CSE 158 – Lecture 15

Web Mining and Recommender Systems

AdWords

Advertising

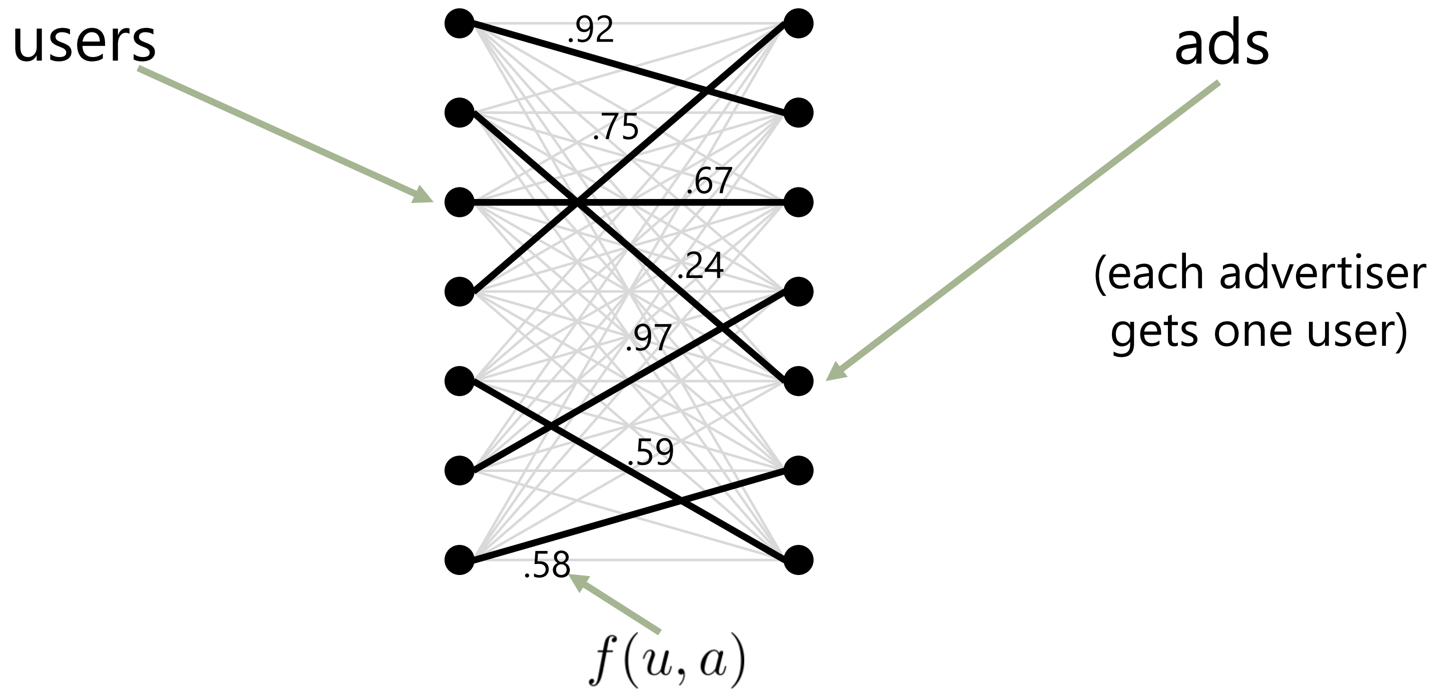
1. We can’t recommend everybody the same thing (even if they all want it!)

- So far, we have an algorithm that takes “budgets” into account, so that users are shown a limited number of ads, and ads are shown to a limited number of users
- **But,** all of this only applies if we see all the users and all the ads **in advance**

- This is what’s called an **offline algorithm**

Bipartite matching

On Monday we looked at **matching problems** which are a flexible way to find compatible user-to-item matches, while also enforcing "budget" constraints



Advertising

2. We need to be **timely**

- But in many settings, users/queries come in one at a time, and need to be shown some (highly compatible) ads
- But we still want to satisfy the same quality and budget constraints

- So, we need **online algorithms** for ad recommendation

What is adwords?

Adwords allows advertisers to bid on keywords

- This is similar to our matching setting in that advertisers have limited **budgets,** and we have limited space to show ads

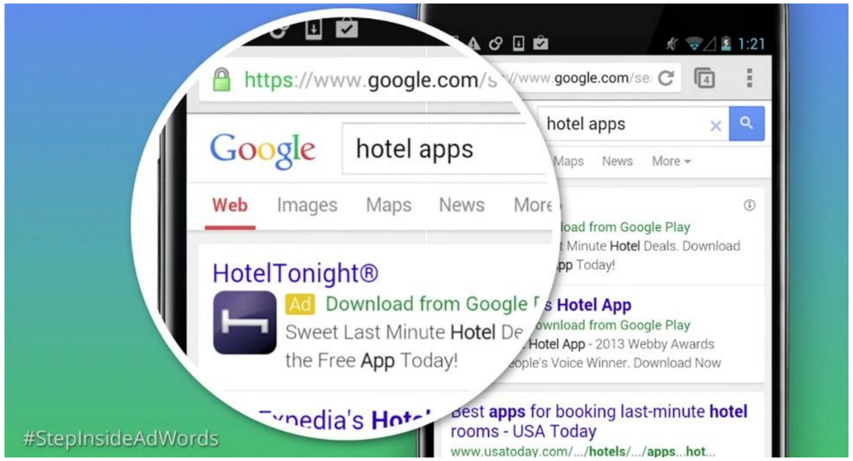


image from blog.adstage.io

What is adwords?

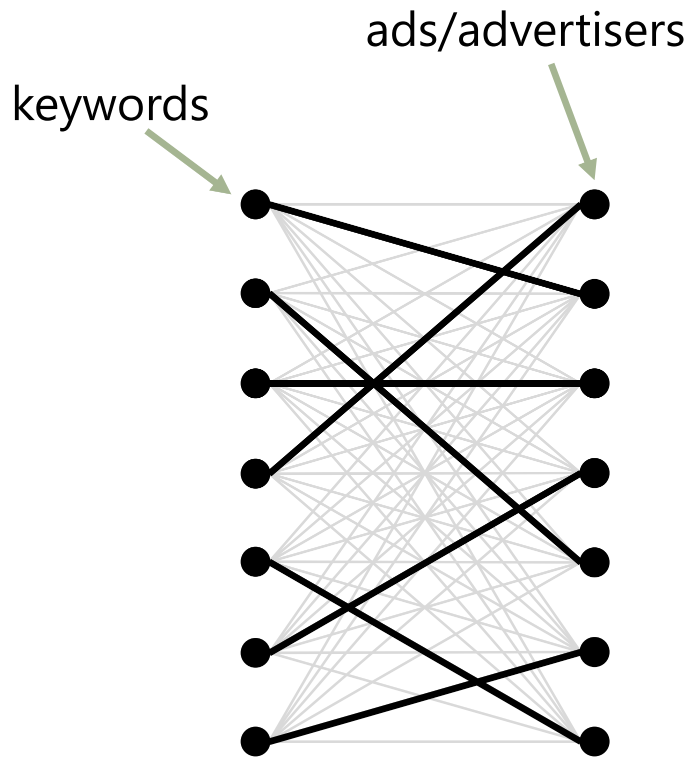
Adwords allows advertisers to bid on keywords

- This is similar to our matching setting in that advertisers have limited **budgets,** and we have limited space to show ads
- **But,** it has a number of key differences:

1. Advertisers don't pay for impressions, but rather they pay when their ads get clicked on
2. We don't get to see all of the queries (keywords) in advance – **they come one-at-a-time**

What is adwords?

Adwords allows advertisers to bid on keywords



- We still want to match advertisers to keywords to satisfy budget constraints
- But can't treat it as a monolithic optimization problem like we did before
- Rather, we need an **online** algorithm

What is adwords?

Suppose we're given

- Bids that each advertiser is willing to make for each query

$$f(q, a)$$

query advertiser

(this is how much they'll pay **if the ad is clicked on**)

- Each is associated with a click-through rate

$$\cancel{ctr}(q, a) \qquad f(q, a) = ctr(q, a) \times p(q, a)$$

- Budget for each advertiser $b(a)$ (say for a 1-week period)
- A limit on how many ads can be returned for each query

What is adwords?

And, every time we see a query

- Return at most the number of ads that can fit on a page
- And which won't overrun the budget of the advertiser (if the ad is clicked on)

Ultimately, what we want is an algorithm that maximizes **revenue** – the number of ads that are clicked on, multiplied by the bids on those ads

Competitiveness ratio

What we'd like is:

the revenue should be as close as possible to what we *would* have obtained if we'd seen the whole problem up front

(i.e., if we didn't have to solve it online)

We'll define the **competitive ratio** as:

$$\frac{\text{revenue of our algorithm}}{\text{revenue of an optimal algorithm}}$$

see http://infolab.stanford.edu/~ullman/mmds/book.pdf for more detailed definition

Greedy solution

Let's start with a simple version of the problem…

1. One ad per query
2. Every advertiser has the same budget
3. Every ad has the same click through rate
4. All bids are either 0 or 1

(either the advertiser wants the query, or they don't)

Greedy solution

Then the greedy solution is…

- Every time a new query comes in, select any advertiser who has bid on that query (who has budget remaining)
- What is the competitive ratio of this algorithm?

Greedy solution

	budget	bid on
A	\$2	"x"
B	\$2	"x", "y"

queries:	x	x	y	y	
greedy:	B (\$1)	B (\$0)	?	?	\$2
optimal:	A (\$1) A (\$0)		B (\$1)	B (\$0)	\$4

competitive ratio: $= \frac{\$2}{\$4} = \frac{1}{2}$

The balance algorithm

A better algorithm…

- Every time a new query comes in, amongst advertisers who have bid on this query, **select the one with the largest remaining budget**

- How would this do on the same sequence?

	x	x	y	y	
Greedy:	B($1)	A($1)	B($0)	?	$3
opt:	A	A	B	B	$4

$C.R. = \frac{3}{4}$

The balance algorithm

A better algorithm…

- Every time a new query comes in, amongst advertisers who have bid on this query, **select the one with the largest remaining budget**

- In fact, the competitive ratio of this algorithm (still with equal budgets and fixed bids) is (1 – 1/e) ~ 0.63

see http://infolab.stanford.edu/~ullman/mmds/book.pdf for proof

The balance algorithm

What if bids aren't equal?

Bidder	Bid (on q)	Budget
A	1	110
B	10	100

queries q q q q q q q q q q

Greedy A A A A A A A A A A

opt. B . . . .

\$10

\$100

C.R. $\frac{1}{10}$

The balance algorithm

What if bids aren't equal?

Bidder	Bid (on q)	Budget
A	1	~~10~~ 100
B	100	10000

q . . . . 100 times . . . . q

Greedy A . . . A $100

op-1 . B . . . . B $10000

C.R. $\frac{1}{100}$

The balance algorithm v2

We need to make two modifications

- We need to consider the bid amount when selecting the advertiser, and bias our selection toward higher bids
- We also want to use some of each advertiser's budget

(so that we don't just ignore advertisers whose budget is small)

The balance algorithm v2

Advertiser: A_i

fraction of budget remaining: f_i $\in [0, 1]$

bid on query *q*: $x_i(q)$

Assign queries to whichever advertiser maximizes:

$$\Psi_i(q) = x_i(q) \cdot \underbrace{(1 - e^{-f_i})}_{\begin{cases} 1 - \frac{1}{e} & \text{if } f_i = 1 \\ 0 & \text{if } f_i = 0 \end{cases}}$$

(could multiply by click-through rate if click-through rates are not equal)

The balance algorithm v2

Properties

0.63

- This algorithm has a competitive ratio of $(1 - \frac{1}{e})$.

- In fact, there **is no online algorithm** for the adwords problem with a competitive ratio **better than** $(1 - \frac{1}{e})$.

(proof is too deep for me...)

Adwords

So far we have seen…

- An **online** algorithm to match advertisers to users (really to queries) that handles both **bids** and **budgets**
- We wanted our **online** algorithm to be as good as the **offline** algorithm would be – we measured this using the **competitive ratio**
- Using a specific scheme that favored high bids while trying to balance the budgets of all advertisers, we achieved a ratio of $(1 - \frac{1}{e})$.
- And no better online algorithm exists!

Adwords

We **haven't** seen...

- AdWords actually uses a **second-price** auction (the winning advertiser pays the amount that the **second** highest bidder bid)
- Advertisers don't bid on specific queries, but inexact matches ('broad matching') – i.e., queries that include subsets, supersets, or synonyms of the keywords being bid on

Questions?

Further reading:

- Mining of Massive Datasets – "The Adwords Problem" http://infolab.stanford.edu/~ullman/mmds/book.pdf
- AdWords and Generalized On-line Matching (A. Mehta) http://web.stanford.edu/~saberi/adwords.pdf

CSE 158 – Lecture 15

Web Mining and Recommender Systems

Bandit algorithms

So far…

1. We've seen algorithms to handle **budgets** between users (or queries) and advertisers
2. We've seen an **online** version of these algorithms, where queries show up one at a time
3. Next, how can we **learn** about which ads the user is likely to click on in the first place?

Bandit algorithms

3. How can we **learn** about which ads the user is likely to click on in the first place?

- If we see the user click on a car ad once, we know that (maybe) they have an interest in cars
  - So… we know they like car ads, should we keep recommending them car ads?

- **No,** they'll become less and less likely to click it, and in the meantime we won't learn anything new about what **else** the user might like

Bandit algorithms

- **Sometimes** we should surface car ads (which we know the user likes),
- **but sometimes,** we should be willing to take a risk, so as to learn what **else** the user might like

one-armed bandit

Setup

. . .

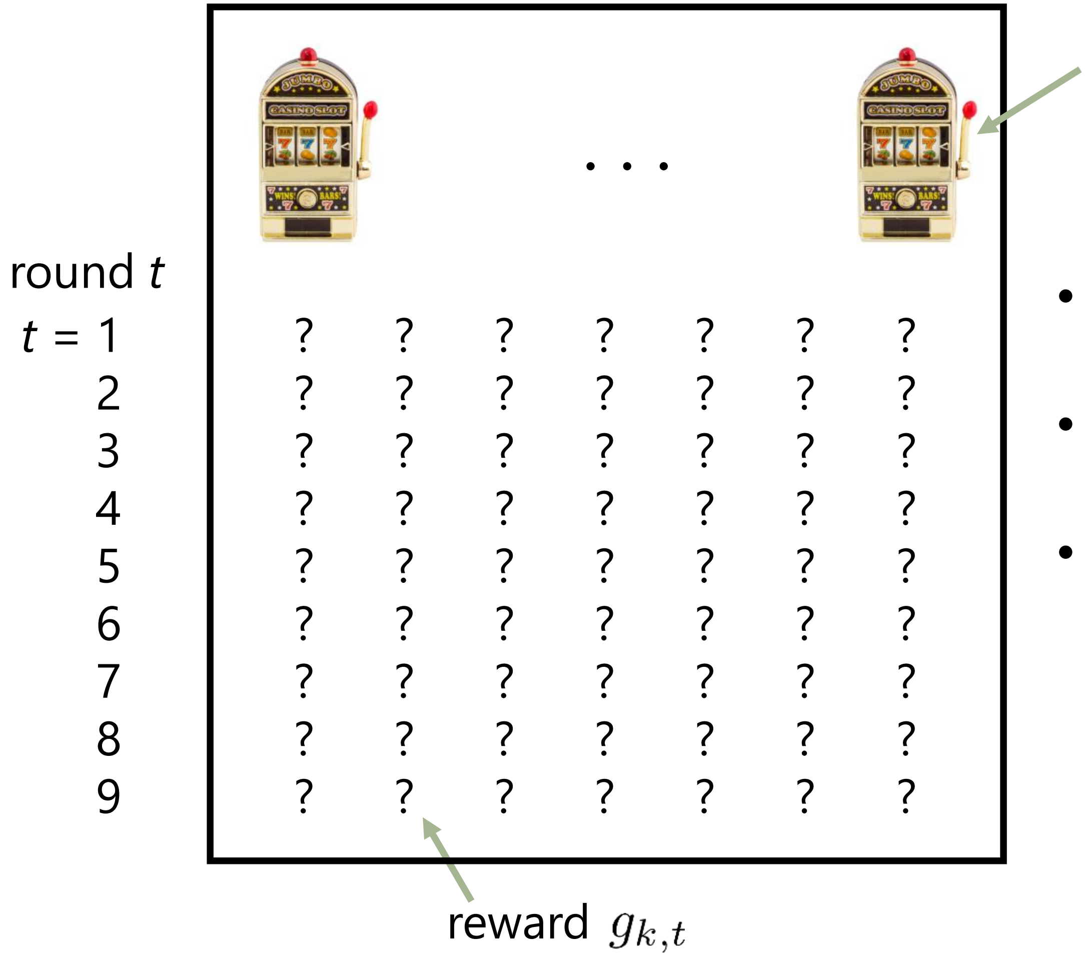
K bandits (i.e., *K* arms)

round *t*							
t = 1	1	0	0	1	1	0	1
2	0	0	1	1	0	1	0
3	1	1	1	0	1	1	0
4	1	0	1	0	0	0	0
5	0	1	0	0	1	0	0
6	0	0	0	0	1	1	0
7	0	0	1	0	0	1	0
8	0	1	1	0	0	1	1
9	1	0	1	0	0	0	1

reward $g_{k,t}$

- At each round *t*, we select an arm to pull
- We'd like to pull the arm to maximize our total reward

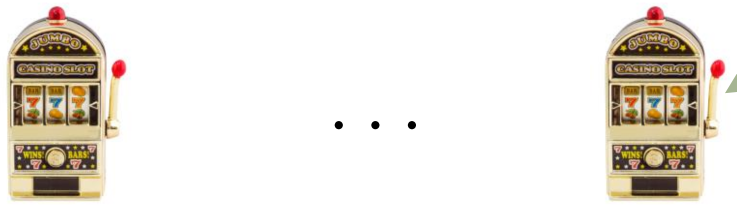
Setup



K bandits (i.e., *K* arms)

- At each round *t*, we select an arm to pull
- We'd like to pull the arm to maximize our total reward
- **But –** we don't get to see the reward function!

Setup



K bandits (i.e., K arms)

round t							
t = 1	**1**	?	?	?	?	?	?
2	?	**0**	?	?	?	?	?
3	?	?	?	?	**1**	?	?
4	?	?	?	?	**0**	?	?
5	**0**	?	?	?	?	?	?
6	?	?	?	**0**	?	?	?
7	?	?	?	?	?	**1**	?
8	?	?	?	?	?	?	**1**
9	?	?	?	?	?	?	**1**

reward $g_{k,t}$

- At each round t, we select an arm to pull
- We'd like to pull the arm to maximize our total reward
- **But –** we don't get to see the reward function!
- All we get to see is the reward we got **for the arm we picked** at each round

Setup

K : number of arms (ads)

n : number of rounds

$g_t = (g_{1,t}, \dots, g_{K,t}) \in [0,1]^K$: rewards

$l_t \in \{1, \dots, K\}$: which arm we pick at each round

$g_{l_t,t} \in [0,1]$: how much (0 or 1) this choice wins us

want to minimize **regret:**

$$R_n = (\max_{i=1\dots K} \mathbb{E} \textstyle\sum_{t=1}^n g_i, t) - \mathbb{E} \textstyle\sum_{t=1}^n g_{l_t,t}$$

reward we **could** have got,
if we had played optimally

reward our strategy would
get (in expectation)

Goal

- We need to come up with a **strategy** for selecting arms to pull (ads to show) that would maximize our expected reward
- For the moment, we're assuming that rewards are static, i.e., that they don't change over time

Strategy 1 – "epsilon first"

- Pull arms at random for a while to learn the distribution, then just pick the best arm
- (show random ads for a while until we learn the user's preferences, then just show what we know they like)

$\epsilon \cdot n$	: Number of steps to sample randomly
$(1-\epsilon) \cdot n$	: Number of steps to choose optimally

Strategy 1 – "epsilon first"

- Pull arms at random for a while to learn the distribution, then just pick the best arm
- (show random ads for a while until we learn the user's preferences, then just show what we know they like)

"best lev"

$$= \max_k \sum_{t=1}^{\epsilon \cdot N} \delta(L_t = k)\, g_{k,t}$$

Strategy 2 – "epsilon greedy"

- Select the best lever most of the time, pull a random lever some of the time
- (show random ads sometimes, and the best ad most of the time)

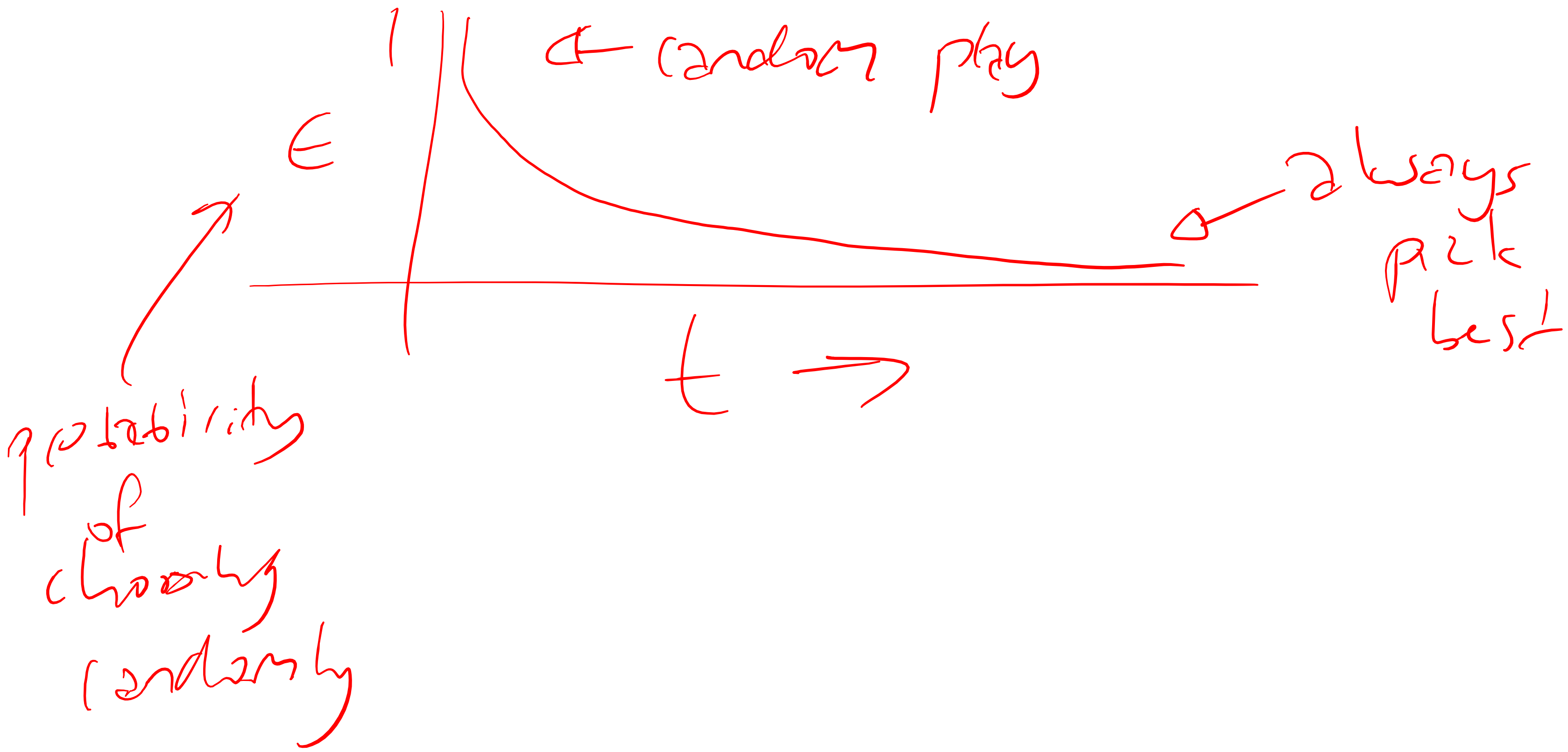
ϵ : Fraction of times to sample randomly

$(1 - \epsilon)$: Fraction of times to choose optimally

- Empirically, worse than epsilon-first
- Still doesn't handle context/time

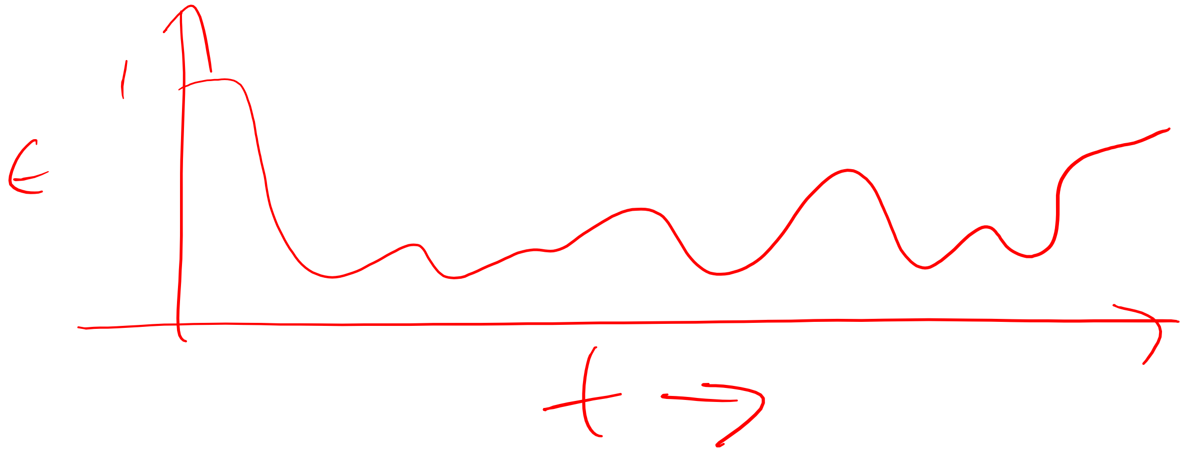
Strategy 3 – "epsilon decreasing"

- Same as epsilon-greedy (Strategy 2), but epsilon decreases over time



Strategy 4 – "**Adaptive** epsilon greedy"

- Similar to as epsilon-decreasing (Strategy 3), but epsilon can increase **and** decrease over time



- payout is less than expected $\Rightarrow$ increase ϵ
- otherwise $\rightarrow$ decrease ϵ

Extensions

- The reward function may not be **static,** i.e., it may change each round according to some process
- It could be chosen by an **adversary**
- The reward may not be [0,1] (e.g. clicked/not clicked), but instead a could be a real number (e.g. revenue), and we'd want to estimate the distribution over rewards

Extensions – Contextual Bandits

- There could be **context** associated with each time step
  - The query the user typed
  - What the user saw during the **previous** time step
  - What other actions the user has recently performed
  - Etc.

$$y_{k,t} = X(t) \cdot \theta_k$$

Applications (besides advertising)

- Clinical trials

(assign drugs to patients, given uncertainty about the outcome of each drug)

- Resource allocation

(assign person-power to projects, given uncertainty about the reward that different projects will result in)

- Portfolio design

(invest in ventures, given uncertainty about which will succeed)

- Adaptive network routing

(route packets, without knowing the delay unless you send the packet)

Questions?

Further reading:

Tutorial on Bandits:

https://sites.google.com/site/banditstutorial/

CSE 158 – Lecture 15

Web Mining and Recommender Systems

Case study – Turning down the noise

Turning down the noise

“Turning down the noise in the Blogosphere”

(By Khalid El-Arini, Gaurav Veda, Dafna Shahaf, Carlos Guestrin)

Goals:

1. Help to **filter** huge amounts of content, so that users see content that is **relevant** – rather than seeing popular content over and over again
2. Maximize **coverage** so that a variety of different content is recommended
3. Make recommendations that are **personalized** to each user

some slides http://www.select.cs.cmu.edu/publications/paperdir/kdd2009-elarini-veda-shahaf-guestrin.pptx

Turning down the noise

"Turning down the noise in the Blogosphere"

(By Khalid El- los Guestrin)

1. Help to at users see conte g popular

2. Maximize nt content is recommended

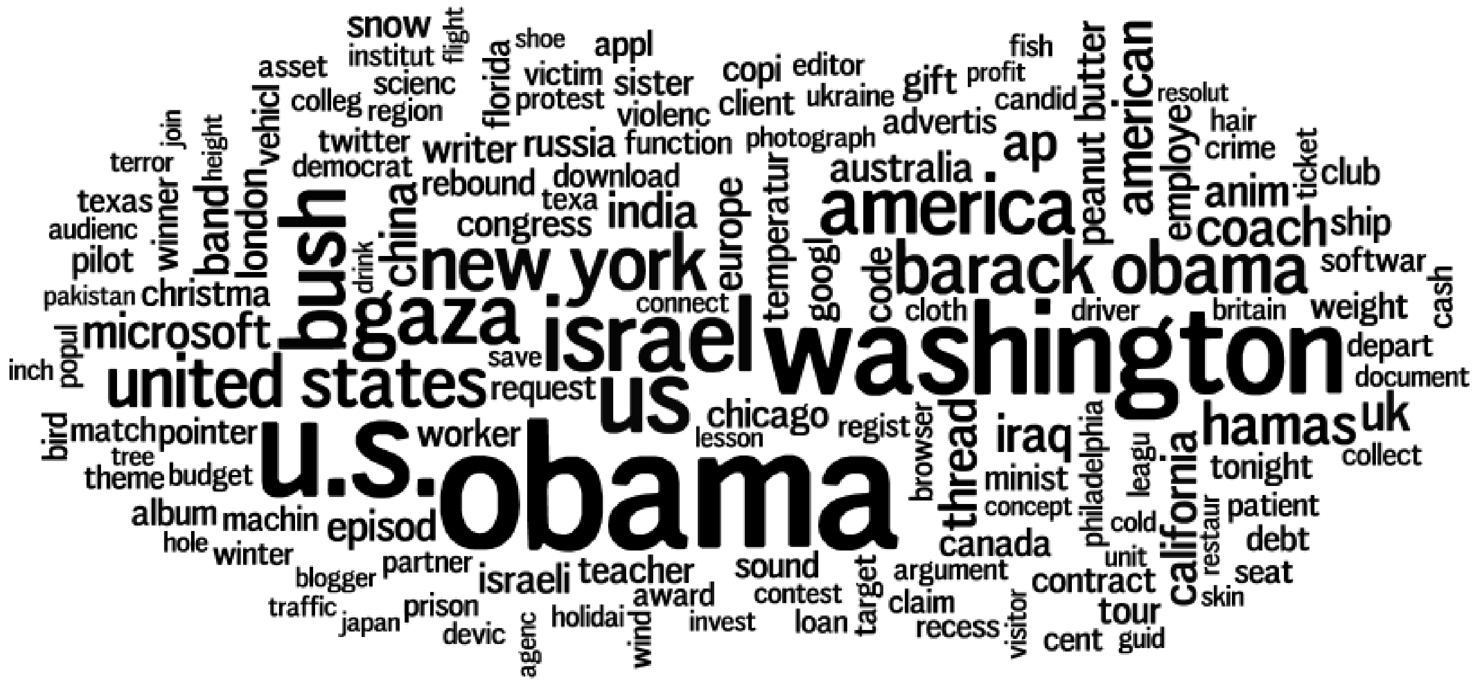
3. Make recommendations that are **personalized** to each user

Similar to our goals with **bandit algorithms**

- **Exploit** by recommending content that we user is likely to enjoy (personalization)
- **Explore** by recommending a variety of content (coverage)

Turning down the noise

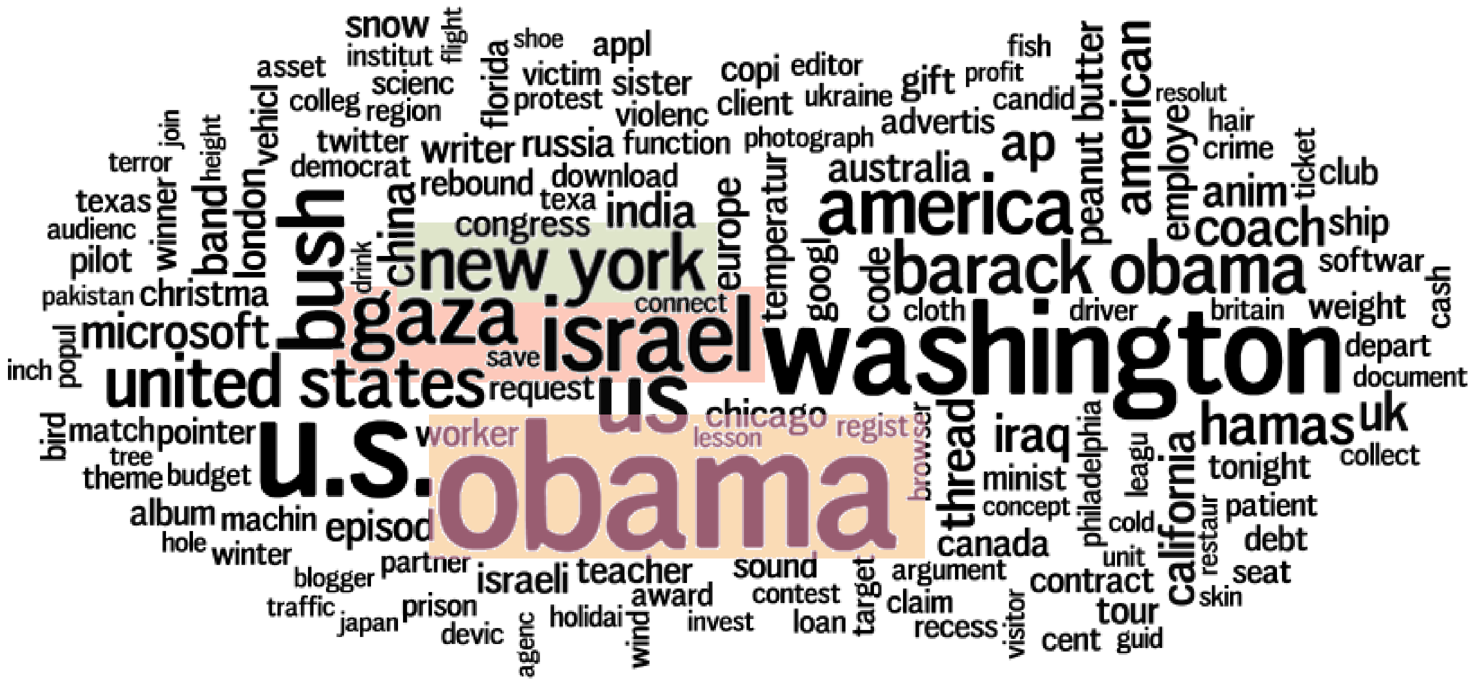
1. Help to **filter** huge amounts of content, so that users see content that is **relevant**



from http://www.select.cs.cmu.edu/publications/paperdir/kdd2009-elarini-veda-shahaf-guestrin.pptx

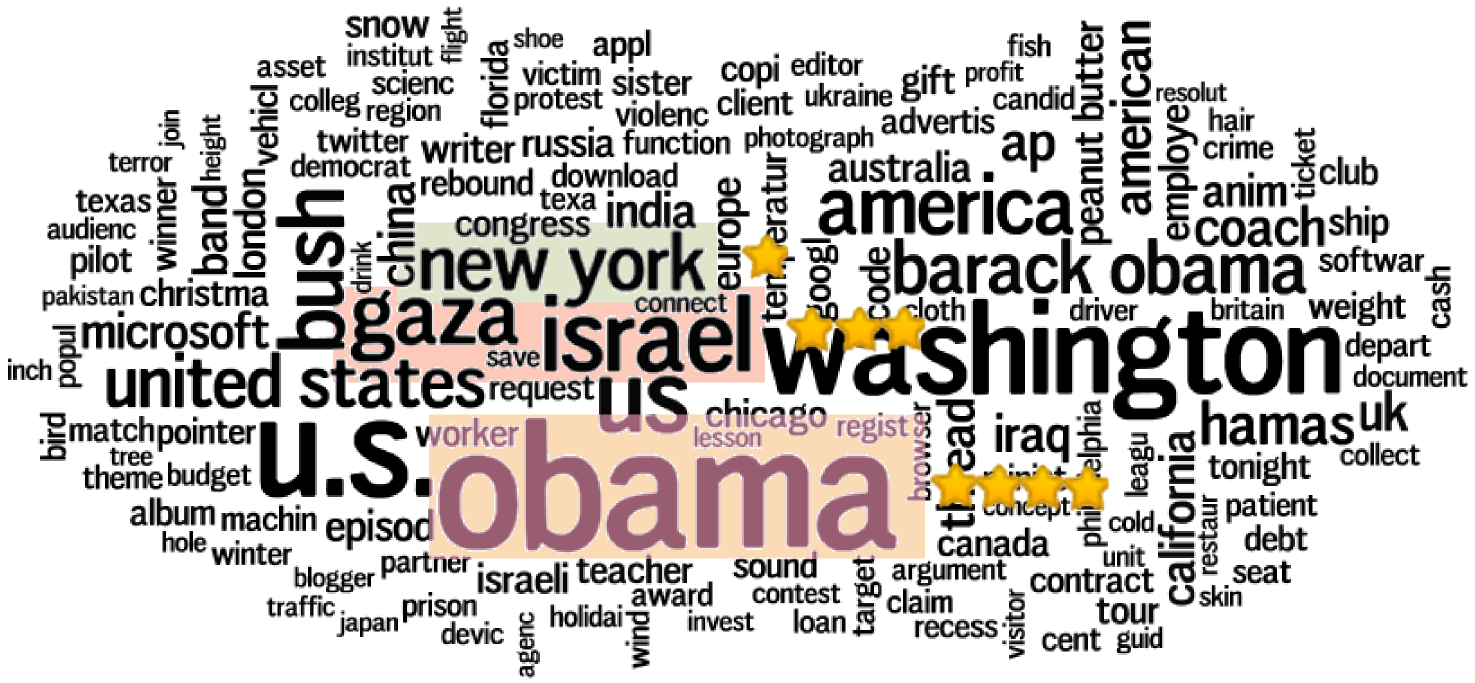
Turning down the noise

2. Maximize **coverage** so that a variety of different content is recommended



Turning down the noise

3. Make recommendations that are **personalized** to each user



1. Data and problem setting

- **Data:** Blogs ("the blogosphere")

THE HUFFINGTON POST

Blogger™

INSTAPUNDIT.COM

WORDPRESS.ORG

engadget

boingboing
A Directory Of Wonderful Things

lifehacker

Wonkette

FANHOUSE

TPM

GOAL
The New York Times Soccer Blog

- **Comparison:** other systems that aggregate blog data

Google™ Blog Search BETA

Y! buzz™ beta

digg™

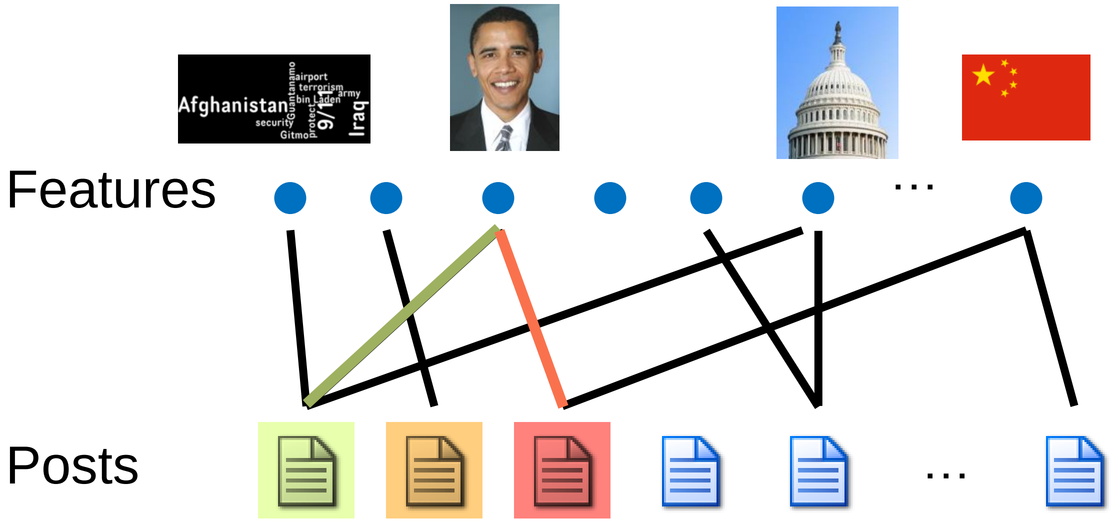
blogpulse™
a service of Nielsen BuzzMetrics

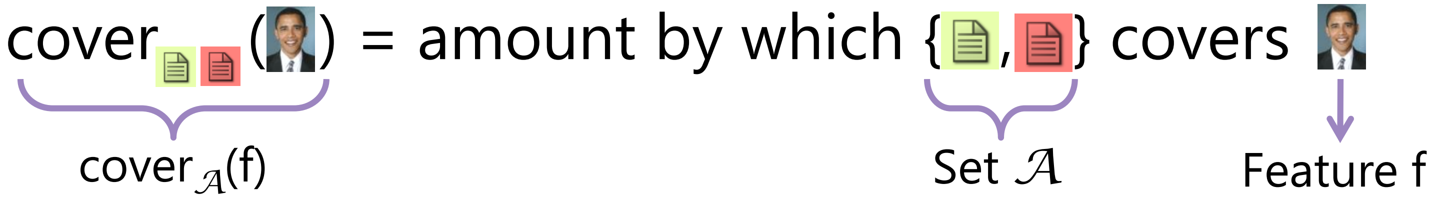
1. Data and problem setting

- **Low-level features**:
  Bags-of-words (week 6/7), noun phrases, named entities

- **High-level features:**
  Low-dimensional document representations, topic models (week 3, week 7)

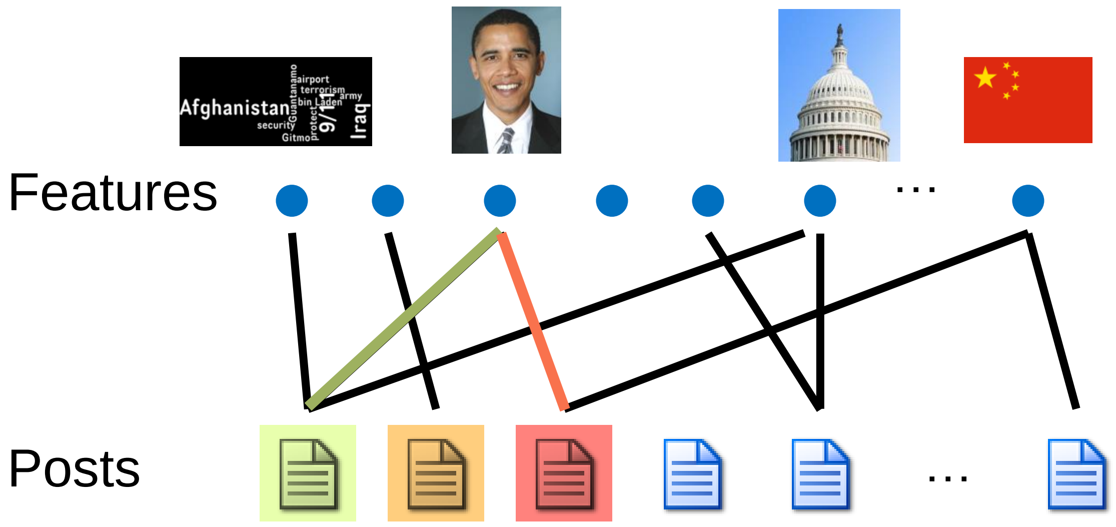
2. Maximize coverage





- We'd like to choose a (small) set of documents that maximally **cover** the set of features the user is interested in (later)

2. Maximize coverage



$$F(\mathcal{A}) = \sum_{f \in \mathcal{U}} w_f \cdot cover_{\mathcal{A}}(f)$$

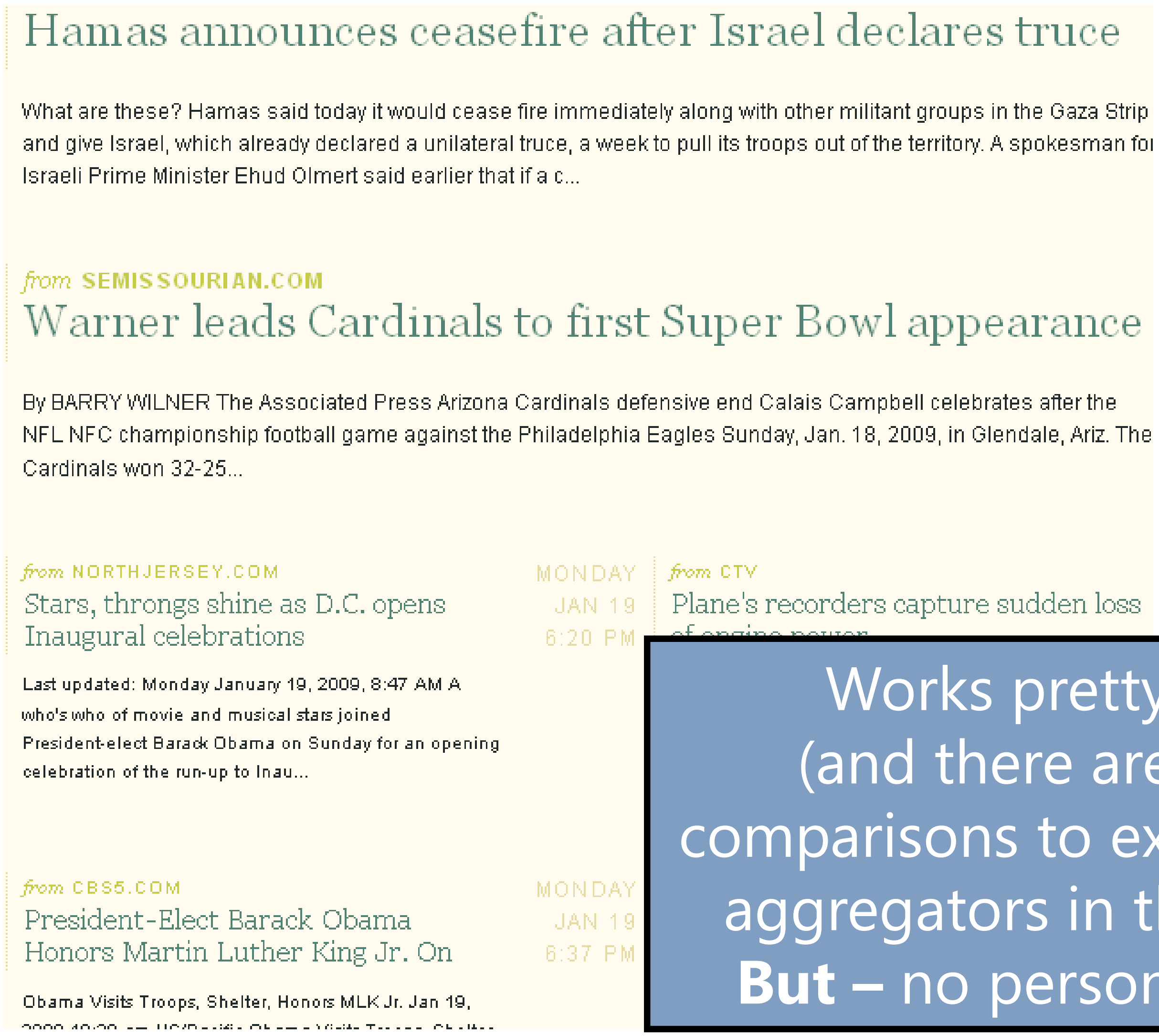
feature set

feature importance

coverage of feature by *A*

- Can be done (approximately) by selecting documents greedily (with an approximation ratio of (1 – 1/e)

2. Maximize **coverage**



Hamas announces ceasefire after Israel declares truce

What are these? Hamas said today it would cease fire immediately along with other militant groups in the Gaza Strip and give Israel, which already declared a unilateral truce, a week to pull its troops out of the territory. A spokesman fo Israeli Prime Minister Ehud Olmert said earlier that if a c...

from SEMISSOURIAN.COM

Warner leads Cardinals to first Super Bowl appearance

By BARRY WILNER The Associated Press Arizona Cardinals defensive end Calais Campbell celebrates after the NFL NFC championship football game against the Philadelphia Eagles Sunday, Jan. 18, 2009, in Glendale, Ariz. The Cardinals won 32-25...

from NORTHJERSEY.COM

MONDAY JAN 19 6:20 PM

Stars, throngs shine as D.C. opens Inaugural celebrations

Last updated: Monday January 19, 2009, 8:47 AM A who's who of movie and musical stars joined President-elect Barack Obama on Sunday for an opening celebration of the run-up to Inau...

from CTV

Plane's recorders capture sudden loss

from CBS5.COM

MONDAY JAN 19 6:37 PM

President-Elect Barack Obama Honors Martin Luther King Jr. On

Obama Visits Troops, Shelter, Honors MLK Jr. Jan 19,

Works pretty well!
(and there are some comparisons to existing blog aggregators in the paper)
But – no personalization

3. Personalize

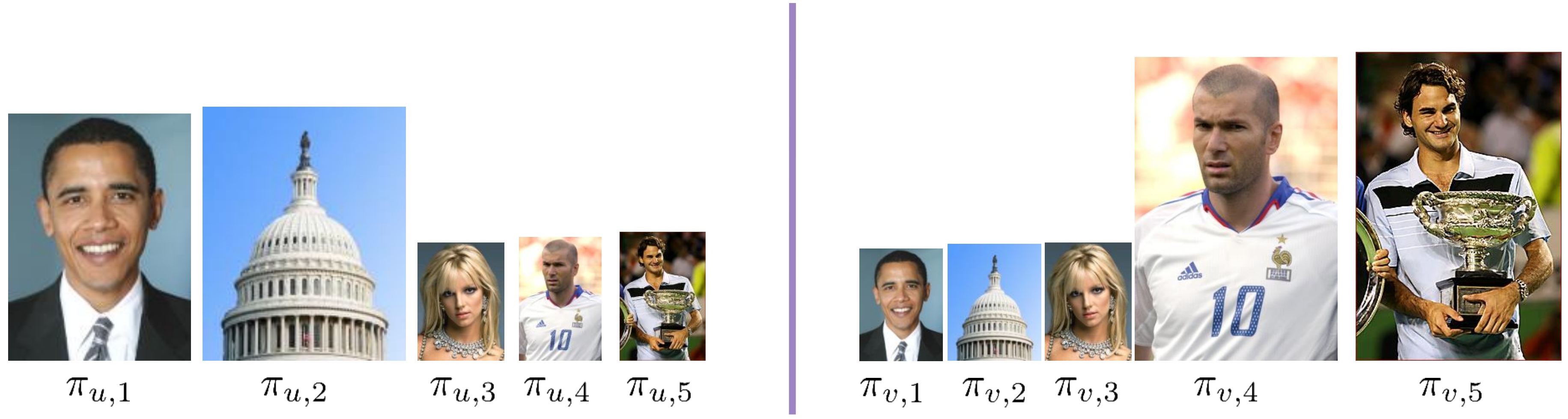
$$F(\mathcal{A}) = \sum_{f \in \mathcal{U}} \pi_{u,f} \cdot w_f \cdot cover_{\mathcal{A}}(f)$$

feature set

personalized feature importance

coverage of feature by *A*

- Need to learn weights for each user based on their **feedback** (e.g. click/not-click) on each post



3. Personalize

$$F(\mathcal{A}) = \sum_{f \in \mathcal{U}} \pi_{u,f} \cdot w_f \cdot cover_{\mathcal{A}}(f)$$

feature set

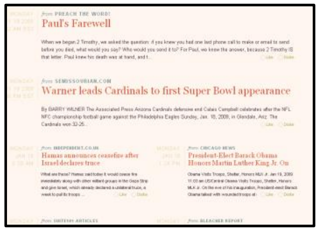
personalized feature importance

coverage of feature by *A*

- Need to learn weights for each user based on their **feedback** (e.g. click/not-click) on each post

- A click (or thumbs-up) on a post **increases** $\pi_{u,f}$ for the features *f* associated with the post
- Not clicking (or thumbs-down) **decreases** $\pi_{u,f}$ for the features *f* associated with the post

3. Personalize


from PREACH THE WORD!
Paul's Farewell
When we began 2 Timothy, we asked the question: if you knew you had one last phone call to make or email to send before you died, what would you say? Who would you send it to? For Paul, we knew the answer, because 2 Timothy IS that letter. Paul knew his death was at hand, and t...
Like Dislike

from SEMISSOURIAN.COM
Warner leads Cardinals to first Super Bowl appearance
By BARRY WILNER The Associated Press Arizona Cardinals defensive end Calais Campbell celebrates after the NFL NFC championship football game against the Philadelphia Eagles Sunday, Jan. 18, 2009, in Glendale, Ariz. The Cardinals won 32-25...
Like Dislike

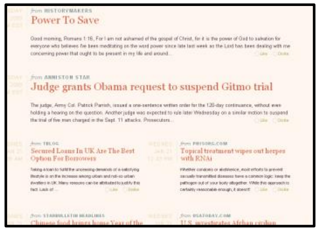
from INDEPENDENT.CO.UK
Hamas announces ceasefire after Israel declares truce
What are these? Hamas said today it would cease fire immediately along with other militant groups in the Gaza Strip and give Israel, which already declared a unilateral truce, a week to pull its troops ...
Like Dislike

from CHICAGO NEWS
President-Elect Barack Obama Honors Martin Luther King Jr. On
Obama Visits Troops, Shelter, Honors MLK Jr. Jan 19, 2009 11:03 am US/Central Obama Visits Troops, Shelter, Honors MLK Jr. On the eve of his inauguration, President-elect Barack Obama talked with wounded troops at
Like Dislike

from SHITTY!! ARTICLES

from BLEACHER REPORT

feedback on articles suggested


from HISTORYMAKERS
Power To Save
Good morning, Romans 1:16, For I am not ashamed of the gospel of Christ, for it is the power of God to salvation for everyone who believes I've been meditating on the word power since late last week as the Lord has been dealing with me concerning power that ought to be present in my life and around...
Like Dislike

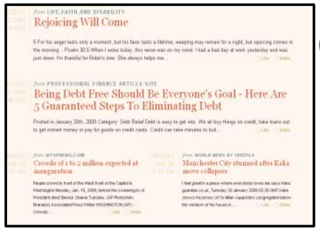
from ANNISTON STAR
Judge grants Obama request to suspend Gitmo trial
The judge, Army Col. Patrick Parrish, issued a one-sentence written order for the 120-day continuance, without even holding a hearing on the question. Another judge was expected to rule later Wednesday on a similar motion to suspend the trial of five men charged in the Sept. 11 attacks. Prosecutors...
Like Dislike

from TBLOG
Secured Loans In UK Are The Best Option For Borrowers
Taking a loan to fulfill the increasing demands of a satisfying lifestyle is on the increase among urban and not-so urban dwellers in UK. Many reasons can be attributed to justify this fact. Lack of ...
Like Dislike

from PHYSORG.COM
Topical treatment wipes out herpes with RNAi
Whether condoms or abstinence, most efforts to prevent sexually transmitted diseases have a common logic: keep the pathogen out of your body altogether. While this approach is certainly reasonable enough, it doesn't
Like Dislike

from STARBULLETIN HEADLINES
Chinese food brings home Year of the

from USATODAY.COM
U.S. investigates Afghan civilian

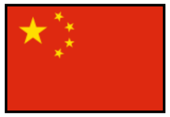

from LIFE,FAITH,AND DISABILITY
Rejoicing Will Come
5 For his anger lasts only a moment, but his favor lasts a lifetime; weeping may remain for a night, but rejoicing comes in the morning. - Psalm 30:5 When I woke today, this verse was on my mind. I had a bad day at work yesterday and was just down. I'm thankful for Robin's love. She always helps me...
Like Dislike

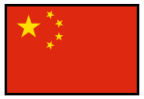
from PROFESSIONAL FINANCE ARTICLE SITE
Being Debt Free Should Be Everyone's Goal - Here Are 5 Guaranteed Steps To Eliminating Debt
Posted in January 20th, 2009 Category: Debt Relief Debt is easy to get into. We all buy things on credit, take loans out to get instant money or pay for goods on credit cards. Credit can take minutes to buil...
Like Dislike

from WTOPNEWS.COM
Crowds of 1 to 2 million expected at inauguration
People crowd in front of the West front of the Capitol in Washington Monday, Jan. 19, 2009, before the swearing-in of President-elect Barack Obama Tuesday. (AP Photo/Alex Brandon) Associated Press Writer WASHINGTON (AP) -- Crowds ...
Like Dislike

from WORLD NEWS BY SPEEPLE
Manchester City stunned after Kaka move collapses
I feel great in a place where everybody loves me says Kaka guardian.co.uk, Tuesday 20 January 2009 02.20 GMT Kaka shows his jersey off to Milan supporters congregated below the window of his house in ....
Like Dislike

weighted interest in topic





day 1

day 2

day 3

Summary

- Want an algorithm that **covers** the set of topics that each user wants to see
- Articles can be chosen **greedily**, while still covering the topics nearly optimally
- The topics to cover can also be **personalized** to each user, by updating their preferences in response to user feedback
- **Evaluated** on real blog data (see paper!)

This week

We've looked at three features to handle the properties unique to online advertising

1. We need to handle **budgets** at the level of users and content (Matching problems)
2. We need algorithms that can operate **online** (i.e., as users arrive one-at-a-time) (AdSense)
3. We need to algorithms that exhibit an explore-exploit tradeoff (Bandit algorithms)

Questions?

Further reading:

- Turning down the noise in the blogosphere (by Khalid El-Arini, Gaurav Veda, Dafna Shahaf, Carlos Guestrin)

http://www.select.cs.cmu.edu/publications/paperdir/kdd2009-elarini-veda-shahaf-guestrin.pptx

http://www.cs.cmu.edu/~dshahaf/kdd2009-elarini-veda-shahaf-guestrin.pdf