Distributed Probabilistic Counting on ClickStream data

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About me

- Software Engineer in London
- Interested in
 - All things scaling
 - Real-time processing
 - Open Source
 - Good whiskey
- Msc in CS, University of Edinburgh

What is ClickStream data?

- Recording of user clicks on a web page or software app
- User actions are logged for further analysis
- USA Gov gives (some of) them for free!

ClickStream use cases

- User behavior analysis
 - Join with CRM, identify users, target ads
- Market research
- Software testing
- UX improvement
- Fraud detection

Problem Find the most visited pages and/or most active users in a set of websites @mvogiatzis

Problem

Find the most visited pages and/or most active users in a set of websites

count++

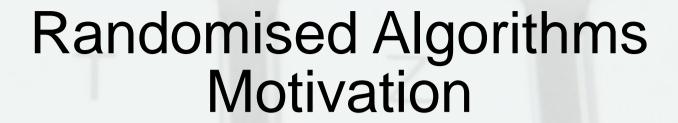


Solved?

Now count clicks on the *Amazon* website in **realtime** including **spikes**.



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Computational & space efficiency

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What if storage / processing times grows exponentially?

- Computational & space efficiency
- Scaling
- No need for exact counts
 - Perhaps top-N most frequent ones

- Randomised approaches are often the most efficient approach to many classes of demanding problems
- Trade-off between error rate and performance
- Bloom filters, Locality sensitive hashing, probabilistic counting, etc.

Probabilistic Counting

- Often referred to as "Approximate counting"
- "The approximate counting algorithm allows the counting of a large number of events using a small amount of memory."
 - Wikipedia
- A randomised counting approach

How It Works

- Every time a new event comes update the counter with probability 2^{-f}
 - where f = current_frequency
- Meaning: Update the counter only if a random generated number (sampled uniformly between 0 and 1) is less than 2^{-f}

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- We now need log(log(f)) bits per counter instead of log(f)
 - This counts in log-space.

Example

If Random_Num < 2^{-prev_count} Count++;

Stream	Prev Count	Random Num	Curr Count
"dummy"	0	0.6	1
"dummy"	1	0.7	1
"dummy"	1	0.3	2
"dummy"	2	0.2	3
"dummy"	3	0.5	3

Exact results

- We may end up over-counting or undercounting
- E[2^f-1] gives the estimated real count
- Decrease the error rate by using a smaller base than 2
 - Updates more frequently

Scale with Storm

Single machine counting may not be enough



- Single machine counting may not be enough
- Use multiple machines for load balancing and fault-tolerance

Storm

- Distributed real-time computation system
- Fault-tolerant
- Fast
- Scalable
- Guaranteed message processing
- Open source
- Multi-language capabilities

Elements

- Streams
 - Set of tuples
 - Unbounded sequence of data
- Spout
 - Source of streams
- Bolt
 - Application logic
 - Streaming aggregations, joins, DB ops

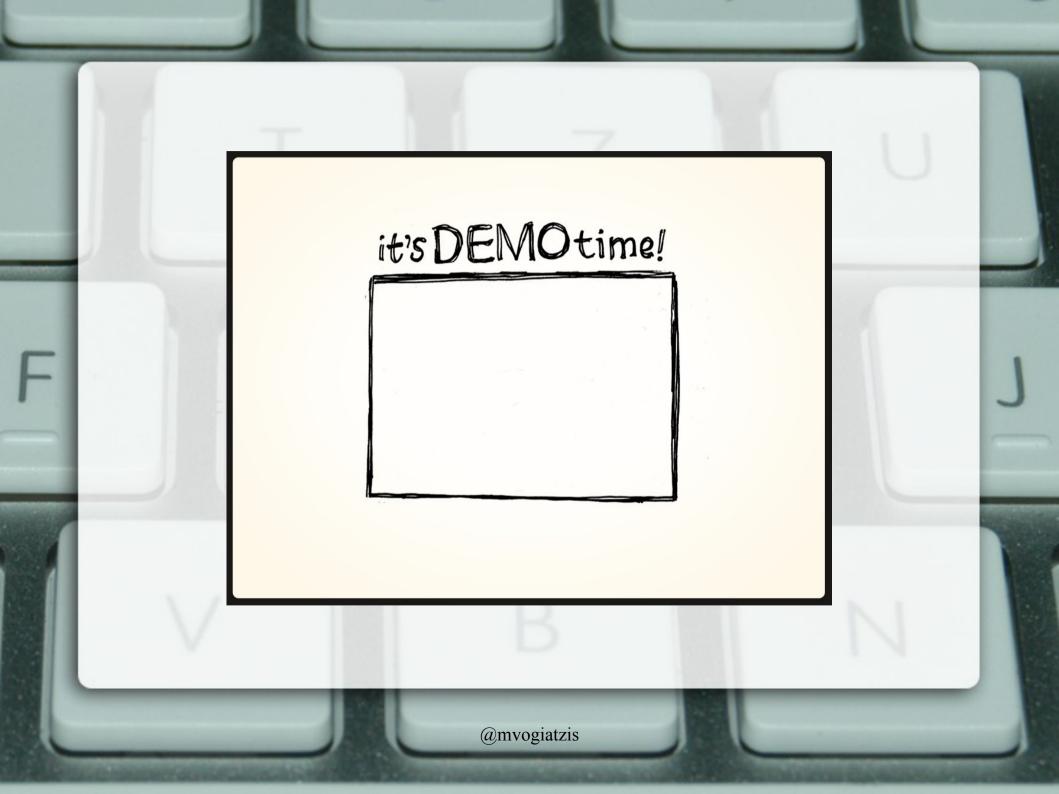
Topology @mvogiatzis



- 1.USA.gov URLs are created whenever anyone shortens a .gov or .mil URL using bitly.
- http://developer.usa.gov/1usagov

Data format

```
"a": USER AGENT,
"c": COUNTRY_CODE, # 2-character iso code
"nk": KNOWN USER, # 1 or 0. 0=first time we've seen this browser
"g": GLOBAL_BITLY_HASH,
"h": ENCODING_USER_BITLY_HASH,
"I": ENCODING_USER_LOGIN,
"hh": SHORT_URL_CNAME,
"r": REFERRING_URL,
"u": LONG URL,
"t": TIMESTAMP,
"gr": GEO_REGION,
"II": [LATITUDE, LONGITUDE],
"CY": GEO_CITY_NAME,
"tz": TIMEZONE
"hc": TIMESTAMP OF TIME HASH WAS CREATED,
"al": ACCEPT LANGUAGE
```



The End

- Code on GitHub
 - .github.com/mvogiatzis/probabilistic-counting
- Follow me: @mvogiatzis
- E-mail me: michael@micvog.com
- Read my blog: http://micvog.com/

