1, w2) =
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- MAP(tweet): for every pair of words w1, w2 in the tweet, EMIT({w1, w2}, 1) with probability

R/(Sqrt(Count{w1} * Count{w2}),

where $R = (\log D)/\varepsilon \approx 100$

- REDUCE({w1, w2}, <1, 1, ...>): EMIT({w1, w2}, (size of value-vector)/R)
- Unbiased estimate of CosineSimilarity, and accurate whp when CosineSimilarity > ε
- Expected Reduce-Key complexity: At most R
- Sequential complexity: Shuffle size goes down from NL^2 to around DRL . ($\approx$ 100B → $\approx$ 100M)

Cosine Similarity [contd]

- In production at Twitter
- Described in recent twitter engineering blog post

Bogah-Zadeh and Goel: Dimension Independent Similarity Computation

MONDAY, NOVEMBER 12, 2012

Dimension Independent Similarity Computation (DISCO)

MapReduce is a programming model for processing large data sets, typically used to do distributed computing on clusters of commodity computers. With large amount of processing power at hand, it's very tempting to solve problems by brute force. However, we often combine clever sampling techniques with the power of MapReduce to extend its utility.

Consider the problem of finding all pairs of similarities between D indicator (0/1 entries) vectors, each of dimension N. In particular we focus on cosine similarities between all pairs of D vectors in R^N. Further assume that each dimension is L-sparse, meaning each dimension has at most L non-zeros across all points. For example, typical values to compute similarities between all pairs of a subset of Twitter users can be:

D = 10M
N = 1B
L = 1000

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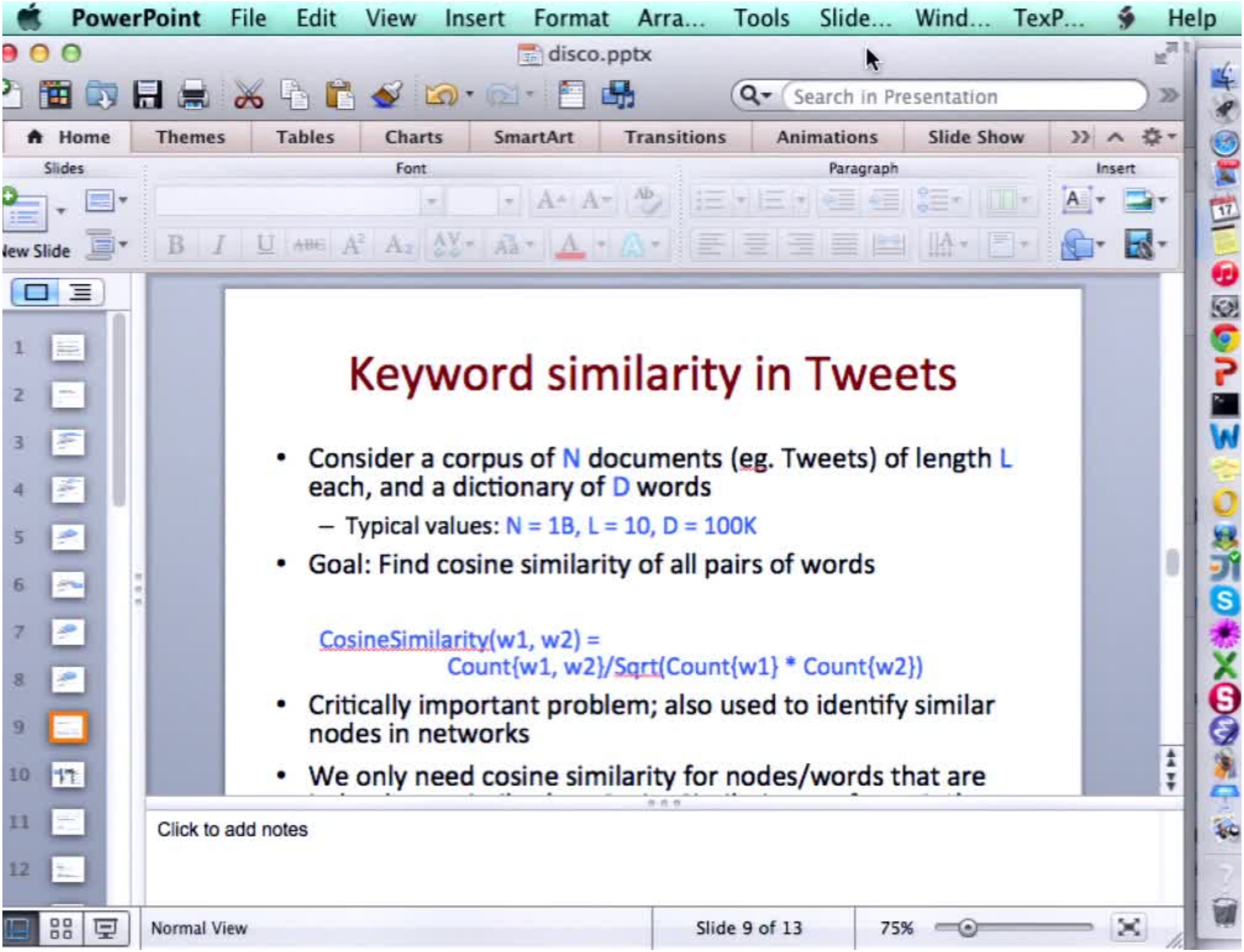
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Incremental PageRank

Updates to social graph are made in real-time

- As opposed to a batched crawl process for web search
- Real-time updates to PageRank are important to capture trending events

Goal: Design an algorithm to update PageRank incrementally (i.e. upon an edge arrival)

- t-th edge arrival: Let (u_t, v_t) denote the arriving edge, $d_t(v)$ denote the out-degree of node v, and $\pi_t(v)$ its PageRank

Incremental PageRank via Monte Carlo

Start with $R = O(\log N)$ random walks from every node

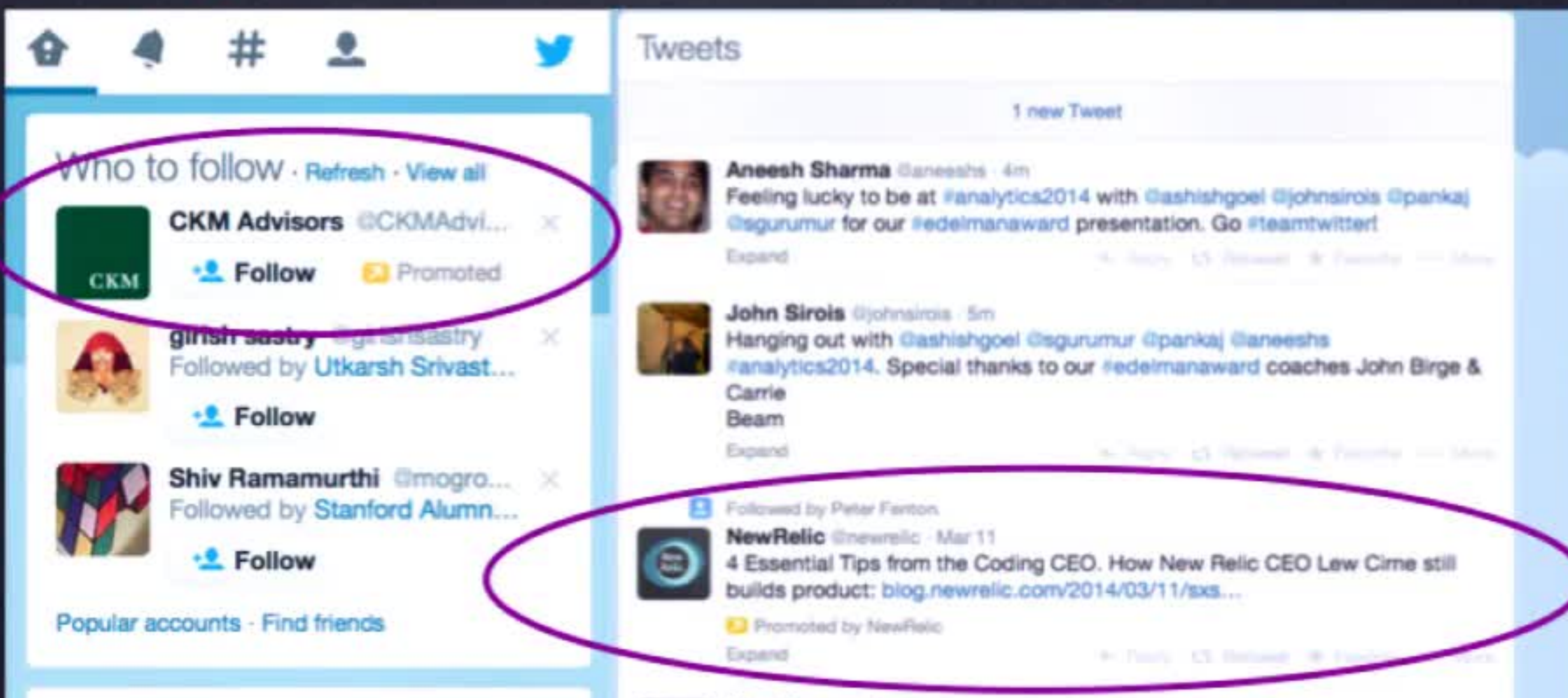
At time t, for every random walk through node u_t, re-route it to use the new edge (u_t, v_t) with probability $1/d_t(u_t)$

- Time/number of network-calls for each re-routing: $O(1/\alpha)$

Claim: This faithfully maintains R random walks after arbitrary edge arrivals

Need the graph and the stored random walks in fast distributed memory

Promoted Tweets and Promoted Accounts



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Incremental PageRank Time

Assume that the edges of the graph are chosen by an adversary, but then presented in random order

Theorem: # of r per arrival goes to 0

Power iteration takes time $M\ R/\alpha$

- t-th arrival: # of N R/(α t))
- Total time over M arrivals = $O((N\ R \log N)/\alpha^2)$
- Comparable to doing power iteration/Monte Carlo just once!

$N \log N/\alpha$ vs M

[Bahmani, Goel, Chowdhury, VLDB 2010]

Personalized PageRank

Network-based Personalized Search is not yet mature

Missing technical piece: Efficient algorithms for Personalized PageRank Queries

- Given source s and target t, estimate the Personalized PageRank of t for s with high accuracy, if it is greater than δ

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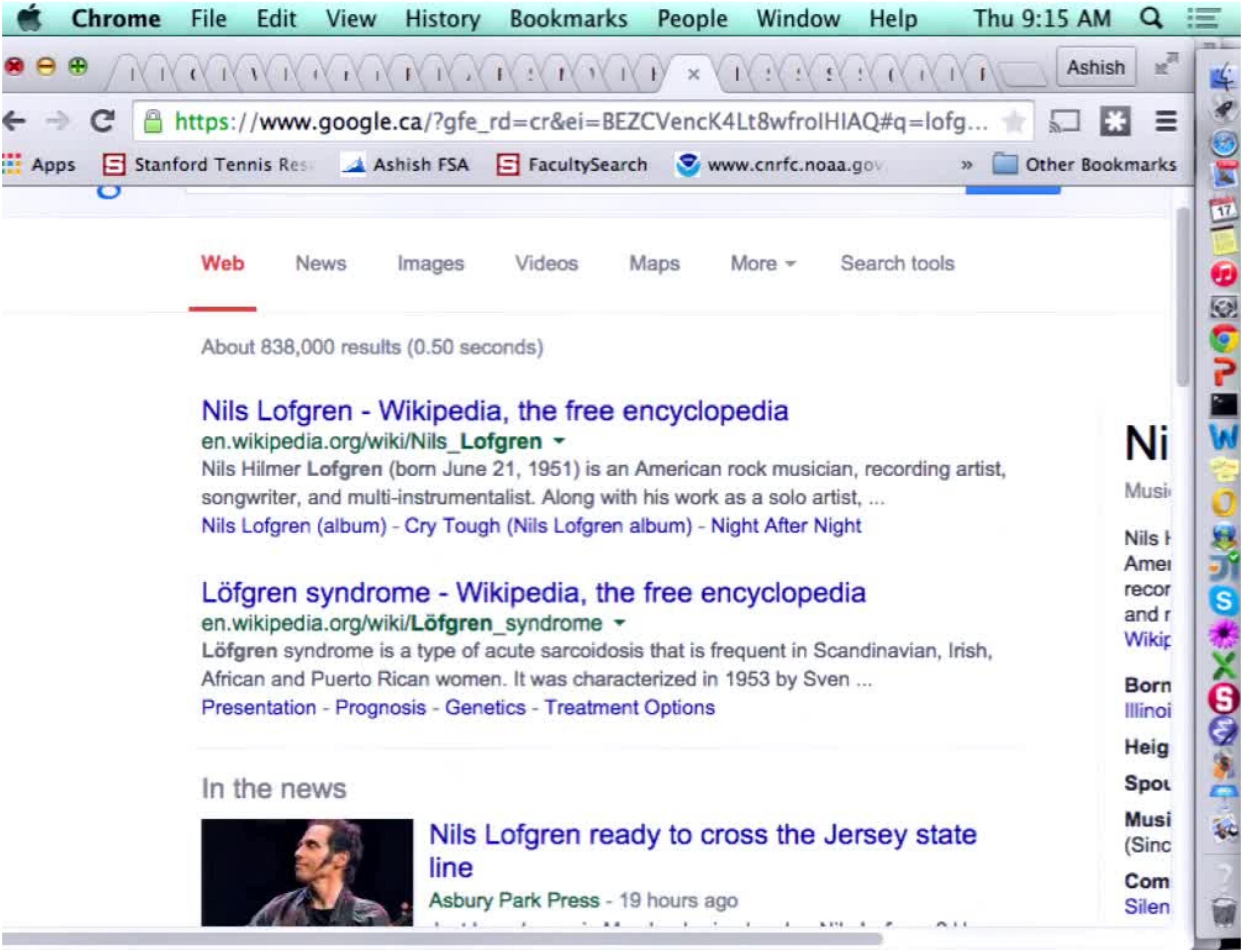

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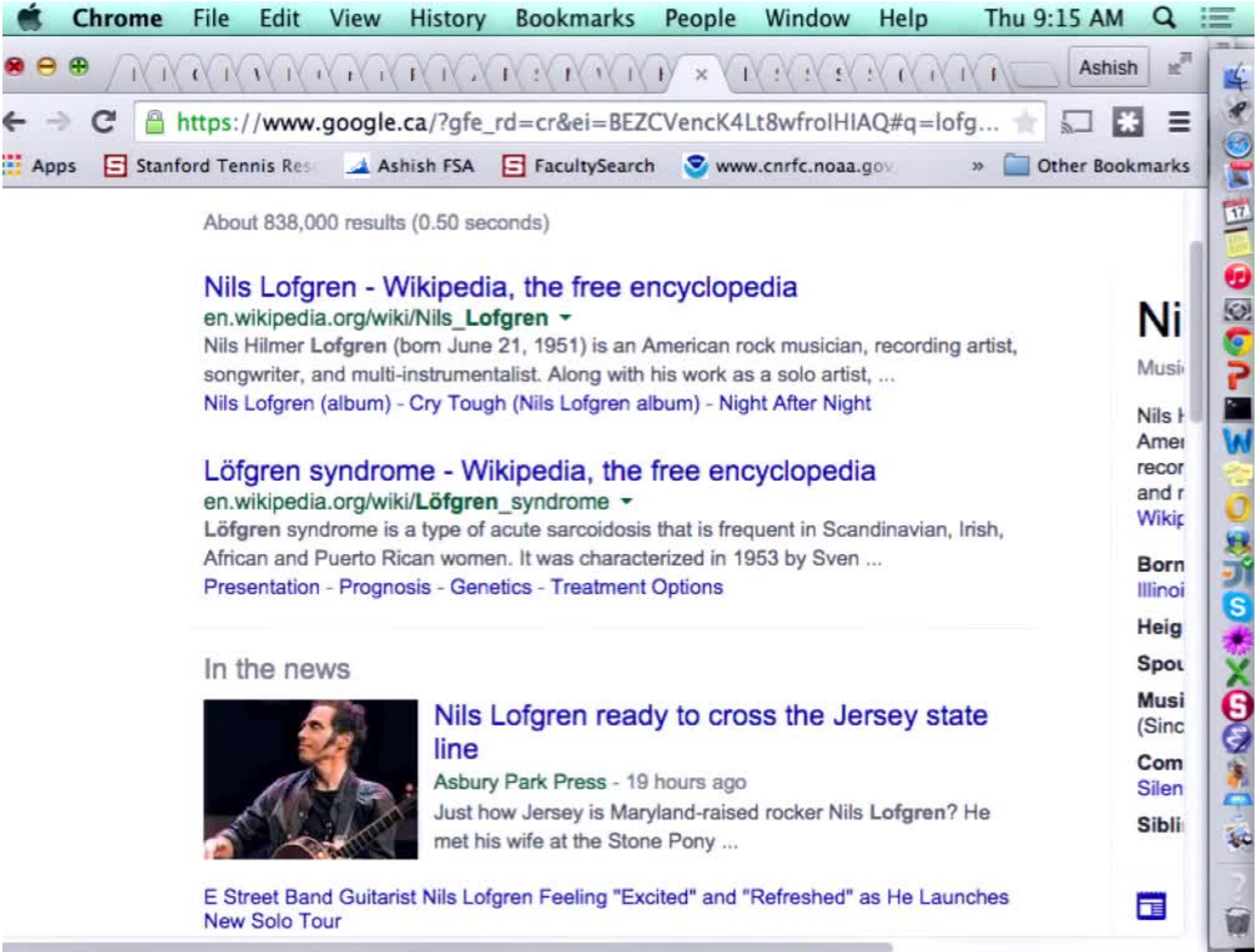

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WFJA Classic Hits and Oldies 105.5 FM - 4 hours ago

More news for lofgren

Nils Lofgren, Musician, Songwriter

www.nils**lofgren**.com/

Nils **Lofgren** is a virtuoso rock guitarist who has recorded and performed with Bruce Springsteen as a member of the E Street Band, Ringo Starr and Neil Young.

U.S. Congresswoman Zoe Lofgren

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https://**lofgren**.house.gov/

Zoe **Lofgren** (D-Calif.), the top Democrat on the House Judiciary Subcommittee on Immigration and Border Security, lamented today's Judiciary subcommittee ...

Löfgren's Syndrome | Doctor | Patient.co.uk

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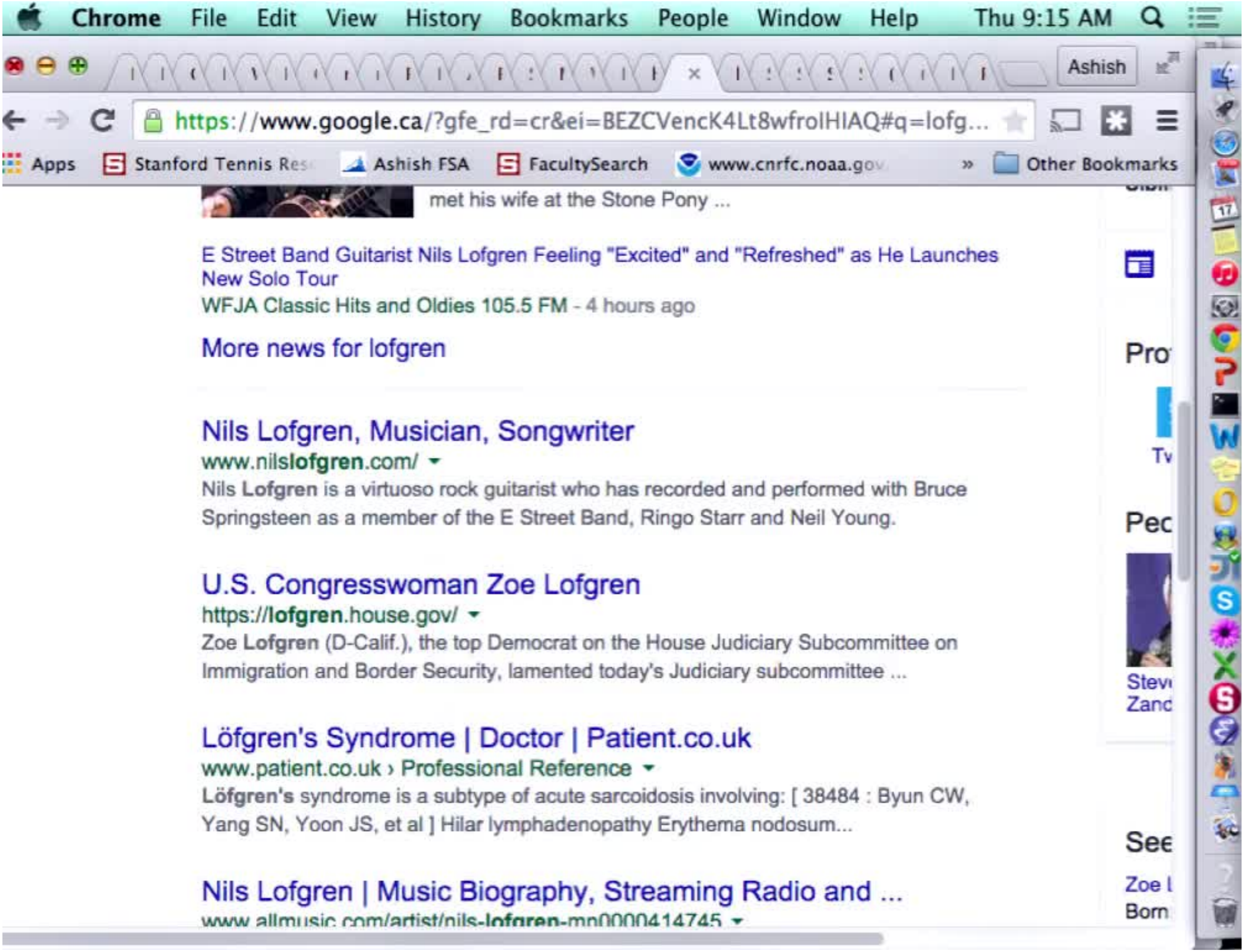
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www.nilslofgren.com/
Nils Lofgren is a virtuoso rock guitarist who has recorded and performed with Bruce Springsteen as a member of the E Street Band, Ringo Starr and Neil Young.
U.S. Congresswoman Zoe Lofgren
https://lofgren.house.gov/
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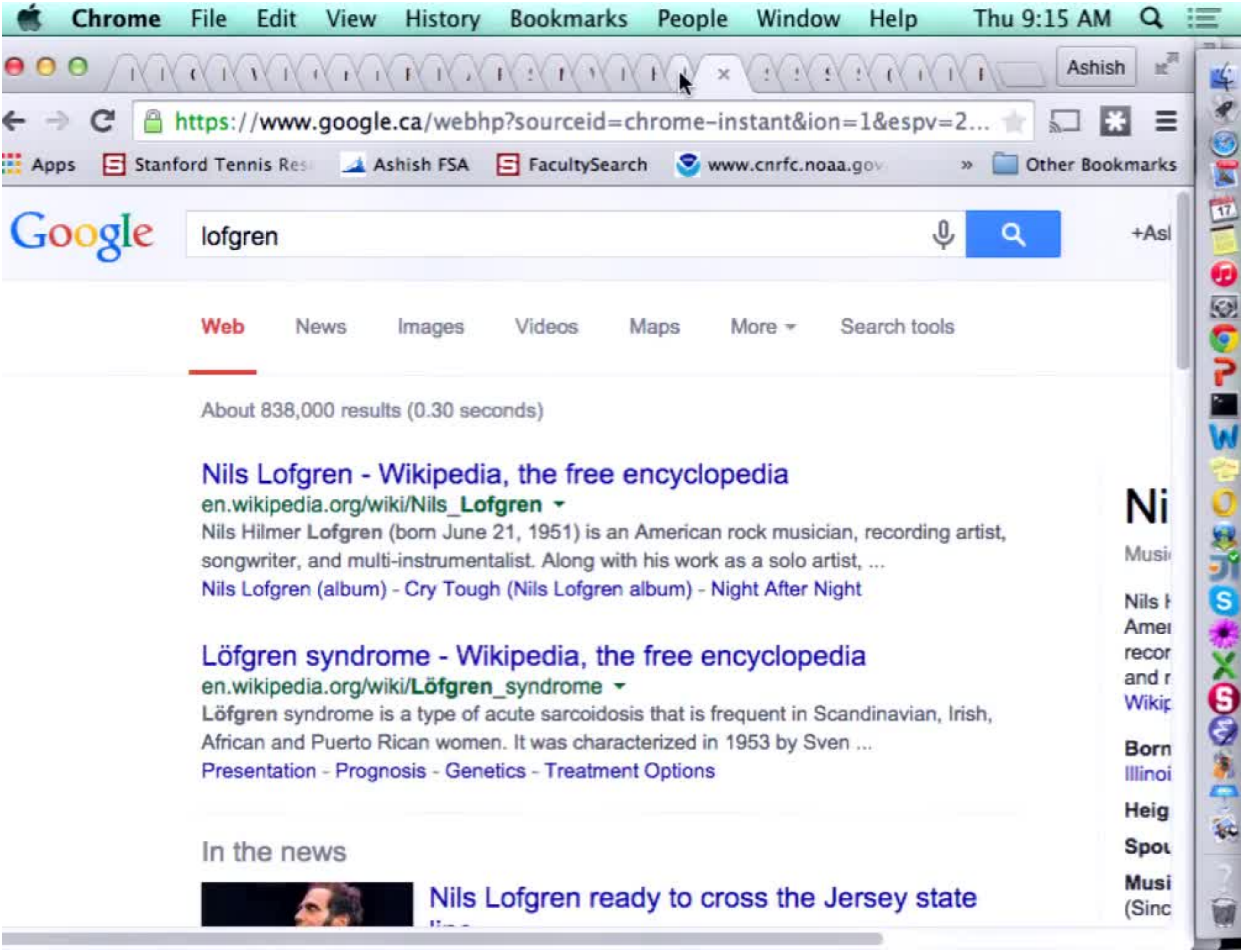
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Nils Lofgren (album) - Cry Tough (Nils Lofgren album) - Night After Night
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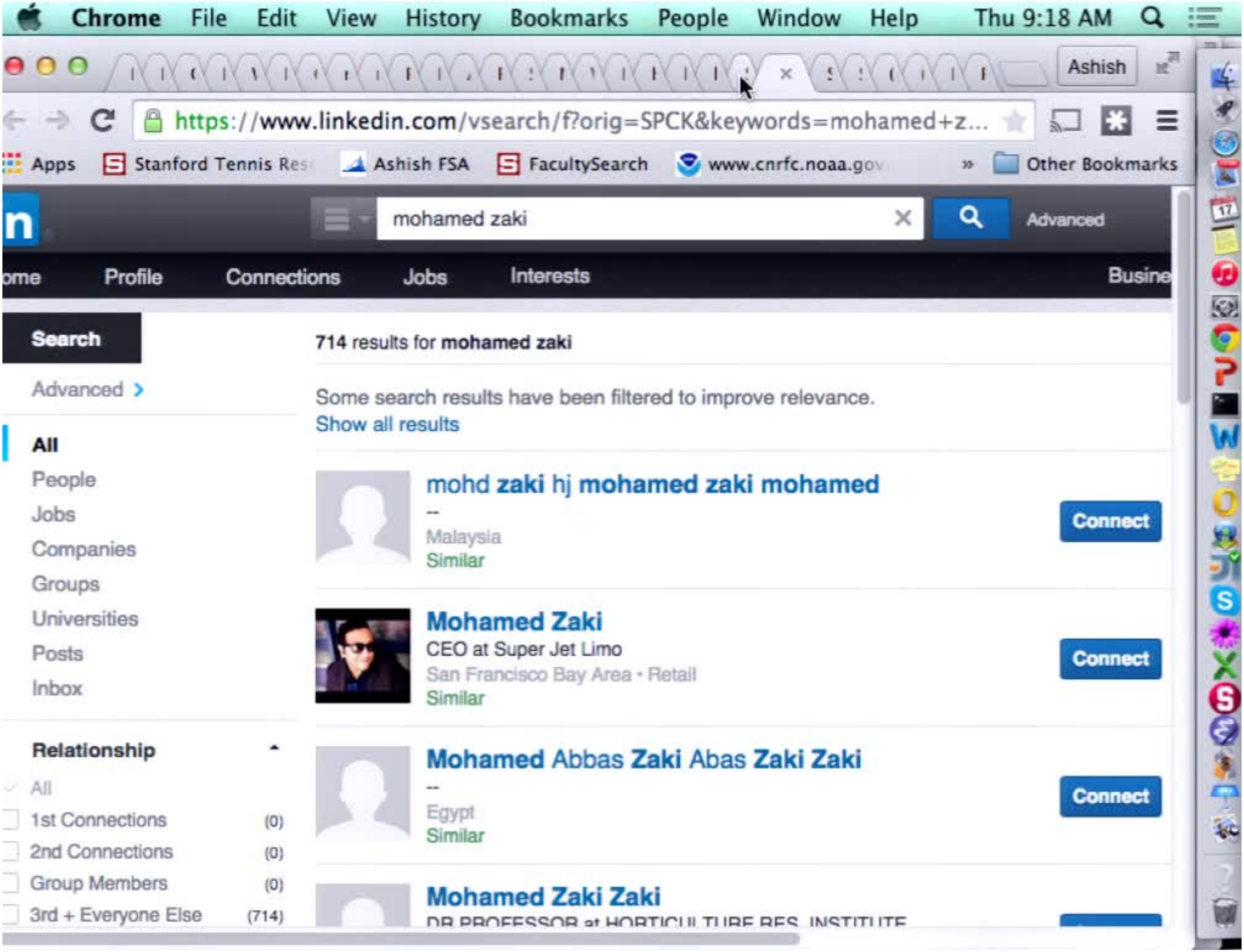
Löfgren syndrome is a type of acute sarcoidosis that is frequent in Scandinavian, Irish, African and Puerto Rican women. It was characterized in 1953 by Sven ...
Presentation - Prognosis - Genetics - Treatment Options
In the news
Nils Lofgren ready to cross the Jersey state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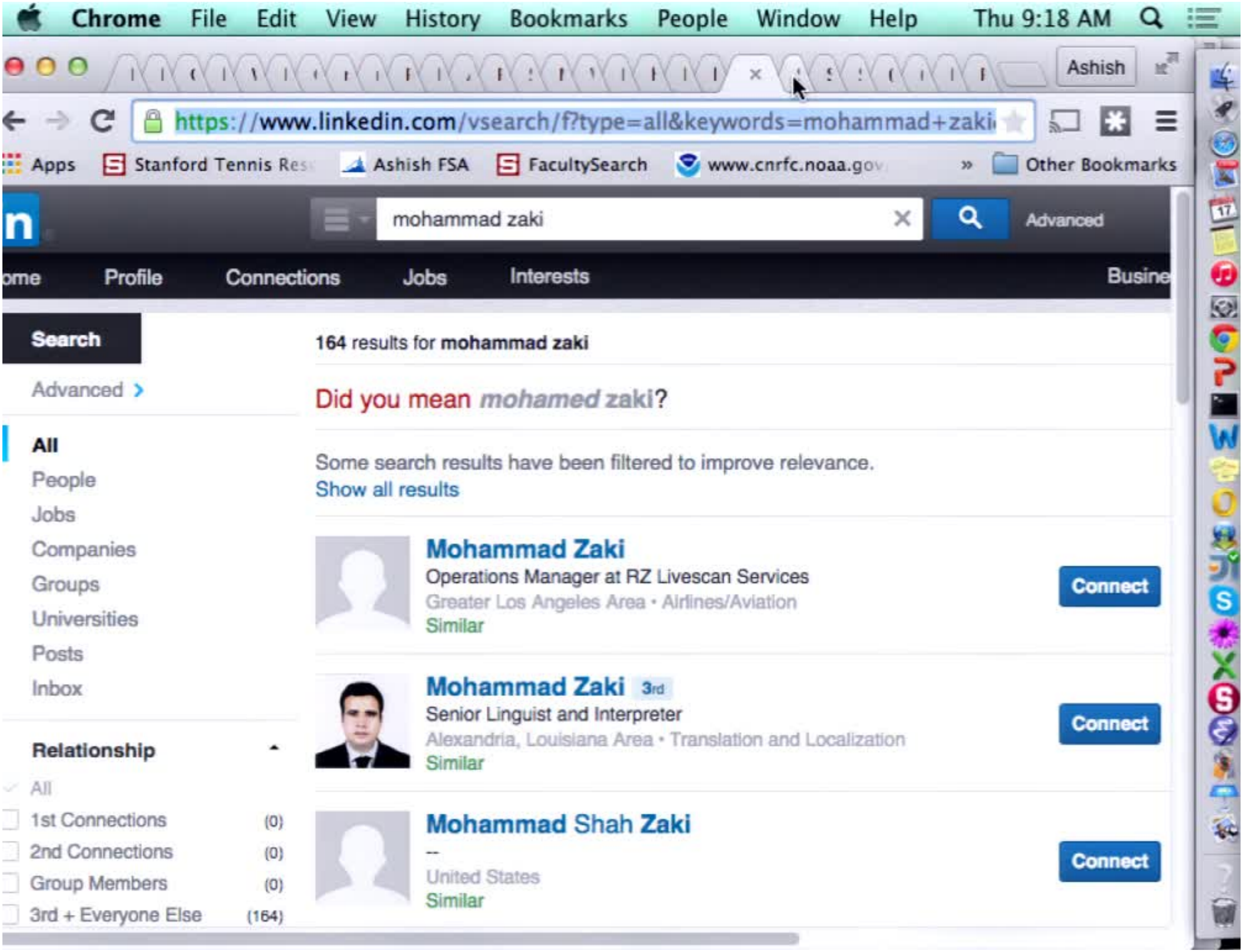
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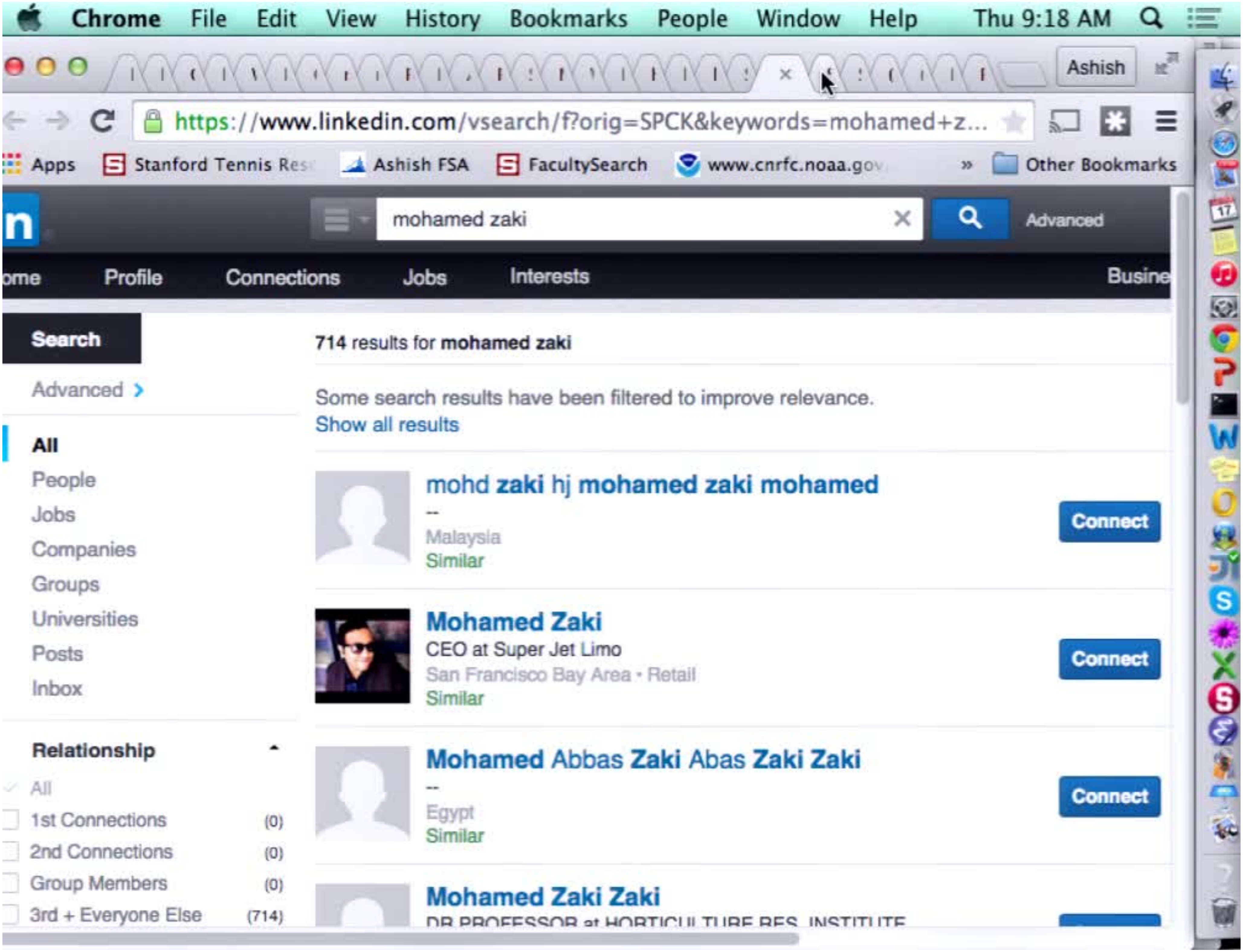
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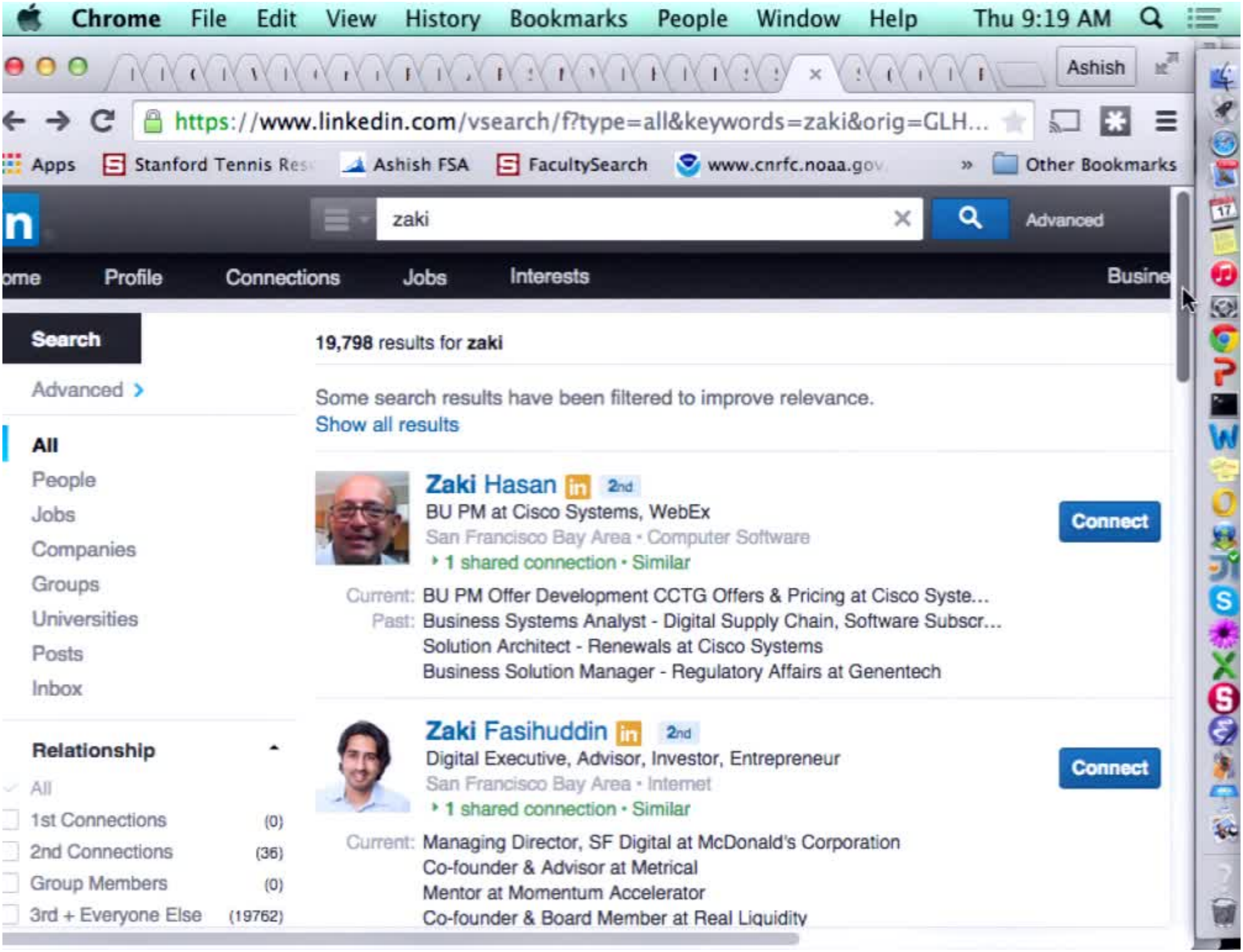
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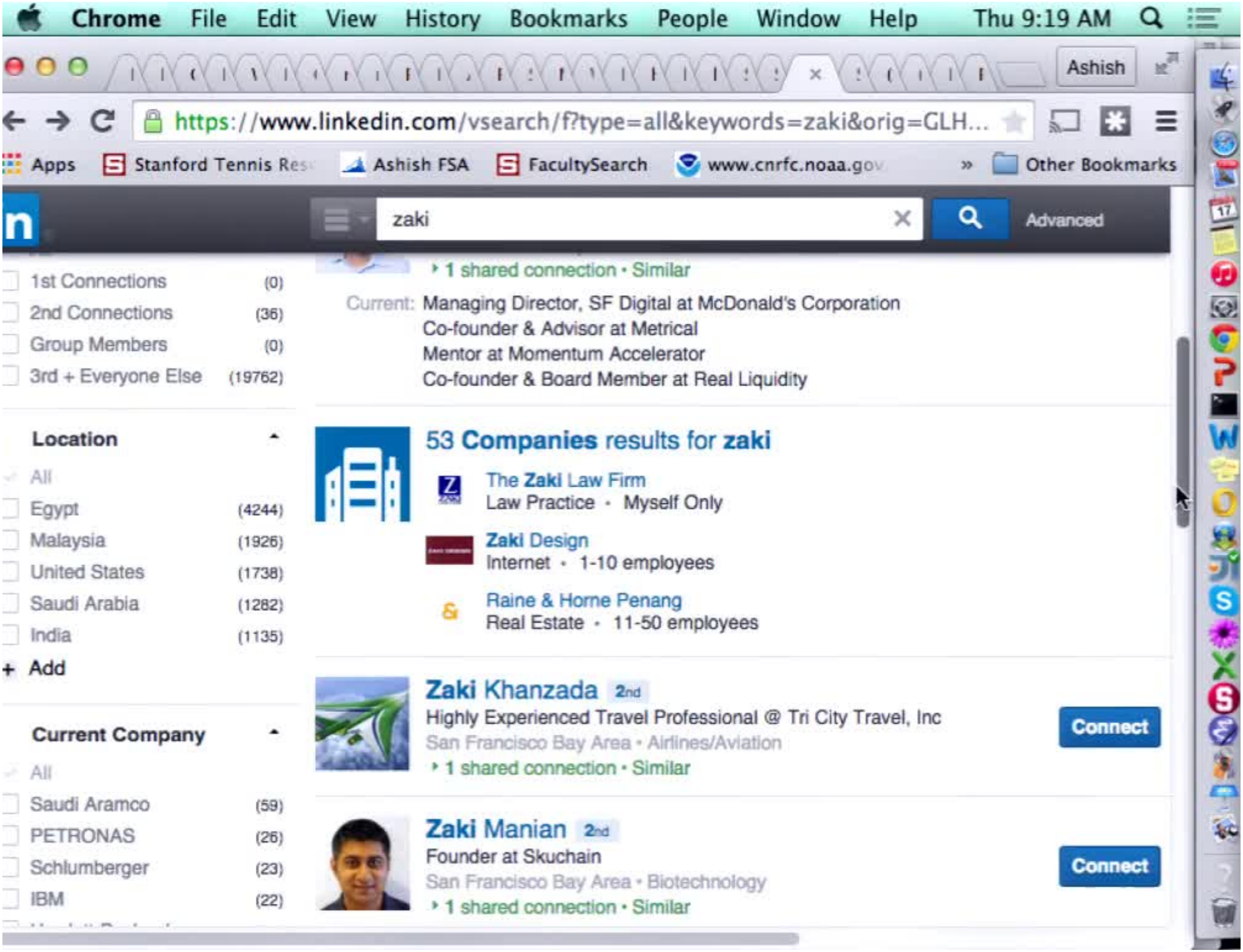
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Zaki Design
Internet • 1-10 employees
Raine & Horne Penang
Real Estate • 11-50 employees
Zaki Khanzada 2nd
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San Francisco Bay Area • Airlines/Aviation
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Zaki Manian 2nd
Founder at Skuchain
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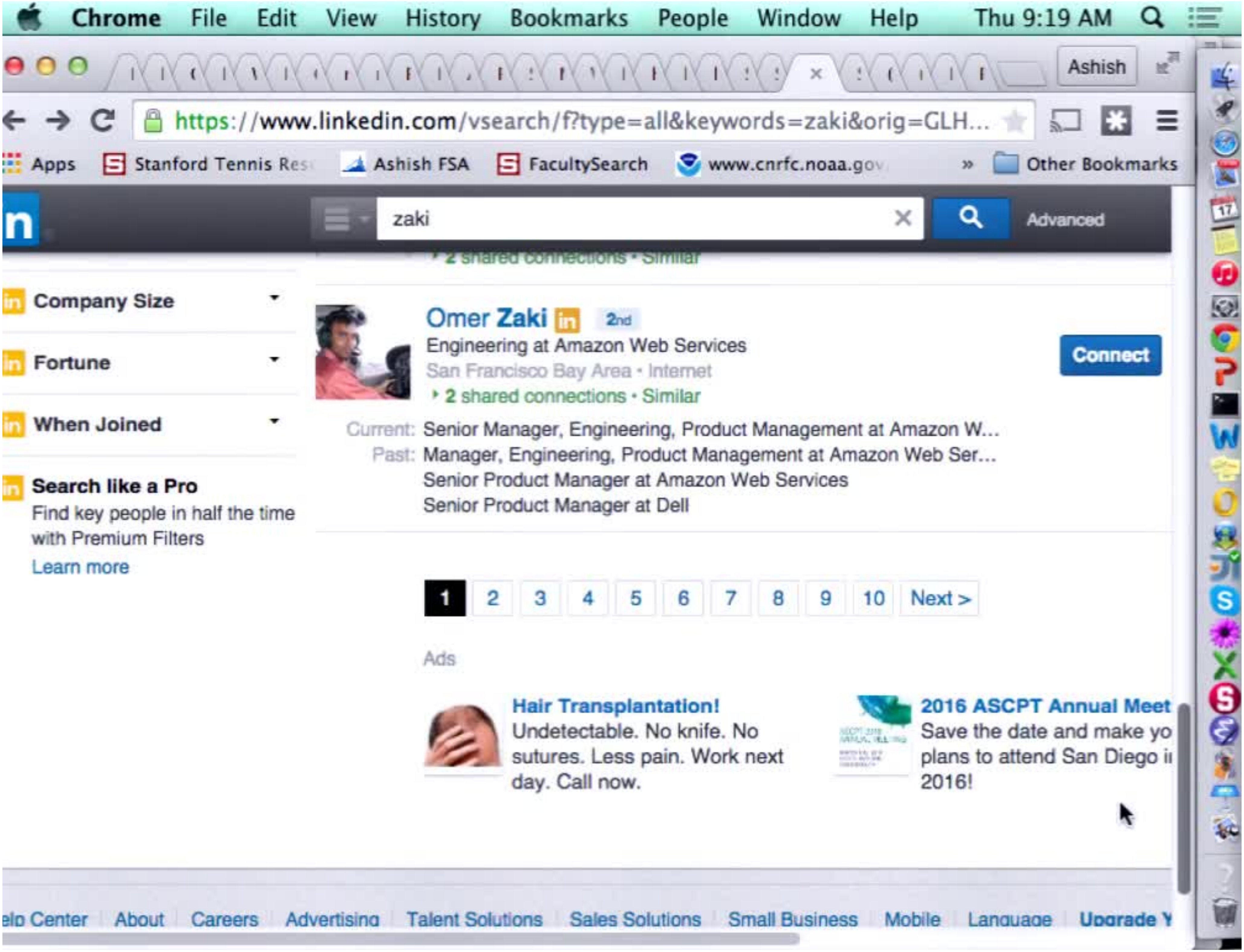
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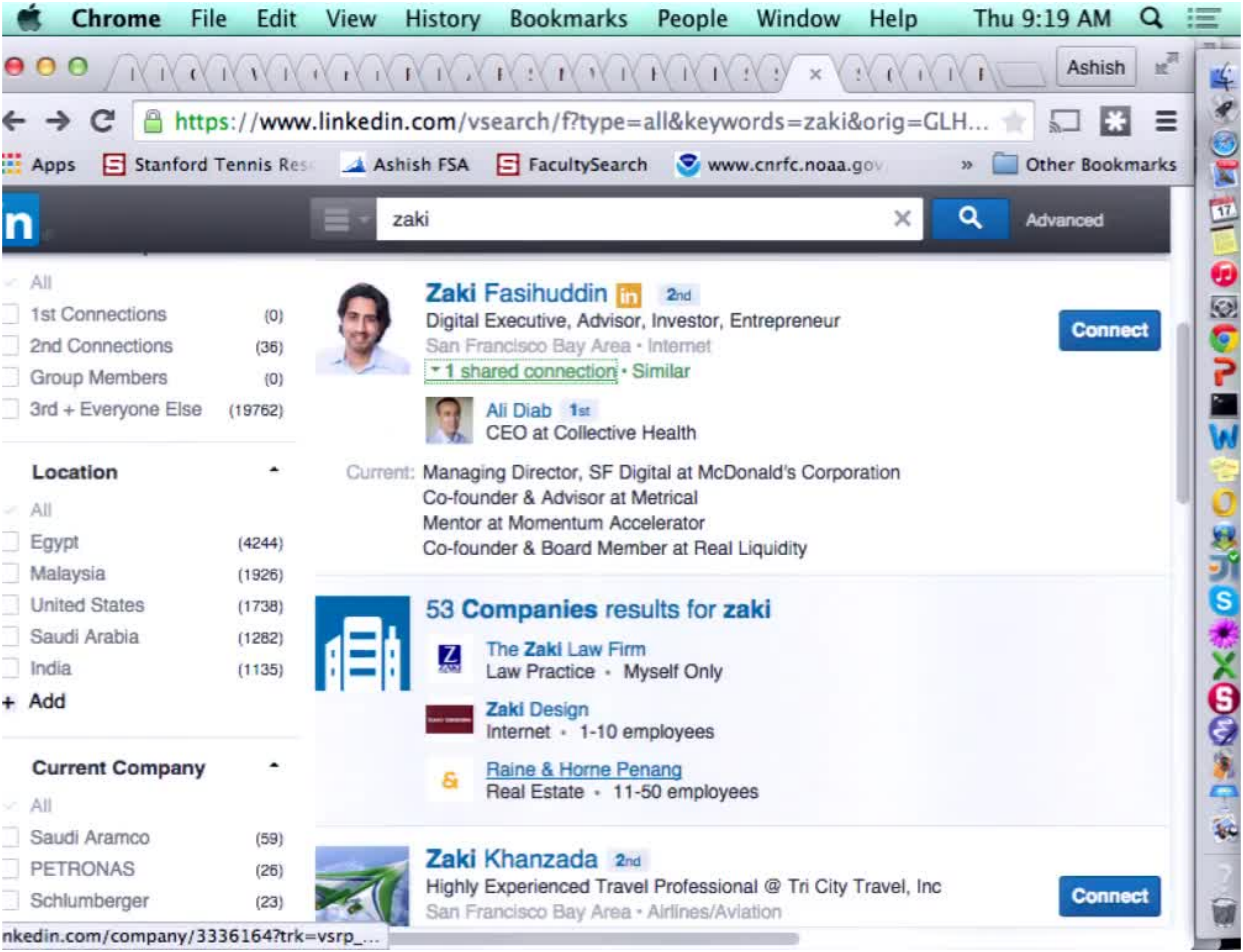
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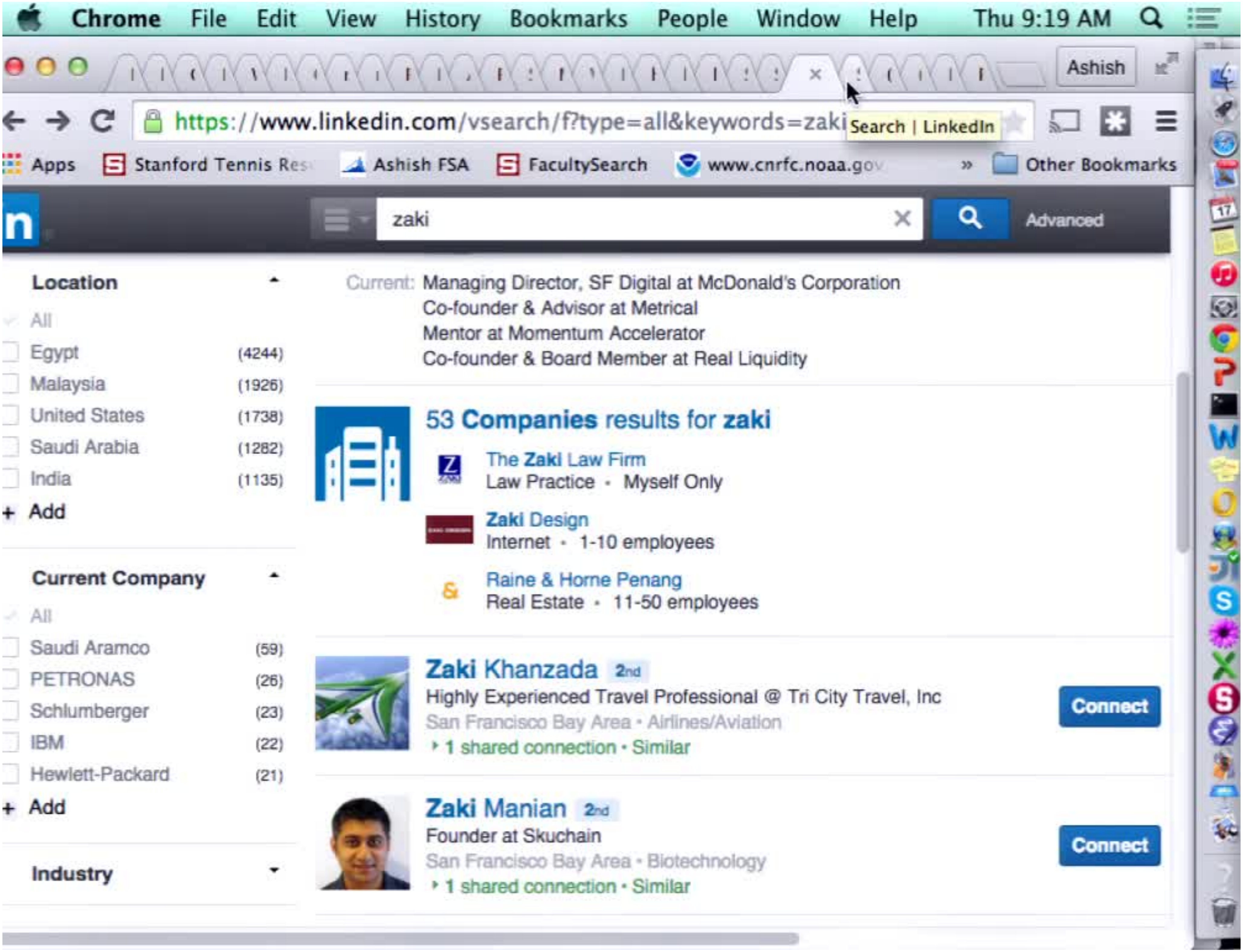
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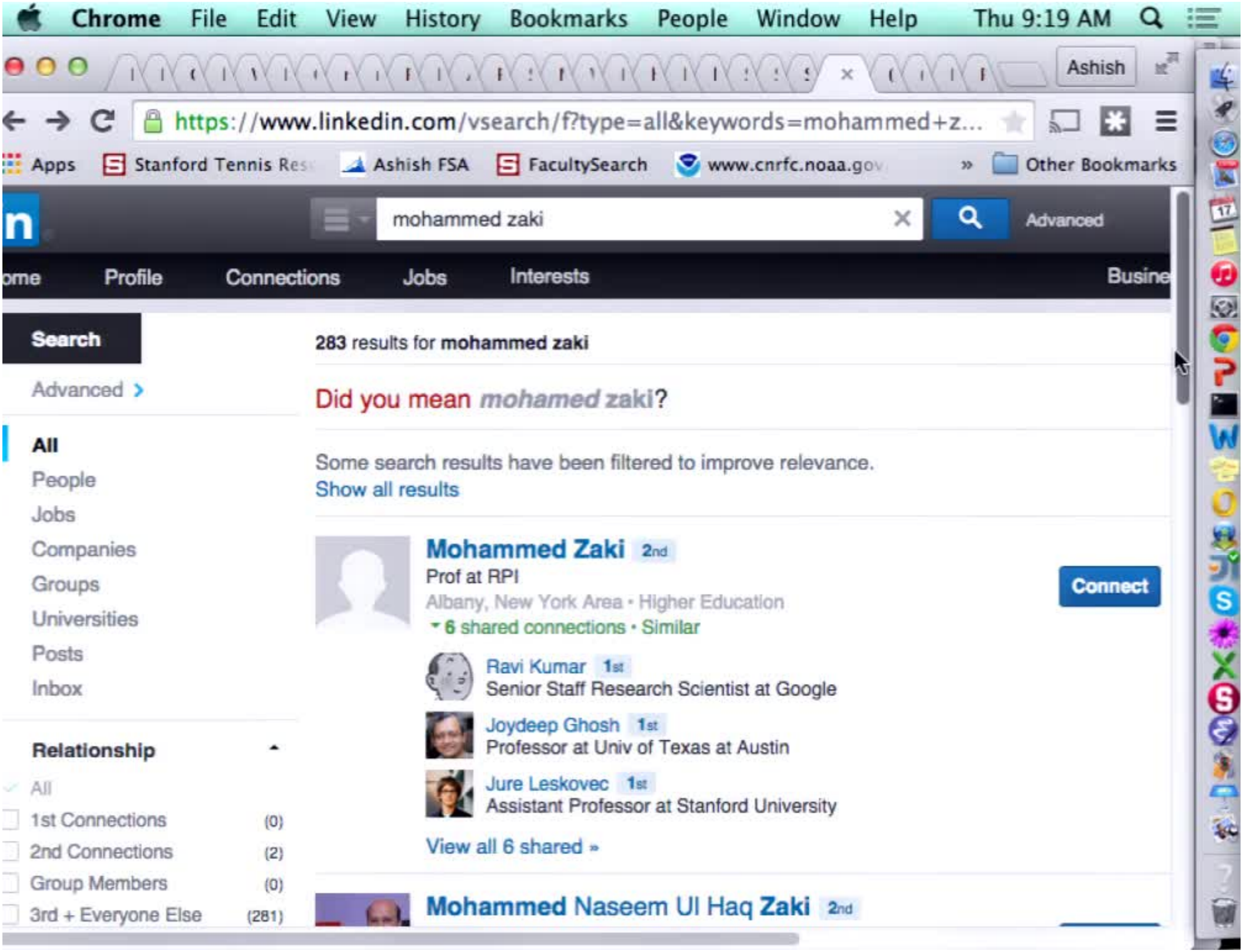
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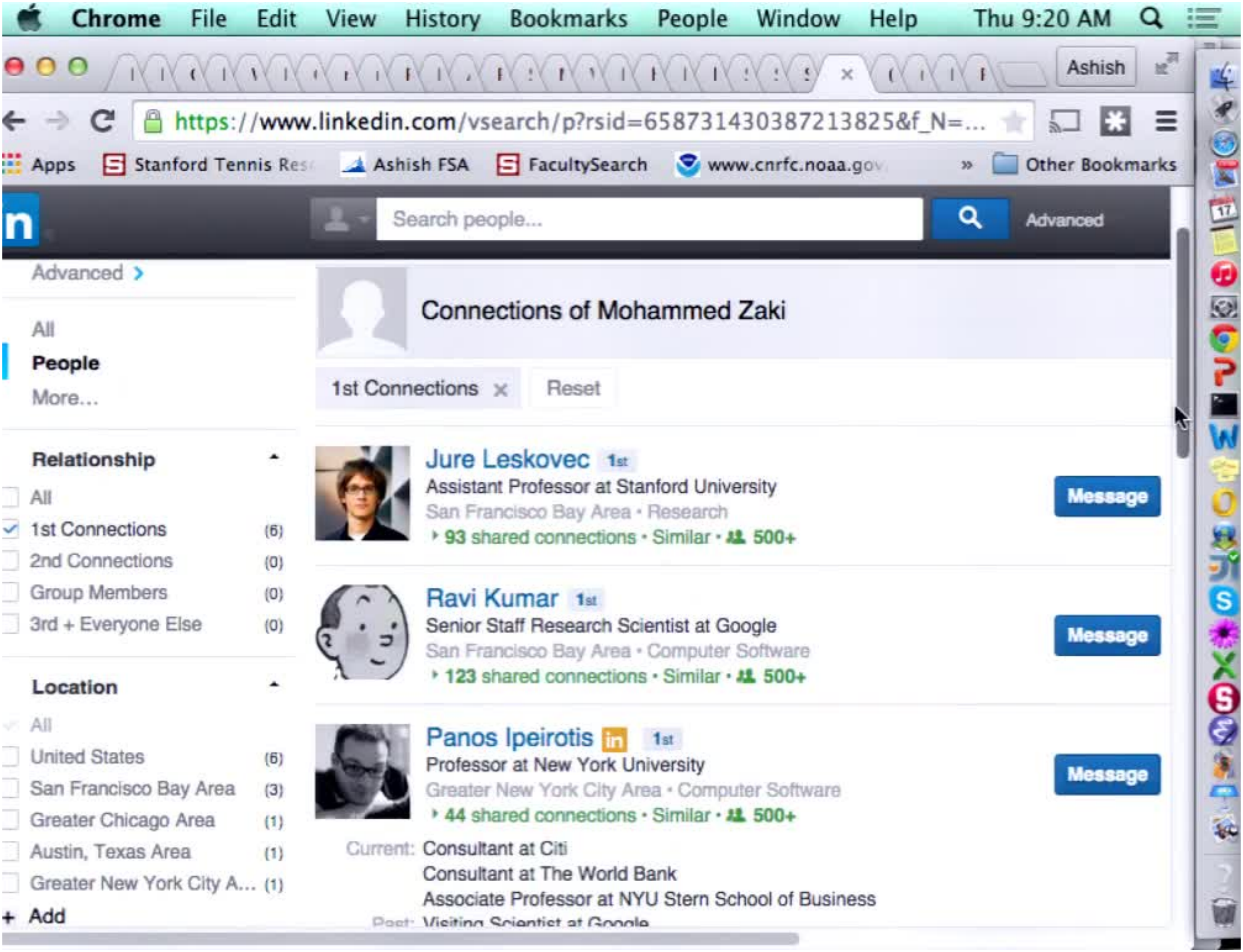
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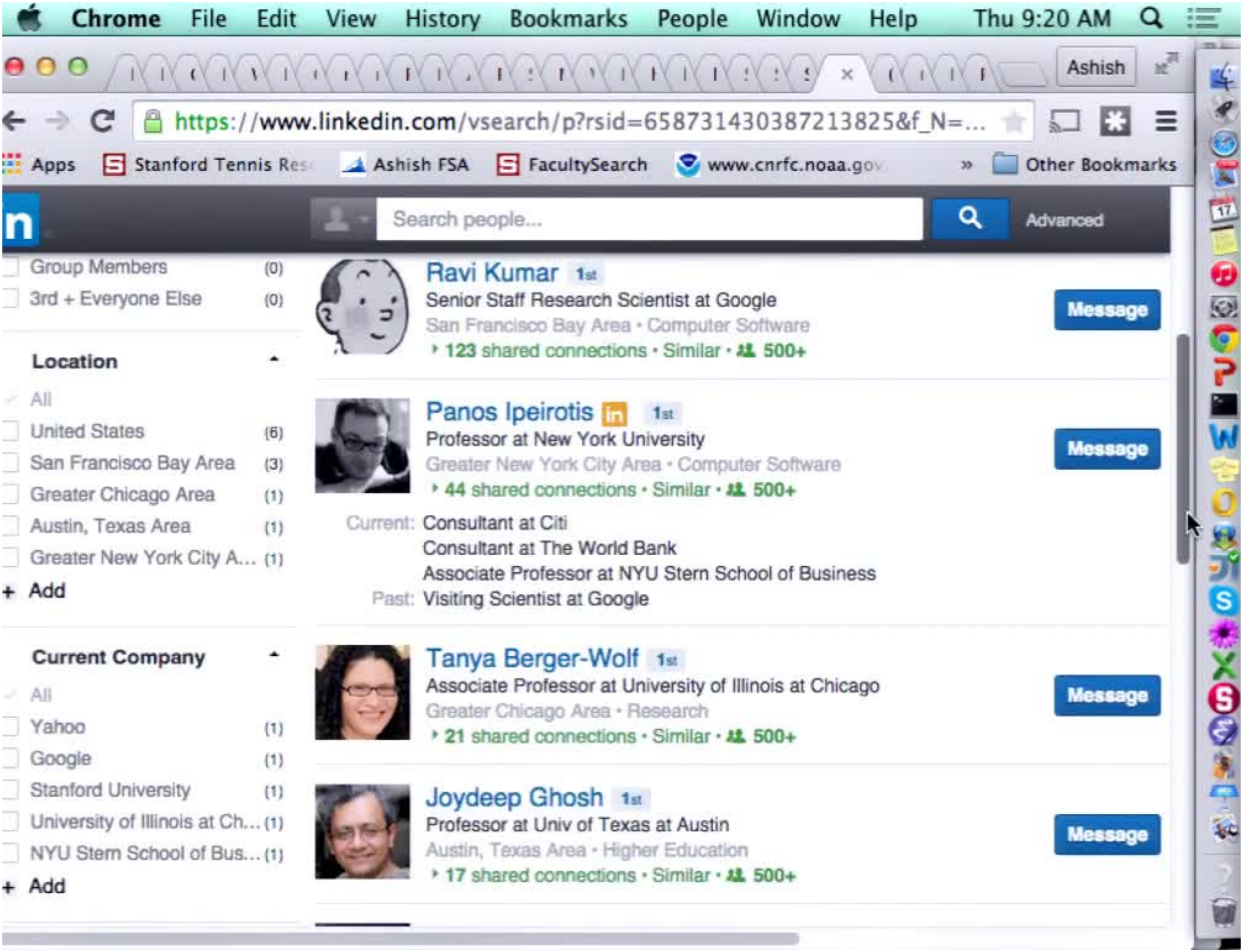
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Personalized PageRank

Network-based Personalized Search is not yet mature

Missing technical piece: Efficient algorithms for Personalized PageRank Queries

- Given source s and target t, estimate the Personalized PageRank of t for s with high accuracy, if it is greater than δ

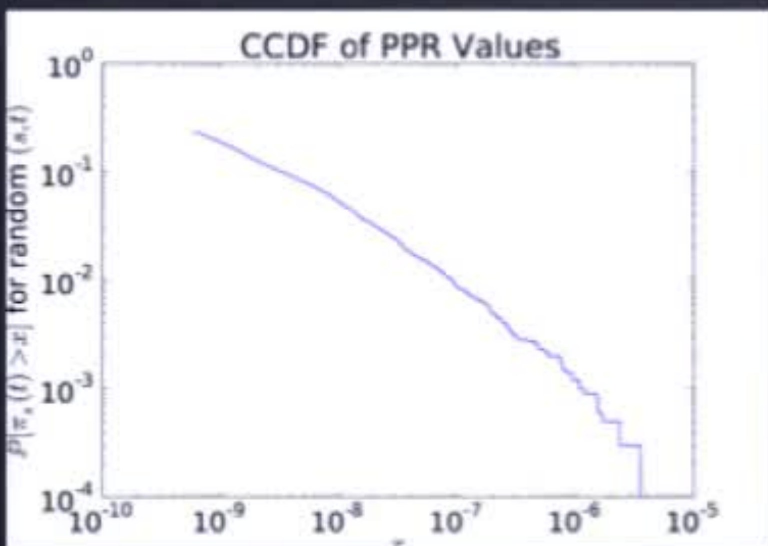
Personalized PageRank

Given a consumer C, perform a random walk on the Follow graph. If the walk is at node v, then the walk:

- Jumps back to node C with probability α
- Follows a random edge out of v with probability $1 - \alpha$

The Personalized PageRank of node Y is the weight of Y in the stationary distribution of this random walk

Existing Methods for PPR Queries



Monte Carlo uses time $> 1/\delta$

"Local Update" uses time d/δ

[d = M/N is the average degree]

On Twitter-2010, if $\delta = \frac{4}{n} \approx 10^{-7}$, then

$$\Pr\left[\pi(s,t) > \delta\right] = 1\%$$

Personalized PageRank

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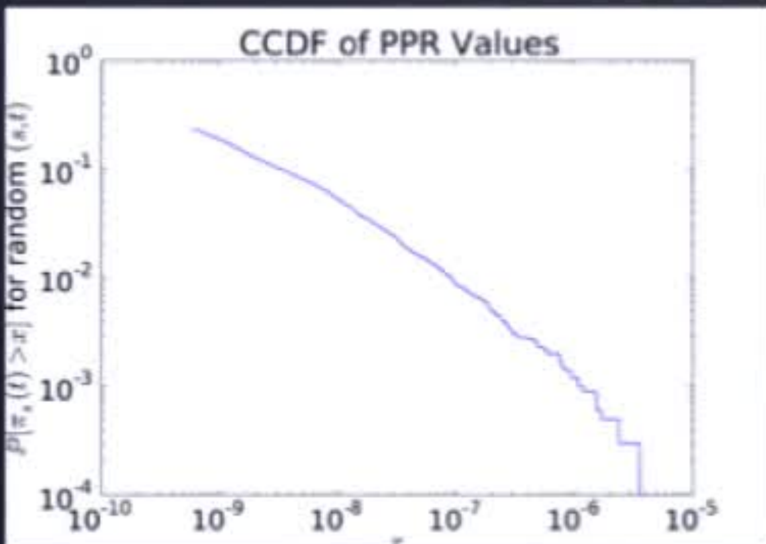

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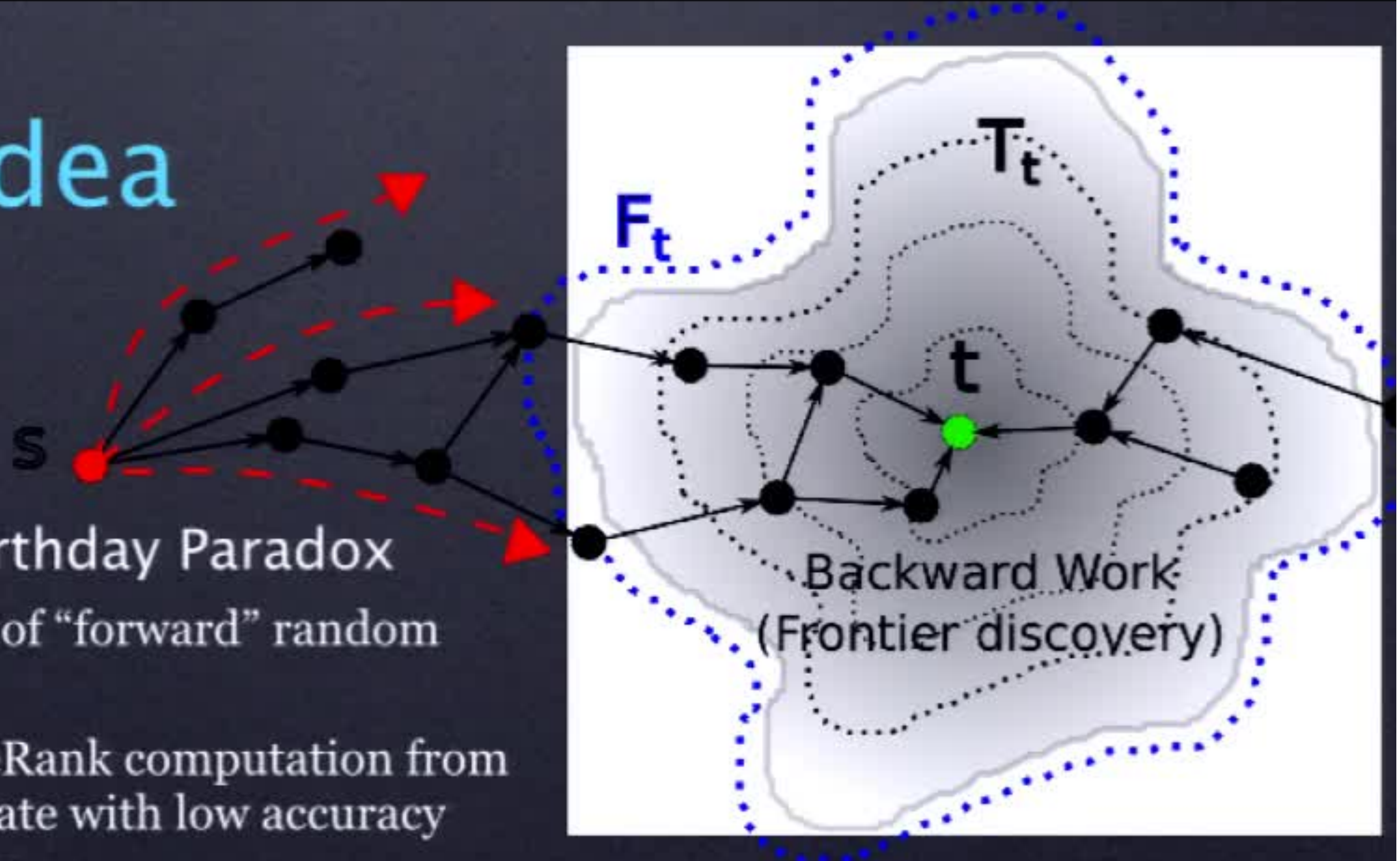
$$\Pr\left[\pi(s,t) > \delta\right] = 1\%$$

FAST PPR

We can answer PPR queries in either

- Average time $\tilde{O}(\sqrt{(d/\delta)})$
- Worst case time $\tilde{O}(\sqrt{(d/\delta)})$ with $\tilde{O}(\sqrt{(d/\delta)})$ storage and pre-processing time per node
- Typical values: $\delta \sim 10^{-8}$, $d \sim 100$; results in a > 100-fold decrease

Basic Idea



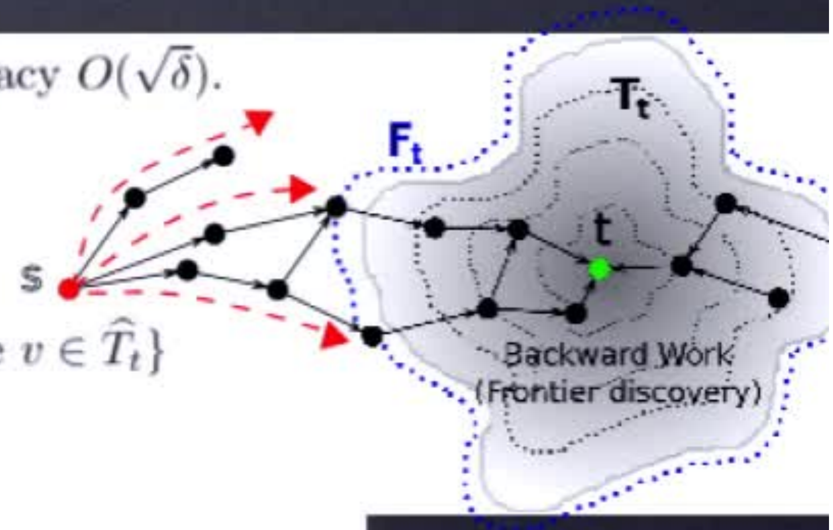
Intuition: The Birthday Paradox

- Do small number of "forward" random walks from s
- Do "reverse" PageRank computation from t using Local Update with low accuracy
- Use number of collisions as an estimator
- Need to "catch" a collision just before it happens

Simple Version of FAST PPR

1. Use Local Update to compute estimates $\hat{\pi}(v,t)$ to accuracy $O(\sqrt{\delta})$.
2. Define

$$\text{Target Set } \widehat{T}_t = \{v \in V : \hat{\pi}(v,t) > \sqrt{\delta}\}$$
$$\text{Frontier } \widehat{F}_t = \{u \in V \setminus \widehat{T}_t : (u,v) \in E \text{ for some } v \in \widehat{T}_t\}$$



3. Take $O\left(\frac{\log(n)}{\sqrt{\delta}}\right)$ Random Walks $\{W_i\}$, terminating each early if it hits $\widehat{F}_t$. Define

$$X_i = \begin{cases} \hat{\pi}(u,t), & W_i \text{ hits } u \in \widehat{F}_t \\ 0, & W_i \text{ does not hit } \widehat{F}_t \end{cases}$$

4. Return empirical mean$\{X_i\}$.

Running Time for Simple Version

For a uniformly random target node t, the average per-query running time is

$$O\left(\frac{1}{\sqrt{\delta}}\left(\bar{d} + \log(n)\right)\right).$$

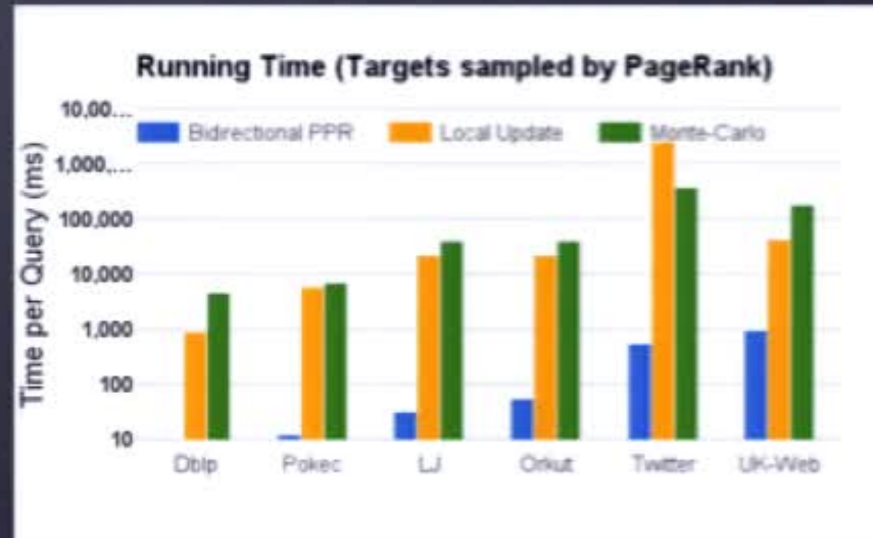
Reverse work
(Local Update)

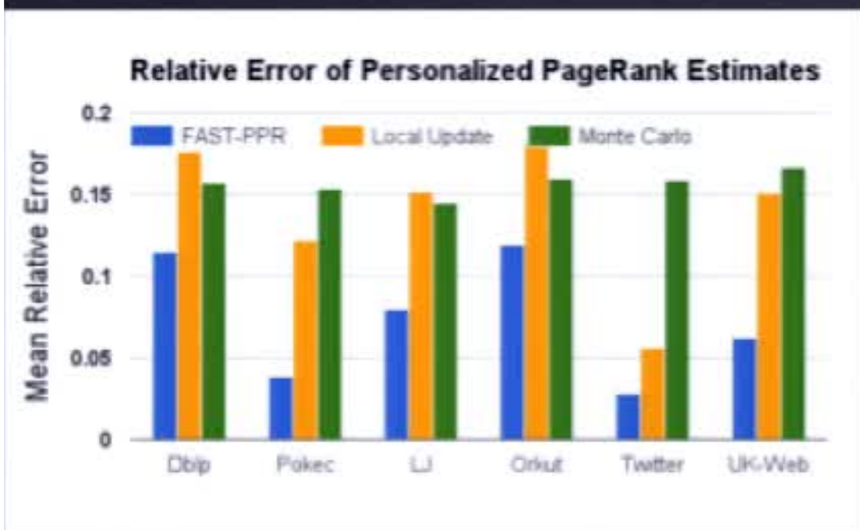
Forward work
(Monte Carlo)

We get final running time of $\tilde{O}(\sqrt{(d/\delta)})$ by using different accuracies in forward and reverse computation

We use $\tilde{O}(\sqrt{(d/\delta)})$ pre-processing/space to go from average to worst case running time

Experiments





- Admits Distributed Implementation (much faster)
- Works when source is a set of nodes
- Lower bound of $1/\sqrt{\delta}$
- Open problem: do we need the $\sqrt{d}$?

[Lofgren, Banerjee, Goel, Seshadhri, KDD, 2014]

Computing via Intersections

Consider "sharding" a graph among K computers, i.e. the vertices of the graph get randomly partitioned into K sets, $V_1, V_2, \ldots, V_K$. one for each compute node. Vertex v —> Shard s(v)

Typical: For each vertex v, store all its edges in Shard s(v) as a key-value pair (v, ADJ(v))

Additional trick: also store the reverse map, i.e. for each node w, store $(w, ADJ(w) \cap V_j)$ on the j-th compute node

Advantage: Intersection of the neighborhood of u and v can be computed efficiently with one scatter-gather query

[Gupta, Satuluri et al., 2014]

Computing via Intersections

Both PPR and All Pairs Cosine Similarity can be efficiently reduced to graph intersections

Also, approximate shortest path reduces to graph intersections

[Lofgren, Goel, Gupta; manuscript]

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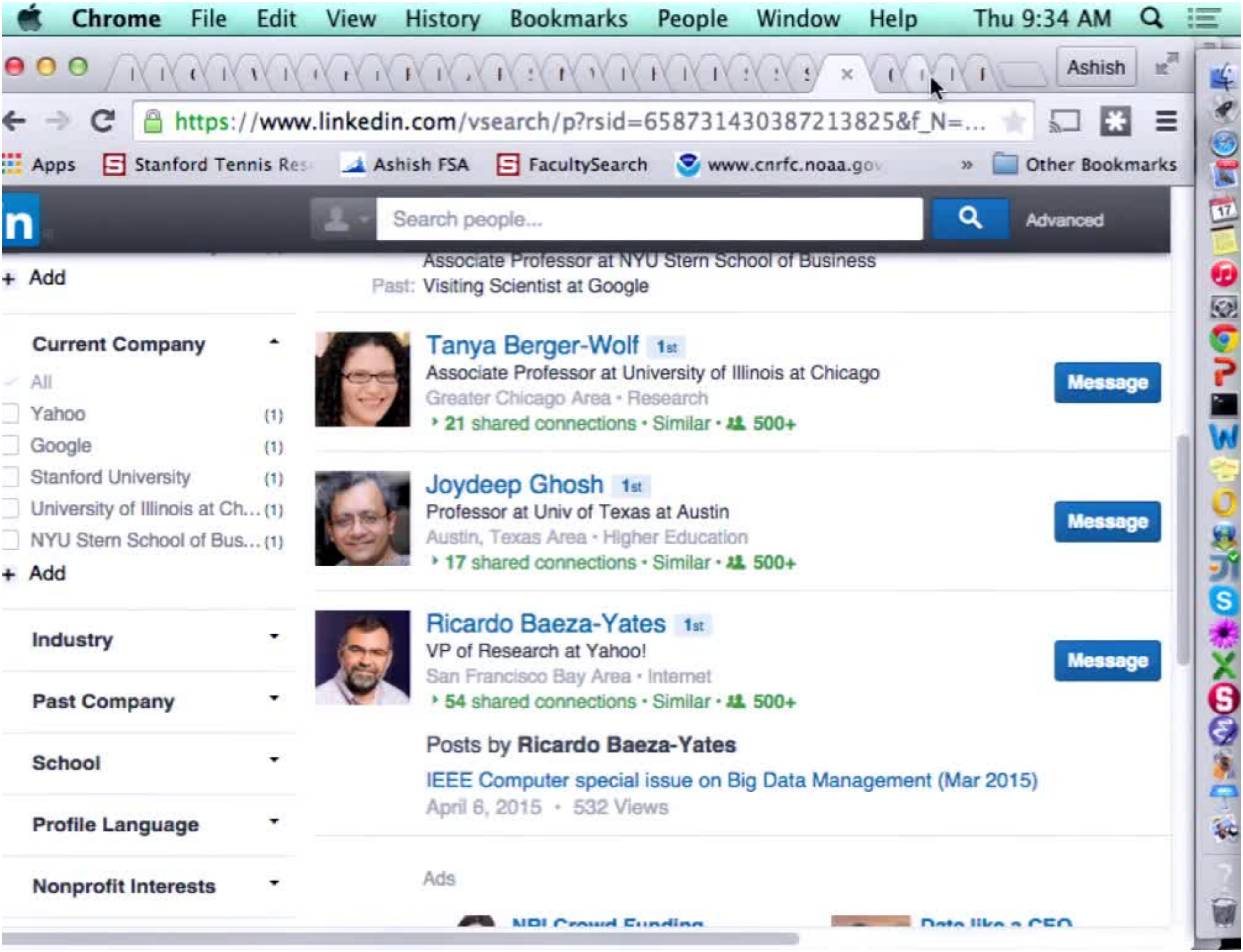
Summary

Personalization algorithms can lead to both growth and monetization in social networks

Random walks and Cosine similarity are particularly efficient

Careful consideration of algorithms and architecture together can lead to efficiency

Next frontier: personalized search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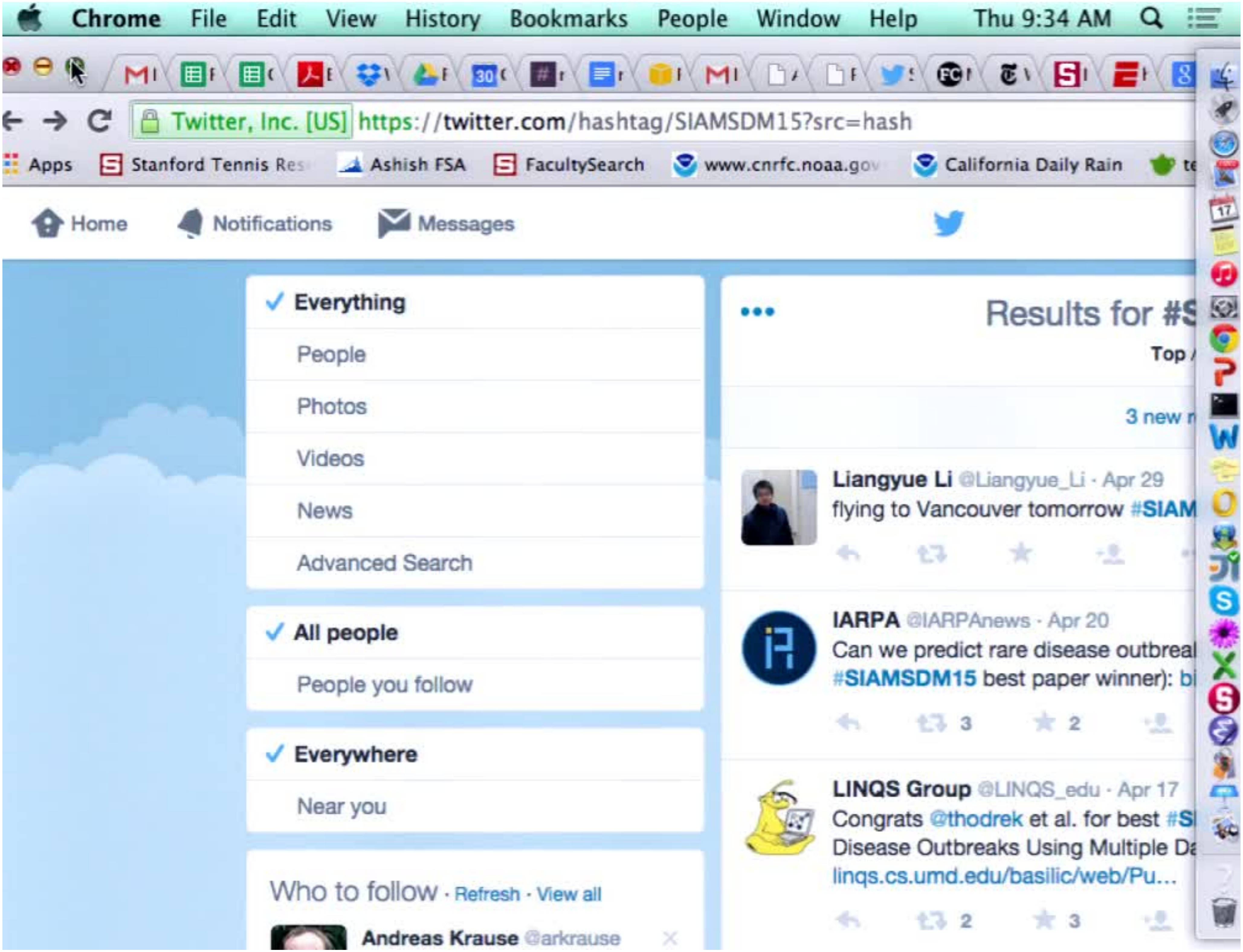
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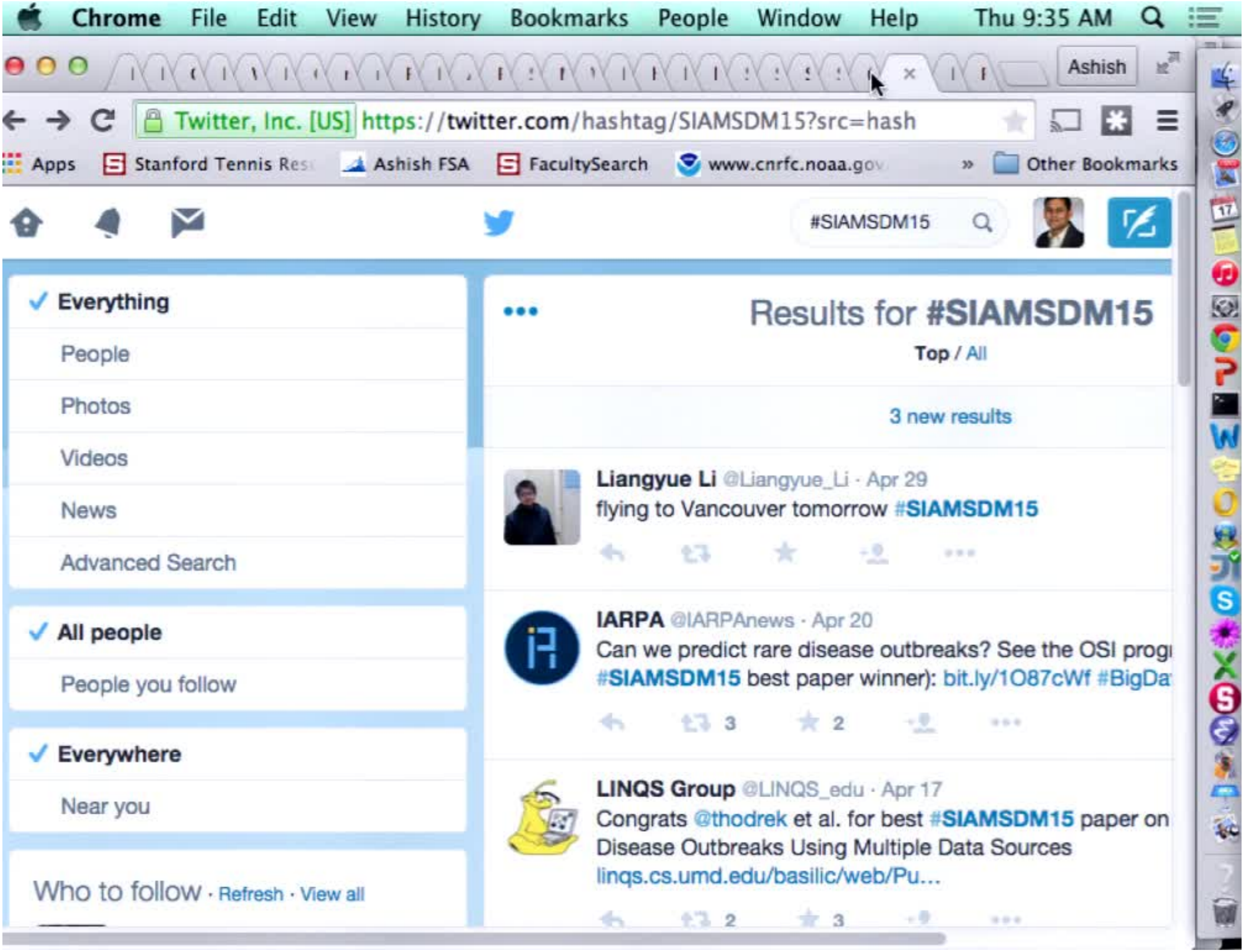
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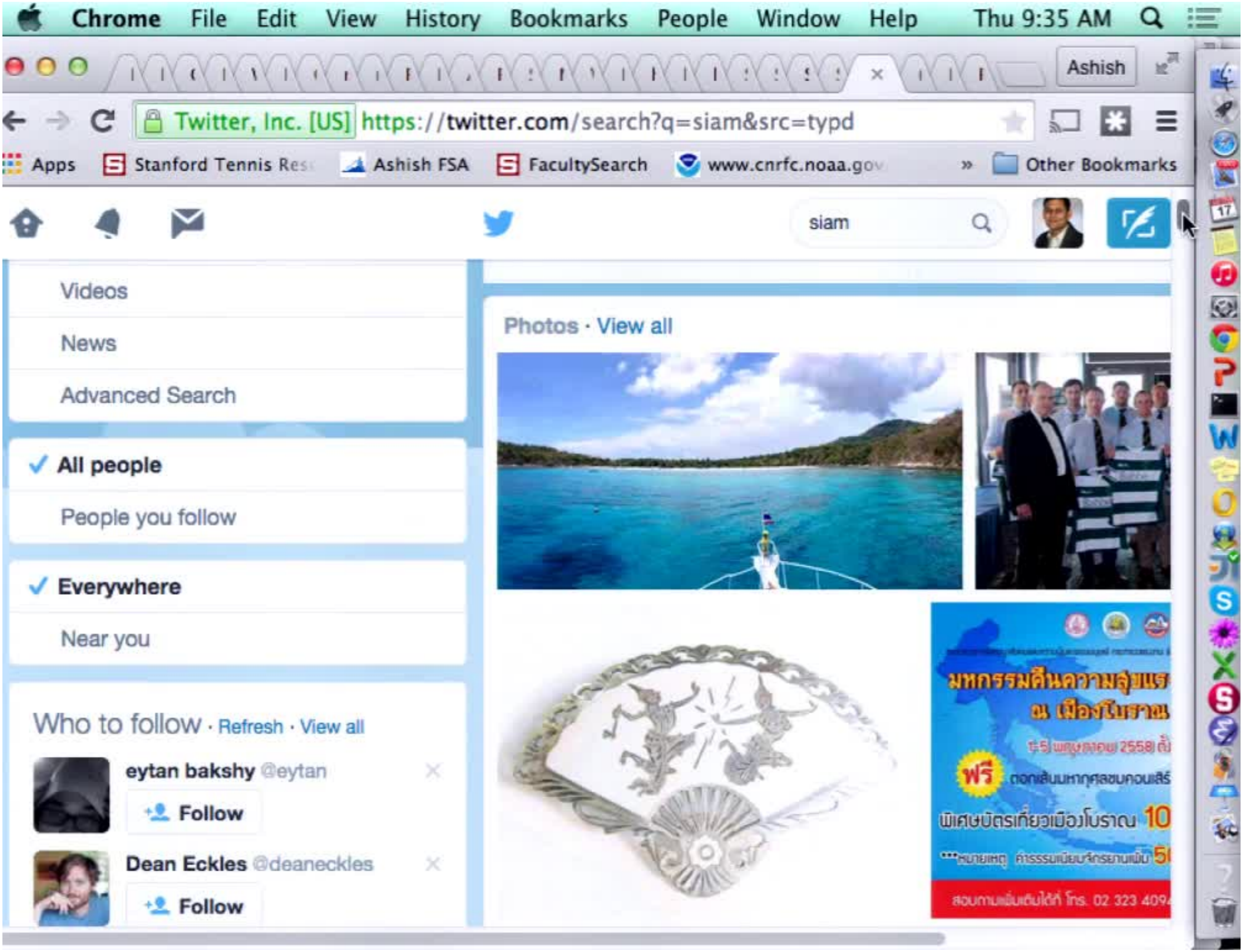
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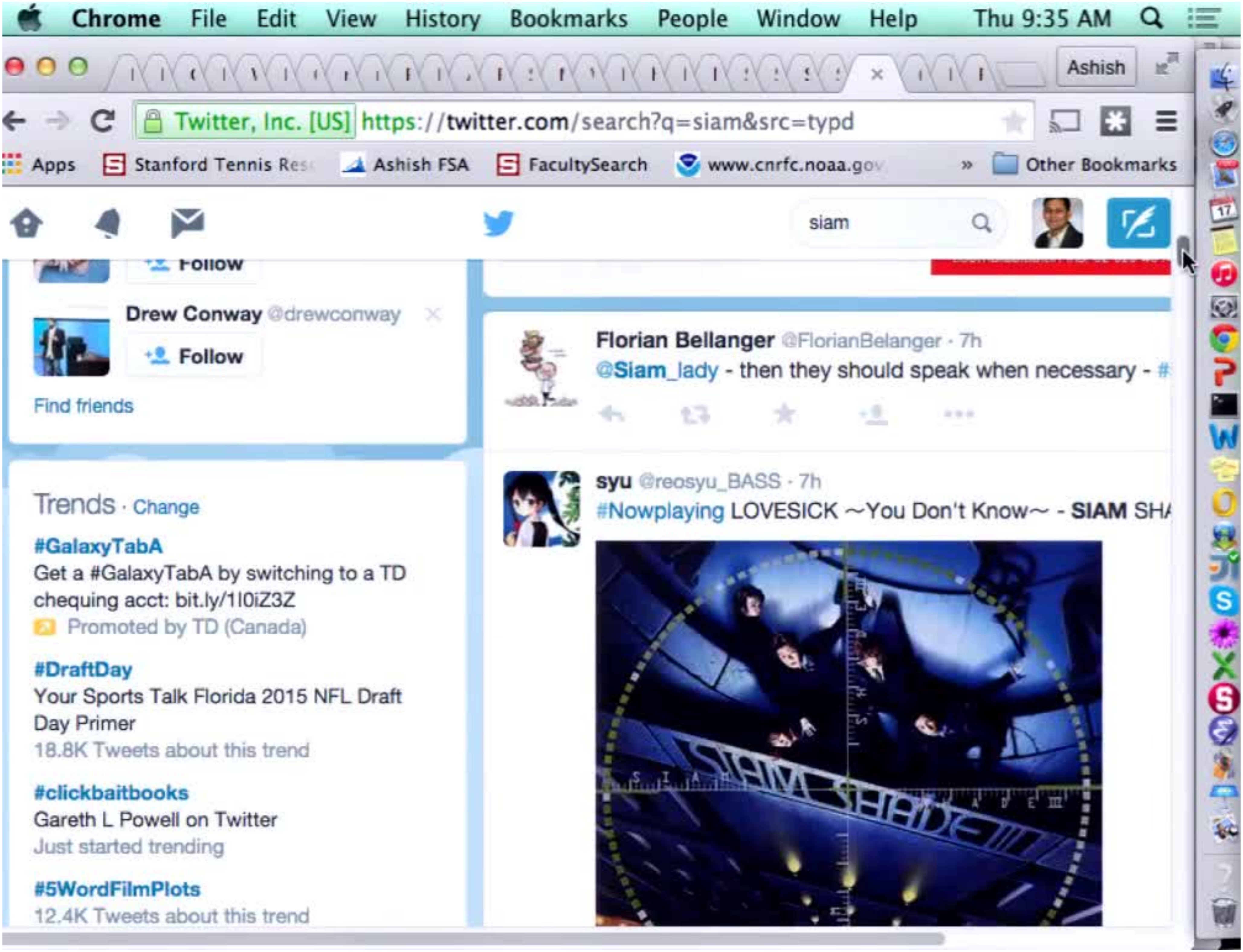
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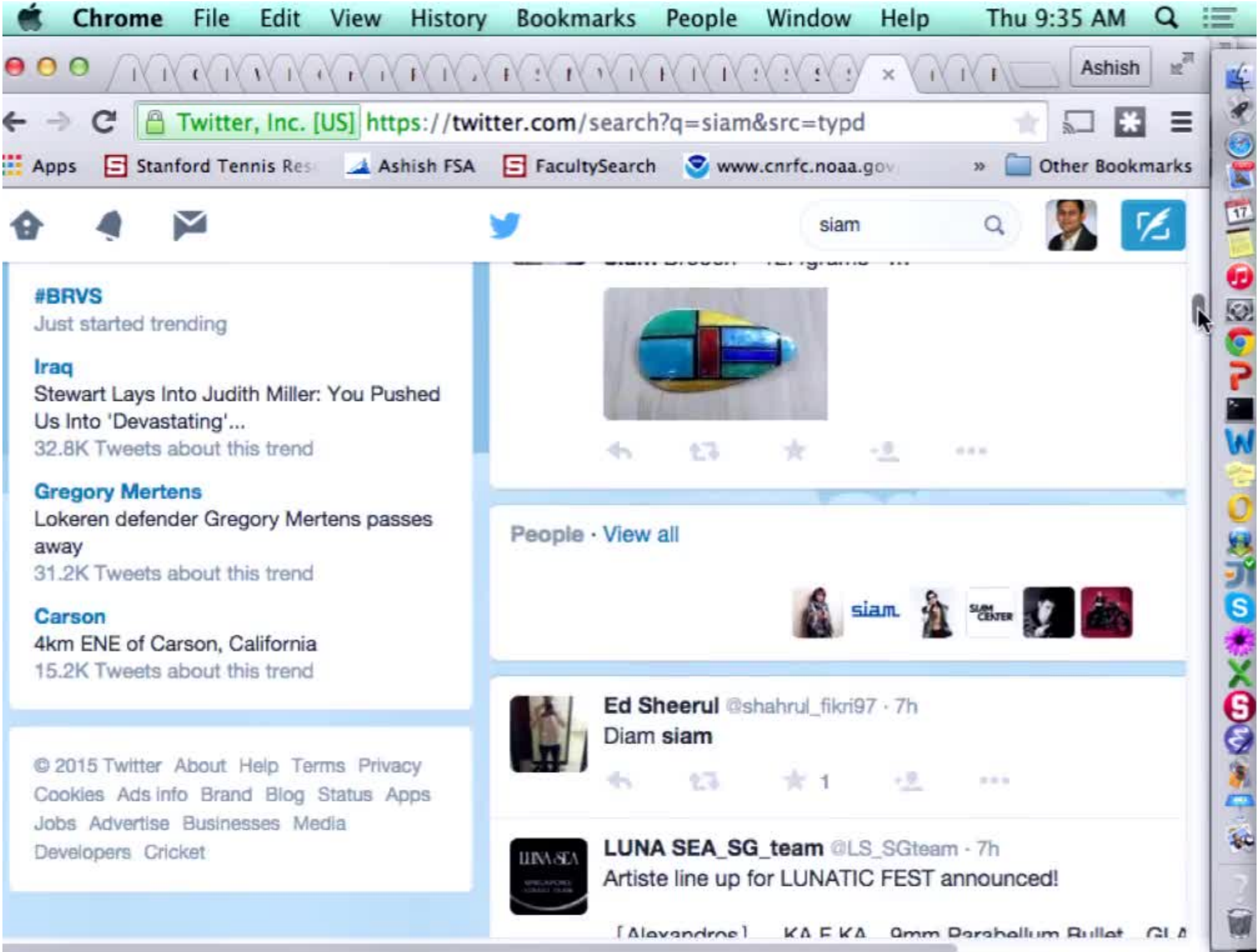

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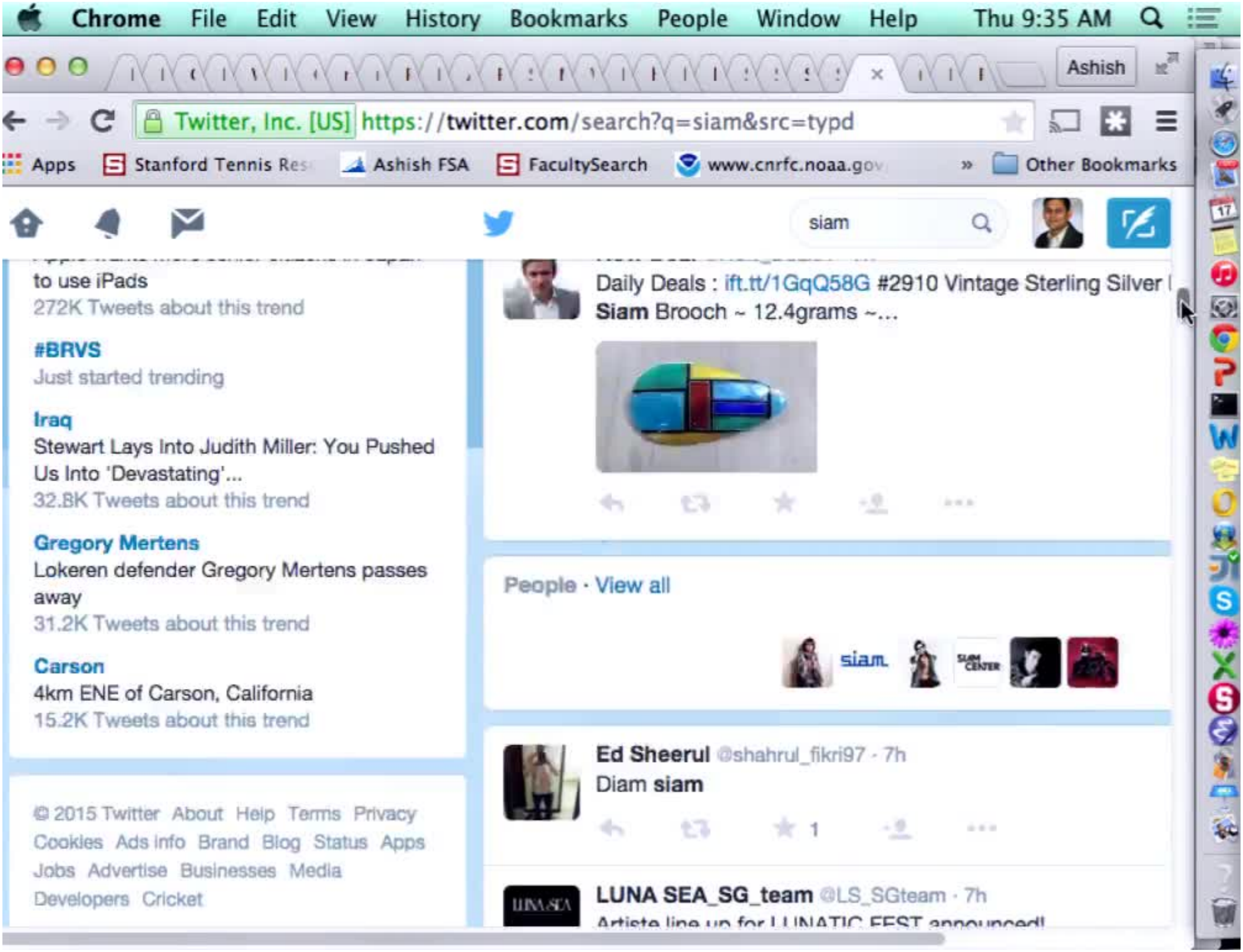
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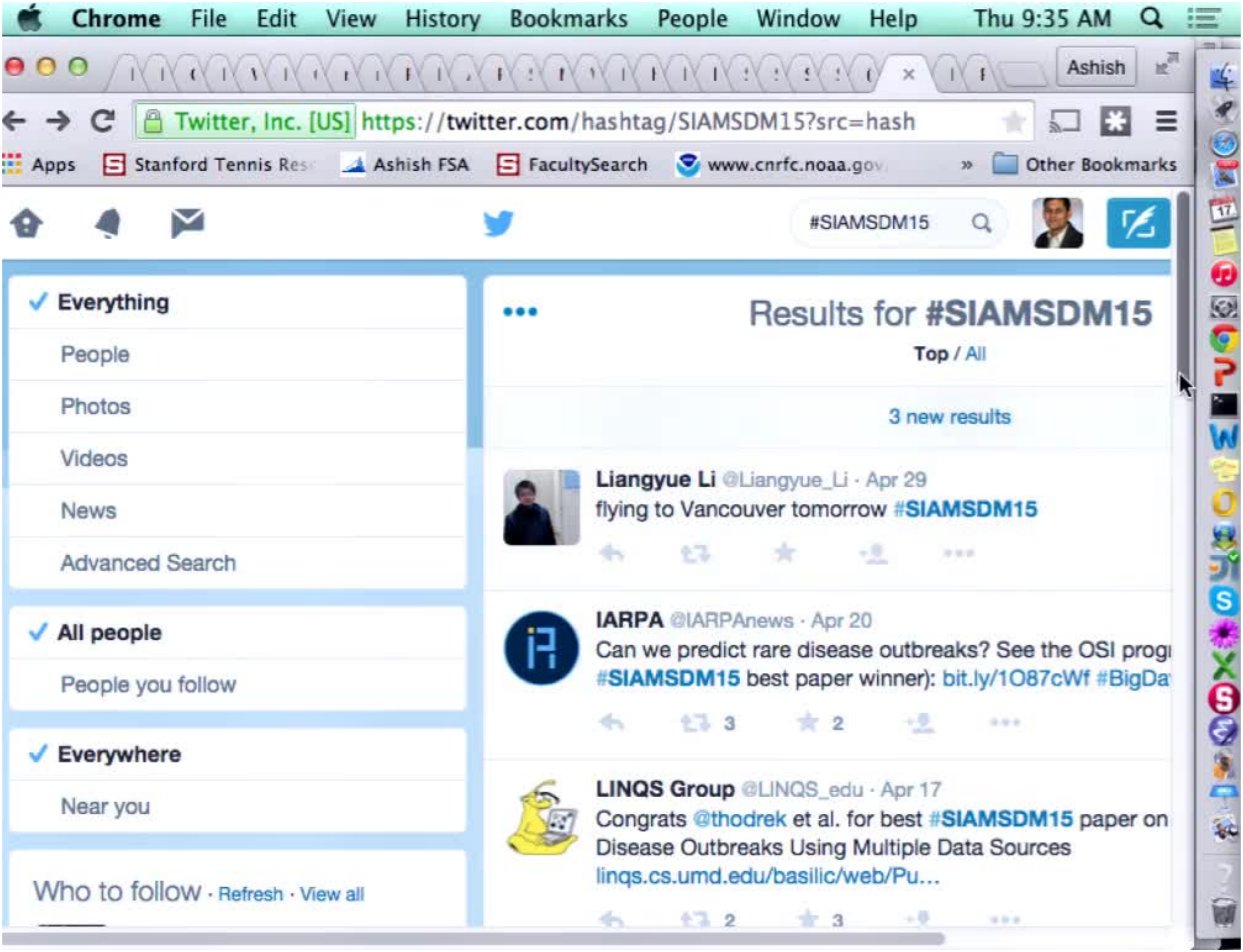
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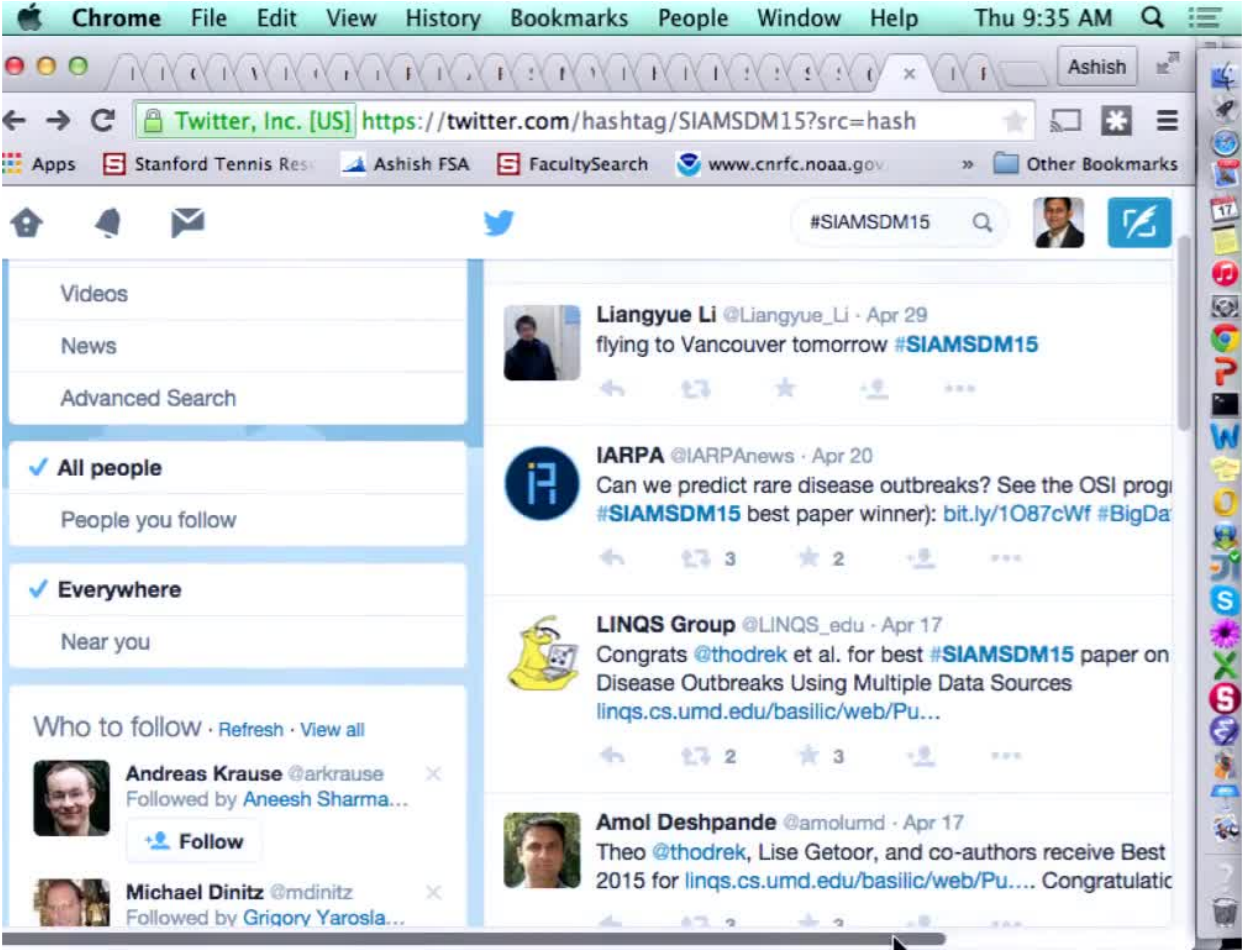
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