NOT IN THE EXAM

15-826: Multimedia Databases and Data Mining

Lecture #32: BONUS LECTURE

Approximate Counting

C. Faloutsos

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Material

- Christopher Palmer, Phillip B. Gibbons and Christos Faloutsos,*ANF: A Fast and Scalable Tool for Data Mining in Massive Graphs*, KDD 2002
- *Efficient and Tunable Similar Set Retrieval*, by Aristides Gionis, Dimitrios Gunopulos and Nikos Koudas, SIGMOD, 2001.
- *New sampling-based summary statistics for improving approximate query answers*, by Phillip B. Gibbons and Yossi Matias, ACM SIGMOD, 1998.

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Outline

- **Flajolet-Martin (and Cohen) – vocabulary size (Problem #1)**
- Application: Approximate Neighborhood function (ANF)
- other, powerful approximate counting tools (Problem #2, #3)

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Problem #1

- Given a multiset (eg., words in a document)
- find the vocabulary size (#, after dup. elimination)

A A A B A B A C A B

Voc. Size = 3 = |{A, B, C}|

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Thanks to

- Chris Palmer (Vivisimo->IBM)

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Problem #2

- Given a multiset
- compute approximate high-end histogram = hot-list query = (*k* most common words, and their counts)

A A A B A B A C A B D D D D D

(for k=2:
A#: 6
D#: 5)

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Problem #3

- Given two documents
- compute quickly their similarity (#common words/ #total-words) == Jaccard coefficient

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Problem #1

- Given a multiset (eg., words in a document)
- find the vocabulary size V (#, after dup. elimination)
- using space O(V), or O(log(V))

(Q1: Applications?)

(Q2: How would you solve it?)

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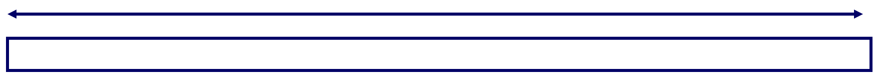
Basic idea (Cohen)

large bit string, initially all zeros



A

A

C

9

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Basic idea (Cohen)

large bit string, initially all zeros

A

hash!

A

C

10

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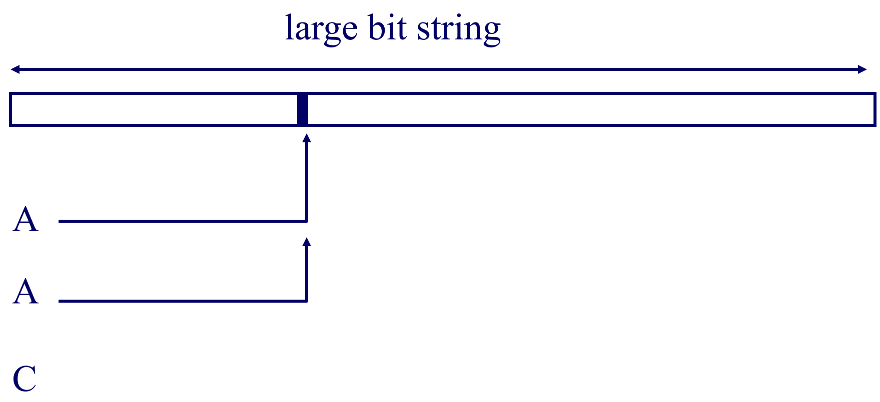
Basic idea (Cohen)



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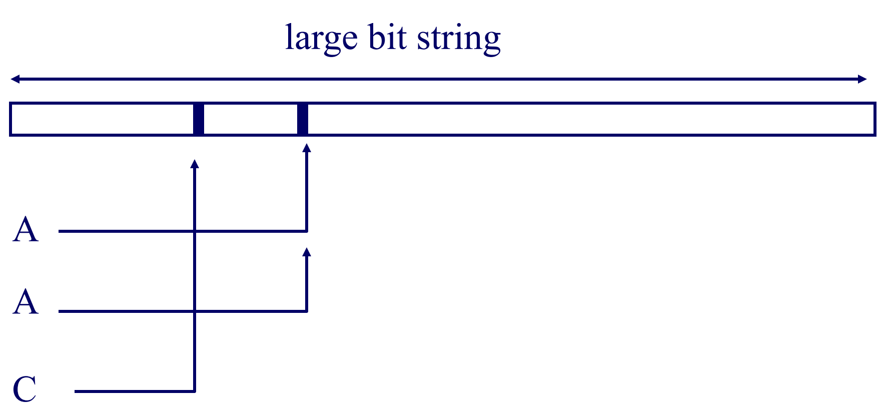
Basic idea (Cohen)



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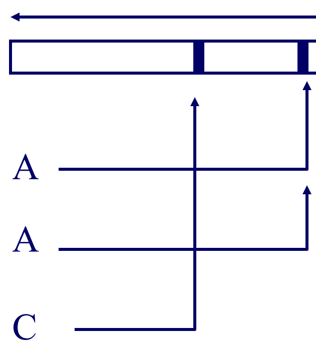
Basic idea (Cohen)

large bit string



the rightmost position depends on the vocabulary size
(and so does the left-most)

Repeat, with several hashing functions, and merge the estimates

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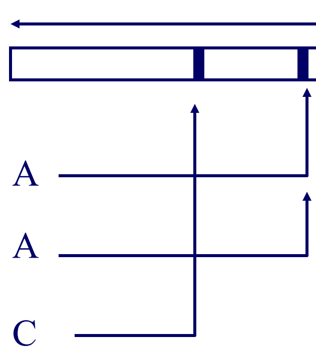
Basic idea (Cohen)

large bit string



the rightmost position depends on the vocabulary size
(and so does the left-most)

Can we do it in less space??

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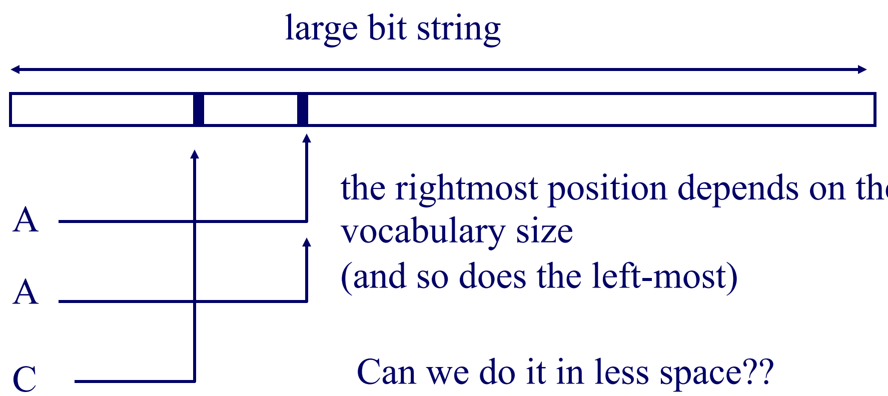
Basic idea (Cohen)



the rightmost position depends on the vocabulary size
(and so does the left-most)

Can we do it in less space??
YES

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How?

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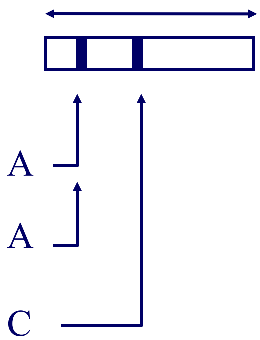
Basic idea (Flajolet-Martin)

O(log(V)) bit string (V: voc. size)



first bit: with prob. ½
second: with prob. ¼
...
i-th: with prob. ½**i

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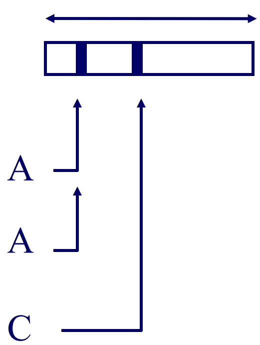
Basic idea (Flajolet-Martin)

O(log(V)) bit string (V: voc. size)



again, the rightmost bit
'reveals' the vocabulary size

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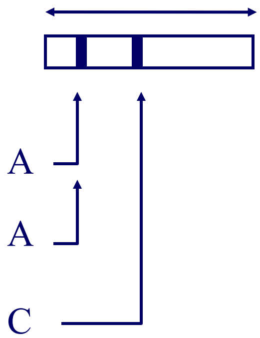
Basic idea (Flajolet-Martin)

O(log(V)) bit string (V: voc. size)



again, the rightmost bit 'reveals' the vocabulary size

Eg.: V=4, will probably set the 2nd bit, etc

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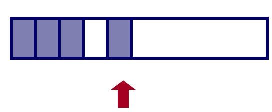
Flajolet-Martin

- Hash multiple values of *X* to same signature
  - Hash each *x* to a bit, using exponential distr.
  - ½ map to bit 0, ¼ map to bit 1, …
- Do several different mappings and average
  - Gives better accuracy
  - Estimate is: 2^b / .77351 / *BIAS*
    - *b* ~ rightmost '1', and actually:



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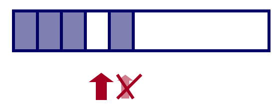
Flajolet-Martin

- Hash multiple values of *X* to same signature
  - Hash each *x* to a bit, using exponential distr.
  - ½ map to bit 0, ¼ map to bit 1, …
- Do several different mappings and average
  - Gives better accuracy
  - Estimate is: $2^b / .77351 / BIAS$
    - *b : average least zero bit in the bitmask*
    - *bias : 1+.31/k for k different mappings*
- Flajolet & Martin prove this works



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FM Approx. Counting Alg.

Assume $X = \{ 0, 1, \ldots, V\text{-}1 \}$
FOR $i = 1$ to k DO *bitmask[i] = 0000…00*
Create k random hash functions, $hash_i$
FOR each element x of M DO
    FOR $i = 1$ to k DO
        $h = hash_i(x)$
        bitmask[i] = bitmask[i] LOR h
Estimate: b = average least zero bit in *bitmask[i]*
            $2^b/.77351/(1+.31/k)$

- How many bits? *log V* + small constant
- What hash functions?

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Random Hash Functions

- Can use linear hash functions. Pick random (a_i, b_i) and then the hash function is:
  - $lhash_i(x) = a_i * x + b_i$
- Gives uniform distribution over the bits
- To make this exponential, define
  - $hash_i(x)$ = least zero bit in $lhash_i(x)$
- Hash functions easy to create and fast to use

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Conclusions

- Want to measure # of distinct elements
- Approach #1: (Flajolet-Martin)
  - Map elements to random bits
  - Keep bitmask of bits
  - Estimate is $O(2^b)$ for least zero-bit b
- Approach #2: (Cohen)
  - Create random permutation of elements
  - Keep least element seen
  - Estimate is: $O(1/le)$ for least rank le

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Approximate counting

- Flajolet-Martin (and Cohen) – vocabulary size
- **Application: Approximate Neighborhood function (ANF)**
- other, powerful approximate counting tools

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details

Fast Approximation of the "neighborhood" Function for Massive Graphs

Christopher R. Palmer
Phillip B. Gibbons
Christos Faloutsos

KDD 2001

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Motivation

- What is the diameter of the Web?
- What is the effective diameter of the Web?
- Are the telephone caller-callee graphs for the U.S. similar to the ones in Europe?
- Is the citation graph for physics different from the one for computer science?
- Are users in India further away from the core of the Internet than those in the U.S.?

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Proposed Tool: neighborhood

Given graph $G=(V,E)$

$N(h)$ = # pairs within h hops or less

= **neighborhood function**

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Proposed Tool: neighborhood

Given graph $G=(V,E)$

$N(h)$ = # pairs within h hops or less

= **neighborhood function**

$N(u,h)$ = # neighbors of node u, within h hops or less

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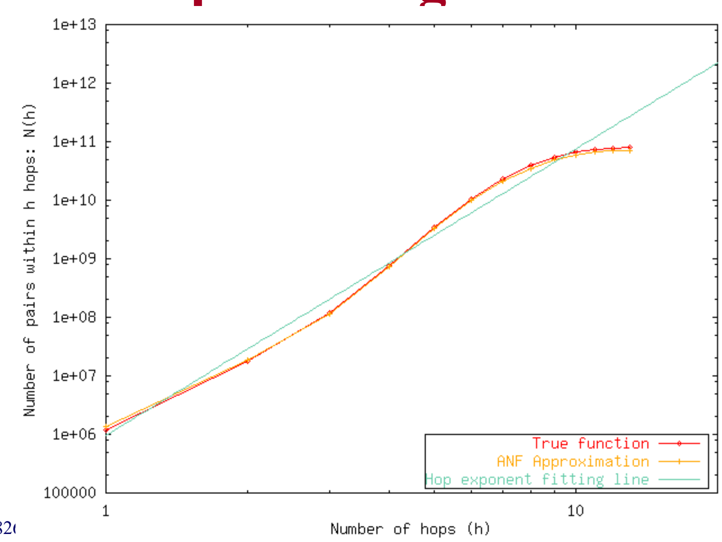
Example of neighborhood



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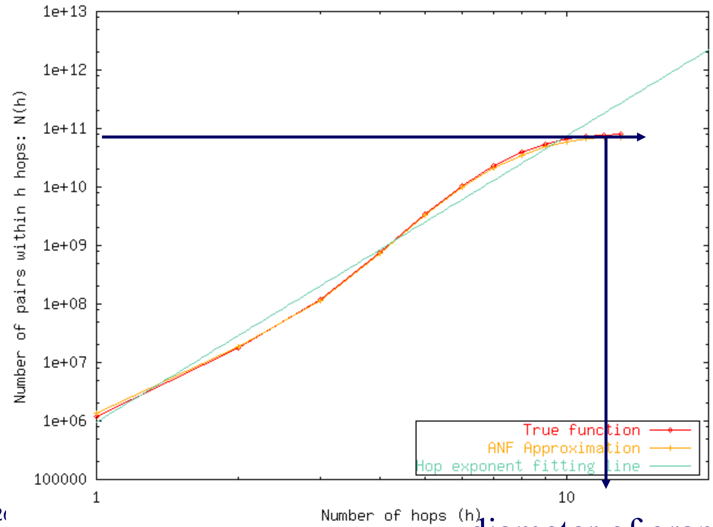
Example of neighborhood



~diameter of graph

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Requirements (for massive g

- *Error guarantees*
- *Fast*: (and must scale linearly with graph)
- *Low storage requirements*: massive graphs!
- *Adapts to available memory*
- *Sequential scans of the edges*
- Also estimates *individual neighborhood functions* |S(u,h)|
  – These are actually quite useful for mining

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How would you compute it?

- Repeated matrix multiply
  - Too slow $O(n^{2.38})$ at the very least
  - Too much memory $O(n^2)$
- Breadth-first search

  FOR each node u DO

  bf-search to compute $S(u,h)$ for each h
  - Best known exact solution!
  - We will use this as a reference
- Approximations? Only 1 that we know of which we will discuss when we evaluate it.

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Intuition

- Guess what we'll use?
  - Approximate Counting!
- Use very simple algorithm:

FOR each node u DO $S(u,0) = \{ (u,u) \}$ initialize to self-only

FOR $h = 1$ to *diameter* of G DO

FOR each node u DO $S(u,h) = S(u,h-1)$ can reach same things

FOR each edge (u,v) in G DO and add one more step

$S(u,h) = S(u,h) \cup \{ (u,v') : (v,v') \in S(v,h-1) \}$

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Intuition

- Guess what we'll use?
  - Approximate Counting!
- Use very simple algorithm:

(distinct) neighbors of u, within h hops

FOR each node u DO $S(u,0) = \{ (u,u) \}$ initialize to self-only

FOR $h = 1$ to *diameter* of G DO

FOR each node u DO $S(u,h) = S(u,h\text{-}1)$ can reach same things

FOR each edge (u,v) in G DO and add one more step

$S(u,h) = S(u,h) \cup \{ (u,v') : (v,v') \in S(v,h\text{-}1) \}$

(distinct) neighbors of v, within h-1 hops

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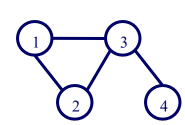
Trace

h=0



{(1,1)}

{(2,2)}

{(3,3)}

{(4,4)}

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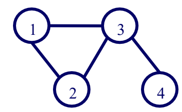
Trace

h=0	h=1
{(1,1)}	{(1,1)}
{(2,2)}	{(2,2)}
{(3,3)}	{(3,3)}
{(4,4)}	{(4,4)}



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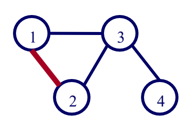
Trace

h=0	h=1
{(1,1)}	{(1,1)}
{(2,2)}	{(2,2)}
{(3,3)}	{(3,3)}
{(4,4)}	{(4,4)}



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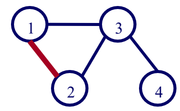
Trace

h=0 h=1



h=0	h=1
{(1,1)}	{(1,1), (1,2)}
{(2,2)}	{(2,2)}
{(3,3)}	{(3,3)}
{(4,4)}	{(4,4)}

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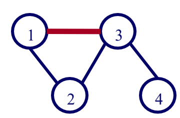
Trace



h=0	h=1
{(1,1)}	{(1,1), (1,2), (1,3)}
{(2,2)}	{(2,2)}
{(3,3)}	{(3,3)}
{(4,4)}	{(4,4)}

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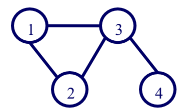
Trace

h=0 h=1



h=0	h=1
{(1,1)}	{(1,1), (1,2), (1,3)}
{(2,2)}	{(2,2), (2,1), (2,3)}
{(3,3)}	{(3,3), (3,1), (3,2), (3,4)}
{(4,4)}	{(4,4), (4,3)}

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Intuition

(distinct) neighbors of u, within h hops

- Guess what we' ll use?
  - Approximate Counting!
- Use very simple algorithm:

FOR each node *u* DO $S(u,0) = \{ (u,u) \}$ initialize to self-only

FOR $h = 1$ to *diameter* of *G* DO

    FOR each node *u* DO $S(u,h) = S(u,h-1)$ can reach same things and add one more step

    FOR each edge (u,v) in *G* DO

        $S(u,h) = S(u,h) \cup \{ (u,v') : (v,v') \in S(v,h-1) \}$

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Intuition

- Guess what we'll use?
  - Approximate Counting!
- Use very simple algorithm:

(distinct) neighbors of u, within h hops

FOR each node u DO $S(u,0) = \{ (u,u) \}$ initialize to self-only
FOR $h = 1$ to *diameter* of G DO
    FOR each node u DO $S(u,h) = S(u,h\text{-}1)$ can reach same things
    FOR each edge (u,v) in G DO and add one more step
        $S(u,h) = S(u,h) \cup \{ (u,v') : (v,v') \in S(v,h\text{-}1) \}$

- Too slow and requires too much memory
- Replace expensive set ops with bit ops

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details

ANF Algorithm #1

FOR each node, u, DO
    $M(u,0)$ = concatenation of $\boldsymbol{k}$ bitmasks of length $log\ n + \boldsymbol{r}$
        each bitmask has 1 bit set (exp. distribution)
DONE

FOR $h = 1$ to *diameter* of G DO
    FOR each node, u, DO $M(u,h) = M(u,h\text{-}1)$
    FOR each edge (u,v) in G DO
        $M(u,h) = (M(u,h)$ OR $M(v,h\text{-}1))$

    Estimate $N(h) = Sum(N(u,h)) = Sum\ 2^{b(u)} / .77351 / (1+.31/k)$
        where $b(u)$ = average least zero bit in $M(u,it)$
DONE

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ANF Algorithm #1

FOR each node, u, DO
  $M(u,0)$ = concatenation of $\boldsymbol{k}$ bitmasks of length $log\ n$ + $\boldsymbol{r}$
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  FOR each edge (u,v) in G DO
    $M(u,h) = (M(u,h)$ OR $M(v,h-1))$

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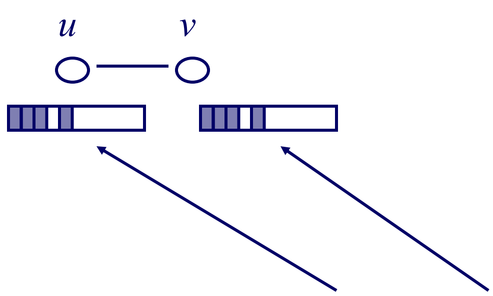
    where $b(u)$ = average least zero bit in $M(u,it)$
DONE

details

ANF Algorithm #1



whatever u can reach with h hops plus whatever v can reach with h-1 hops
Duplicates: automatically eliminated!

$M(u,h) = (M(u,h)$ OR $M(v,h-1))$

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Properties

- **Has error guarantees**: (from F&M)
- **Is fast**: $O((n+m)d)$ for n nodes, m edges, diameter d (which is typically small)
- **Has low storage requirements**: $O(n)$
- **Easily parallelizable**: Partition nodes among processors, communicate after full iteration
- **Does sequential scans of edges**.
- **Estimates individual neighborhood functions**
- DOES NOT work with limited memory

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Conclusions

- Approximate counting (ANF / Martin-Flajolet) take minutes, instead of hours
- and discover interesting facts quickly

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Outline

- Flajolet-Martin (and Cohen) – vocabulary size (Problem #1)
- Application: Approximate Neighborhood function (ANF)
- other, powerful approximate counting tools (**Problem #2**, #3)

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Problem #2

- Given a multiset
- compute approximate high-end histogram = hot-list query = (*k* most common words, and their counts)

A A A B A B A C A B D D D D D

(for *k*=2:
A#: 6
D#: 5)

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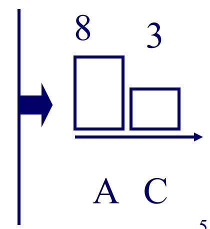
Hot-list queries

- Given a stream of product ids (with duplicates)
- Compute
  - the *k* most frequent products,
  - and their counts
- with a SINGLE PASS and O(*k*) memory

A A B A C A B C A A D E A C A

k=2



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Applications?

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Applications?

- Best selling products
- most common words
- most busy IP destinations/sources (DoS attacks)
- summarization / synopses of datasets
- high-end histograms for DBMS query optimization

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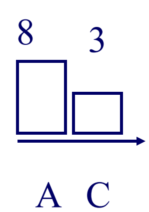
Hot-list queries

•Given a stream of product ids (with duplicates)
•Compute
  •the *k* most frequent products,
  •and their counts
•with a SINGLE PASS and O(*k*) memory

A A B A C A B C A A D E A C A

Exact: impossible
Thus: **approximate**

k=2



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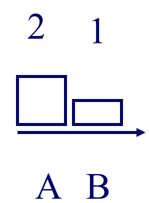
Hot-list queries - idea

- Keep the (approx.) *k* best so far, plus counts
- for a new item, if it is in the hot list
  - increment its count

A A B A C A B C A A D E A C A

k=2



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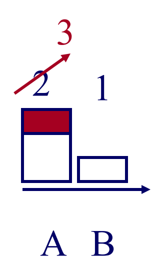
Hot-list queries - idea

- Keep the (approx.) *k* best so far, plus counts
- for a new item, if it is in the hot list
  - increment its count

A A B A C A B C A A D E A C A

k=2



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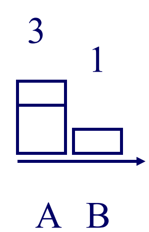
Hot-list queries - idea

- Keep the (approx.) *k* best so far, plus counts
- for a new item, if it is in the hot list
  - increment its count
  - else ??

A A B A C A B C A A D E A C A

k=2



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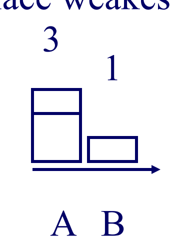
Hot-list queries - idea

- Keep the (approx.) *k* best so far, plus counts
- for a new item, if it is in the hot list
  - increment its count
  - else TOSS a coin, and possibly displace weakest

A A B A C A B C A A D E A C A

k=2



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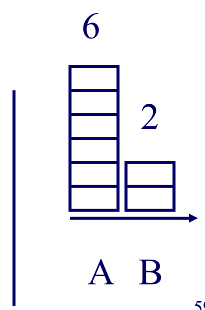
Hot-list queries - idea

- Biased coin - what are the Head/Tail prob.?

A A B A C A B C A A D E A C A

k=2



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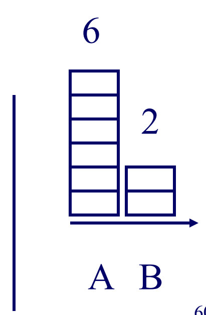
Hot-list queries - idea

- Biased coin - what are the Head/Tail prob.?
- A: depends on count(weakest)

A A B A C A B C A A D E A C A

k=2



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Hot-list queries - idea

- Biased coin - what are the Head/Tail prob.?
- A: depends on count(weakest)
- and the new item ('D'), if it wins, it gets the **count of the item it displaced**.

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Hot-list queries - idea

- See [Gibbons+Matias 98] for proofs

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Outline

- Flajolet-Martin (and Cohen) – vocabulary size (Problem #1)
- Application: Approximate Neighborhood function (ANF)
- other, powerful approximate counting tools
  - Problem #2,
  - **Problem #3**

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Problem #3

- Given two documents
- compute quickly their similarity (#common words/ #total-words) == Jaccard coefficient

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Problem #3'

- Given a query document *q*
- and many other documents
- compute quickly the *k* nearest neighbors of *q*, using the Jaccard coefficient

D1: {A, B, C} q: {A, C, D, W}
D2: {A, D, F, G}
…

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Applications?

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Applications?

- Set comparisons eg.,
  - snail-mail address (set of trigrams)
- search engines - 'similar pages'
- social networks: people with many joint friends (facebook recommendations)

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Problem #3'

- Given a query document *q*
- and many other documents
- compute quickly the *k* nearest neighbors of *q*, using the Jaccard coefficient

- Q: how to extract a fixed set of numerical features, to index on?

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Answer

- Approximation / hashing - Cohen:

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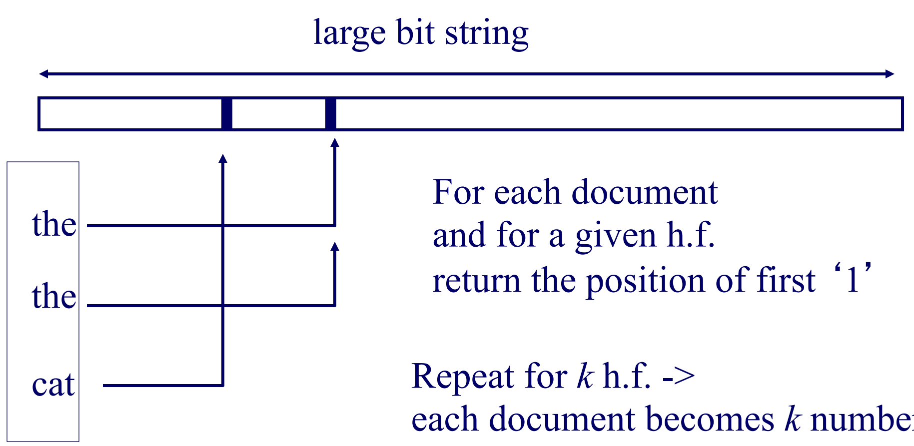
Basic idea (Cohen)



For each document
and for a given h.f.
return the position of first '1'

Repeat for *k* h.f. ->
each document becomes *k* numbers

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Idea

- Doc1: n1, n2, ... nk
- Doc2: n1', n2', ... nk'

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Idea

- Doc1: n1, n2, ... nk
- Doc2: n1', n2', ... nk'

1 *m*

- say they agree on *m* values

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Idea

- Doc1: n1, n2, ... nk
- Doc2: n1', n2', ... nk'

- say they agree on *m* values,
- then

Jaccard(Doc1, Doc2) ~ *m/k*

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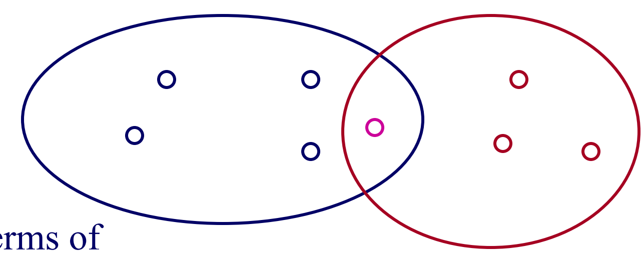
Intuition behind proof

Andrew Tomkins

- Venn diagram



voc. terms of Doc.#1

voc. terms of Doc.#2

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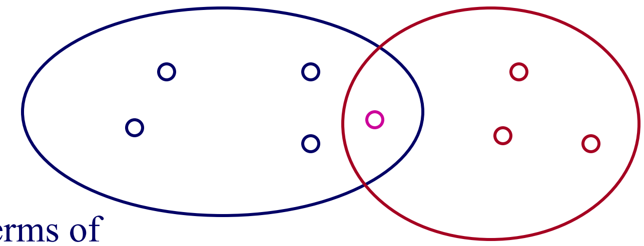
Intuition behind proof

- Venn diagram



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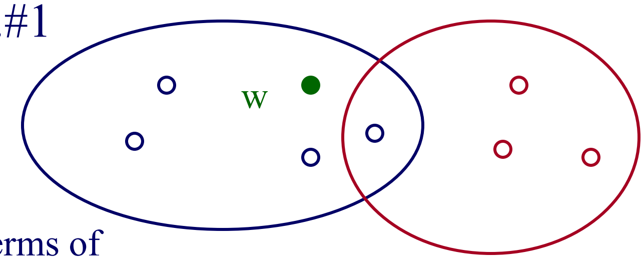
Intuition behind proof

- Venn diagram - let w be the voc. word with the overal smallest hash value, for h.f.#1



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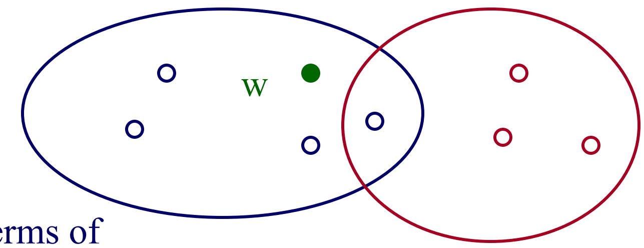
Intuition behind proof

- Prob. that w is smallest on both is exactly Jaccard: #common / #union



voc. terms of Doc.#1

voc. terms of Doc.#2

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Conclusions

- Approximations can achieve the impossible!
- MF and ANF for neighborhood function
- hot-lists
- Jaccard coeff. / ‘similar pages’

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