GIGASPACES

SINGLE PLATFORM. COMPLETE SCALABILITY.

GigaSpaces Technologies

Real Time Analytics for Big Data Lessons from Twitter..

The Real Time Boom..

Facebook Real Time Social Analytics

SaaS Real Time User Tracking

Google Real Time Web Analytics

Twitter paid tweet analytics

New Real Time Analytics Startups..

mixpanel

totango

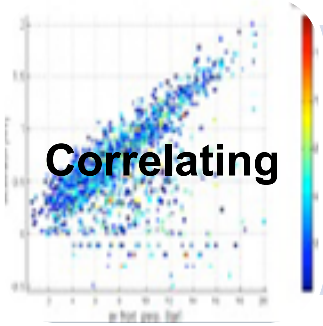
Google Real Time Search

GIGASPACES

Analytics @ Twitter

Counting

- How many request/day?
- What’s the average latency?
- How many signups, sms, tweets?



Correlating

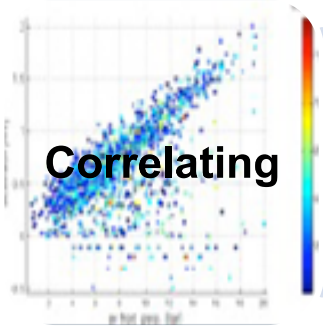
- Desktop vs Mobile user ?
- What devices fail at the same time?
- What features get user hooked?

Research

- What features get re-tweeted
- Duplicate detection
- Sentiment analysis

Note the Time dimension

- Real time (msec/sec)

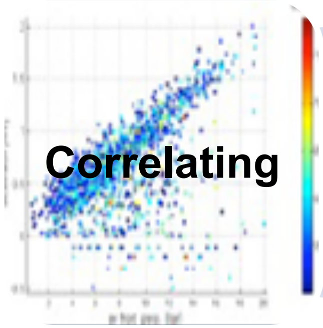


- Near real time(Min/Hours)

- Batch (Days..)

The data resolution & processing models

- Mostly Event Driven
- High resolution – every tweet counts



- Ad-hoc queries
- Mid resolution - Aggregated counters

- Pre generated reports
- Cross grain resolution – trends,..

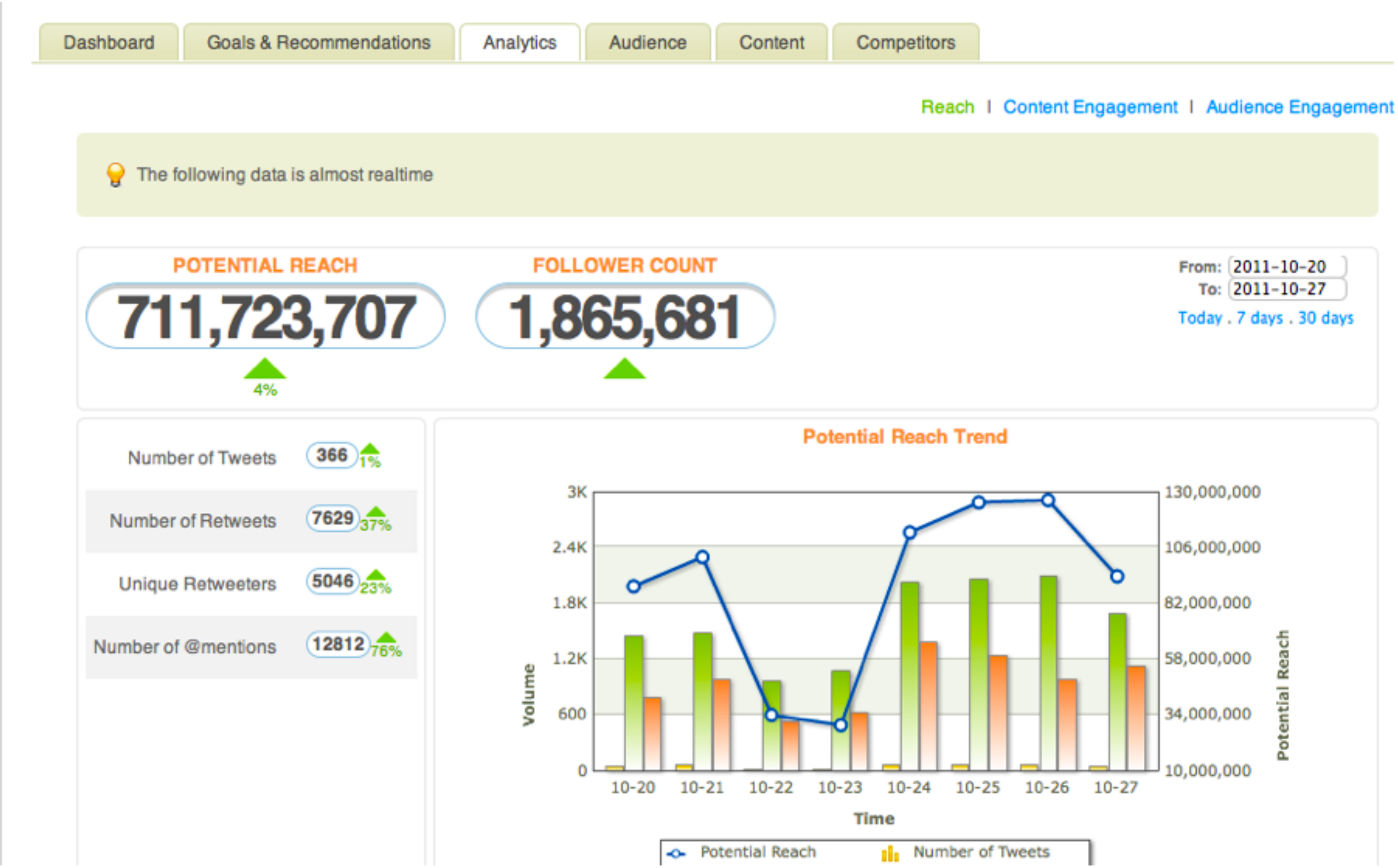
Twitter Real-time Analytics System

Twitter by the numbers

1 Bylion.	• It takes 1 week for users to send a billion Tweets.
140 million.	• The average number of Tweets people sent per day
177 million.	• Tweets sent on March 11, 2011.
6,939	• Current TPS record,
460,000.	• Average number of new accounts per day over the last month.
5%	• 5% of twitter users create 75% of the content

Real-time Analytics for Twitter Reach

Reach is the number of unique people exposed to a URL on Twitter



Dashboard | Goals & Recommendations | Analytics | Audience | Content | Competitors

Reach | Content Engagement | Audience Engagement

The following data is almost realtime

POTENTIAL REACH: 711,723,707 (4%)

FOLLOWER COUNT: 1,865,681

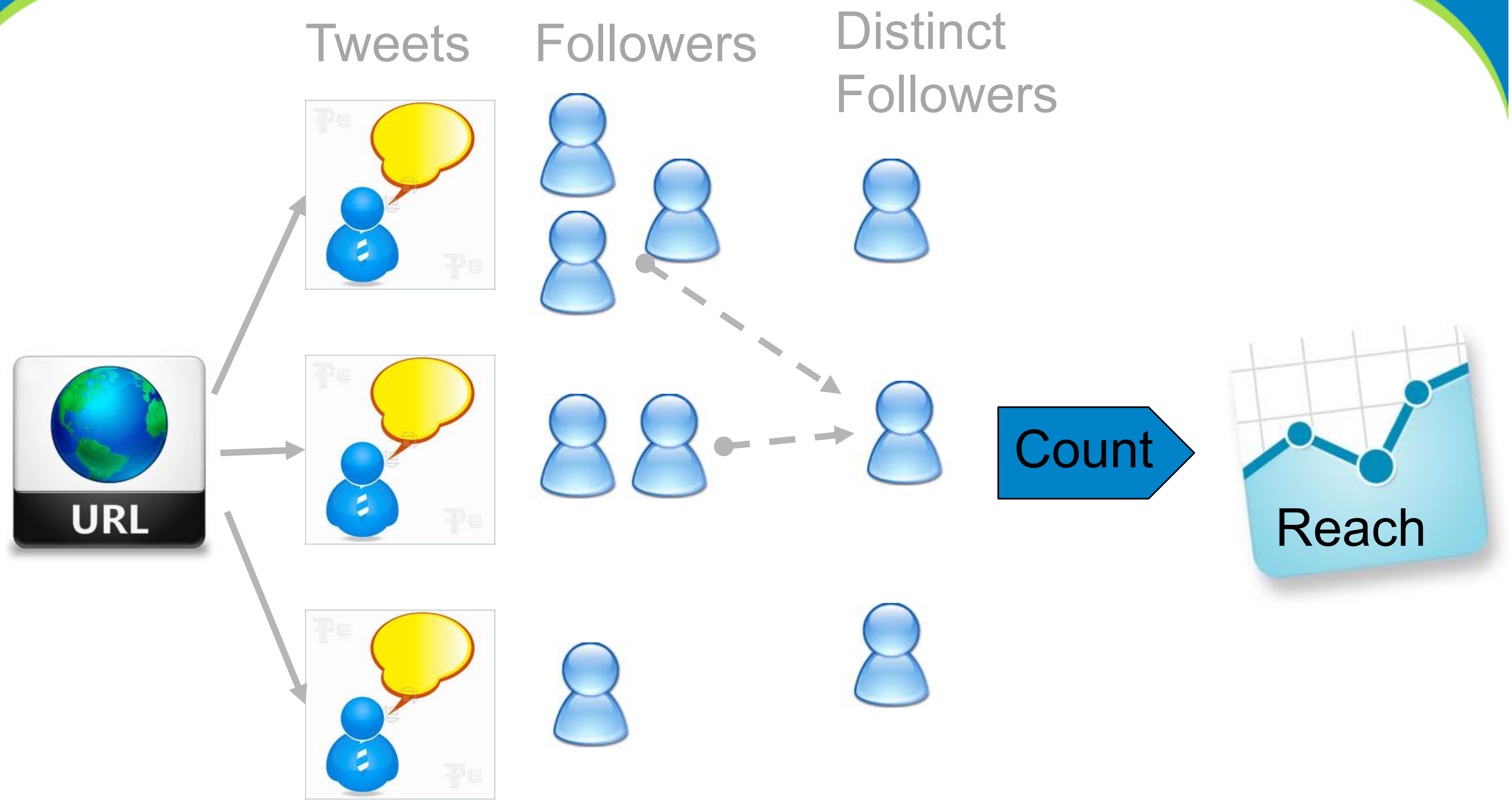
From: 2011-10-20

To: 2011-10-27

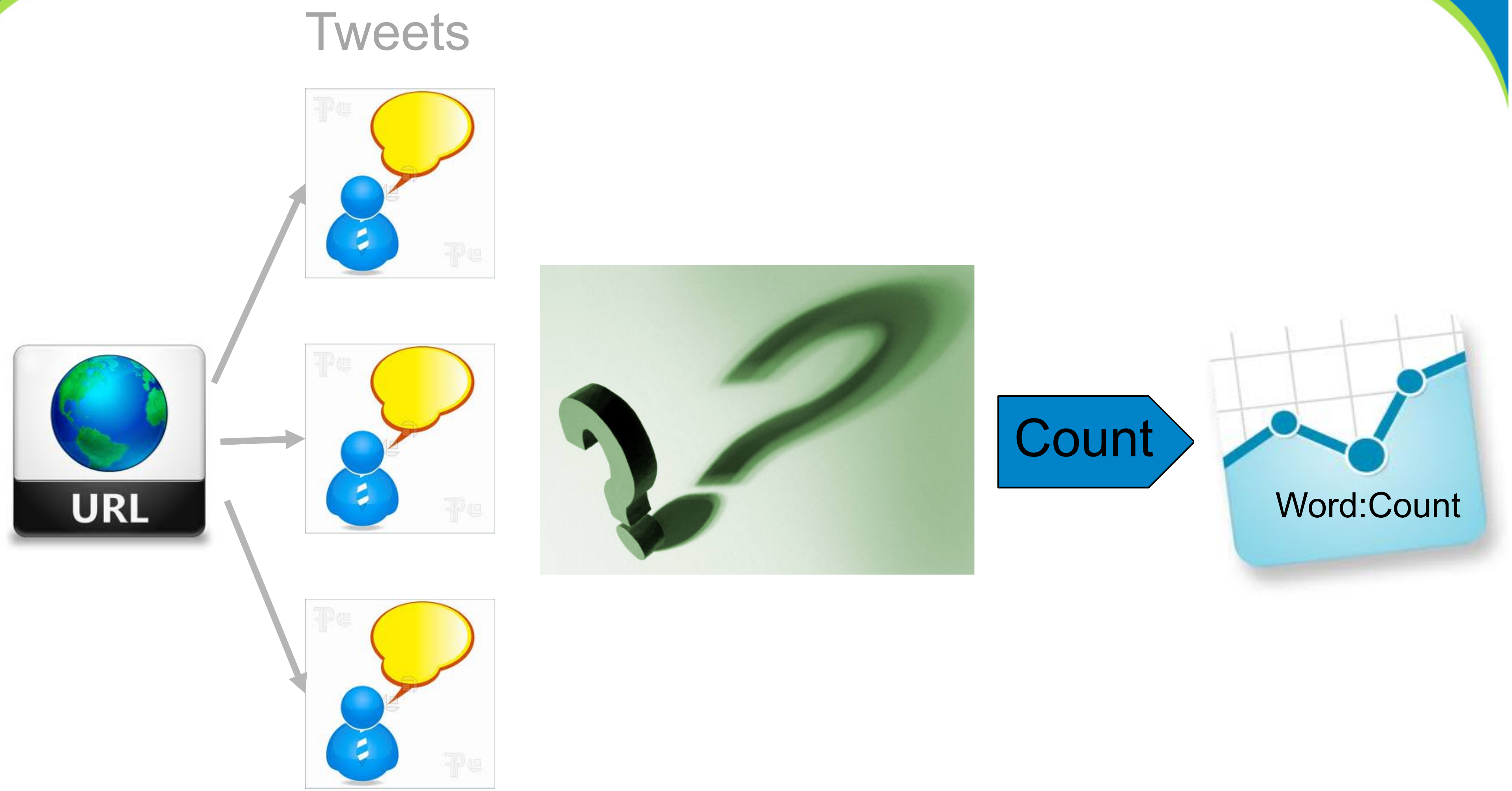
Today . 7 days . 30 days

Number of Tweets	366	1%
Number of Retweets	7629	37%
Unique Retweeters	5046	23%
Number of @mentions	12812	76%

Computing Reach



Challenge – Word Count



Tweets

Count

Word:Count

Challenge 1: Collect twitter feeds

- Collect feeds from a @<twitter id>
  - Write scalability 10k tweets/sec
  - Reliability – no message loss
  - Message size: 140 char
  - Latency – x msec
  - Store at least an hour

Challenge 2: Parse tweets

- Parse every tweets into word/count token
  - Which technology to use
    - Database
    - Hadoop, Batch
    - Event processing
  - Models for processing reliability
    - Ensure once and only once processing
    - Replay , handling replay of workflow
  - Message ordering
  - Message locality
  - Avoiding backlog

Challenge 3: Global indexing

- Collect the word/count into global index
  - Scalability
  - Consistency
  - Backlog

Challenge: 4 – Storing the data

- Sizing? Yearly storage
- Performance?
- Compression?

Challenge 5: Query the data

- Collecting specific word count
- Word count trend
- Collecting word count per user/region
- Collecting real-time stream
- Monthly/Yearly trend analysis

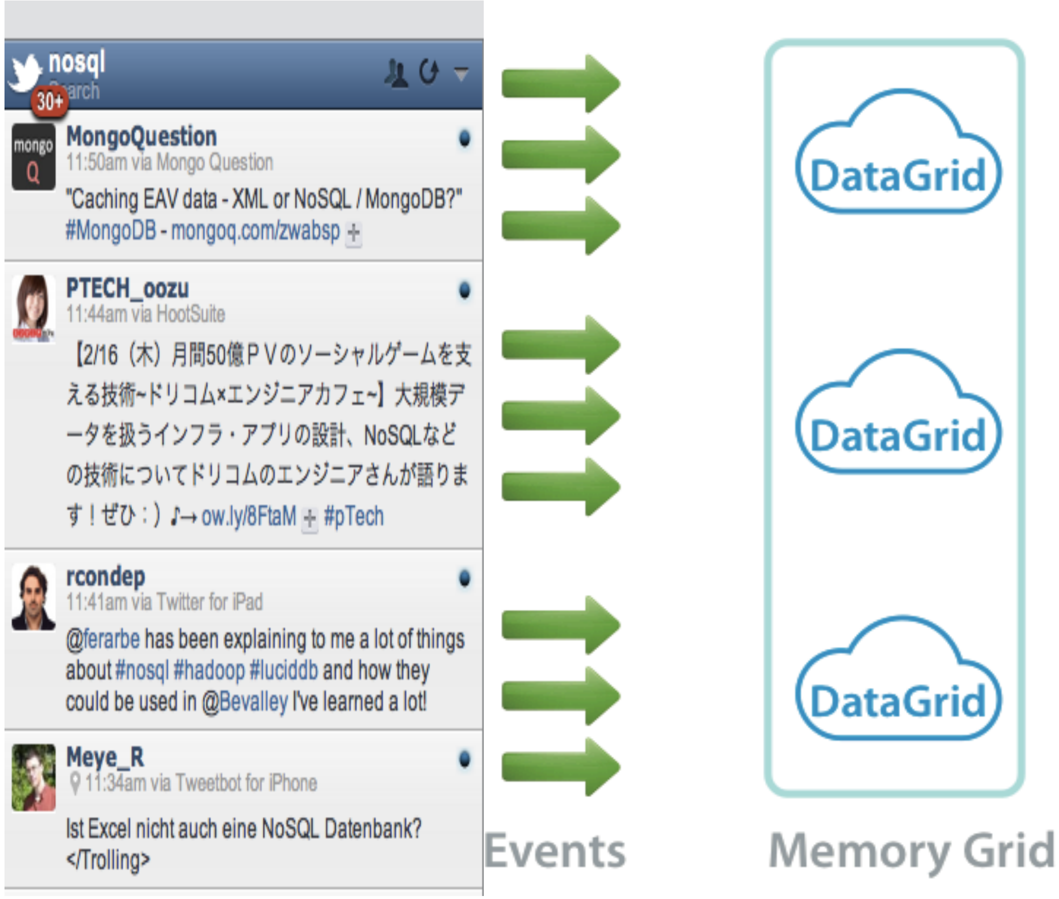
Challenge 6: Managing the system

- Deploy the cluster in a cloud
- Elasticity – increase instances based on load without breaking the system and without manual intervention
- Design the system for continues development
- Monitoring – provide consistent monitoring for all the various parts
- Trouble shooting – through Log analysis

Real-time Analytics System With GigaSpac

Performance/Latency

- Instead of treating memory as a cache, why not treat it as a primary data store?
  - Facebook keeps 80% of its data in Memory (Stanford research)
  - RAM is **100-1000x** faster than Disk (Random seek)
    - Disk - 5 -10ms
    - RAM – x0.001msec



MongoQuestion
11:50am via Mongo Question
"Caching EAV data - XML or NoSQL / MongoDB?" #MongoDB - mongoq.com/zwabsp

PTECH_oozu
11:44am via HootSuite
【2/16（木）月間50億ＰＶのソーシャルゲームを支える技術~ドリコム×エンジニアカフェ~】大規模データを扱うインフラ・アプリの設計、NoSQLなどの技術についてドリコムのエンジニアさんが語ります！ぜひ：）♪→ ow.ly/8FtaM #pTech

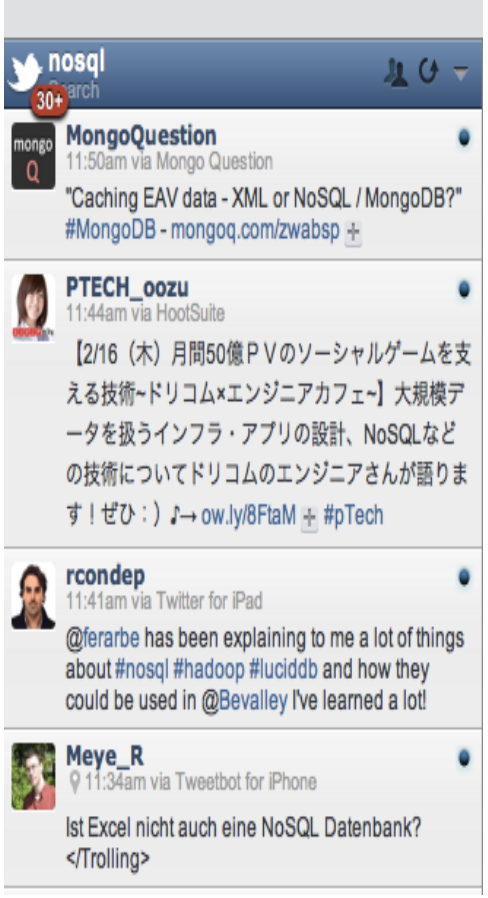
rcondep
11:41am via Twitter for iPad
@ferarbe has been explaining to me a lot of things about #nosql #hadoop #luciddb and how they could be used in @Bevalley I've learned a lot!

Meye_R
11:34am via Tweetbot for iPhone
Ist Excel nicht auch eine NoSQL Datenbank? </Trolling>

ONE Data any API’s:

The right API for the JOB

- Document
  - Storing tweets
- Key/Value
  - Atomic-counters
- JPA
  - Complex query
- Executors
  - Real Time Map/ Reduce
  - Aggregated join query



nosql
Search
30+

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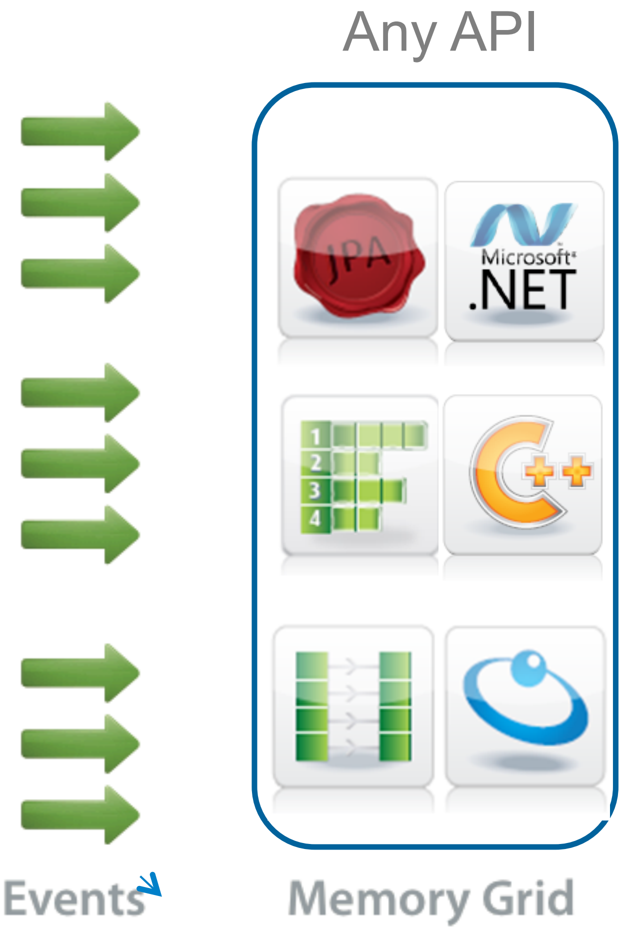
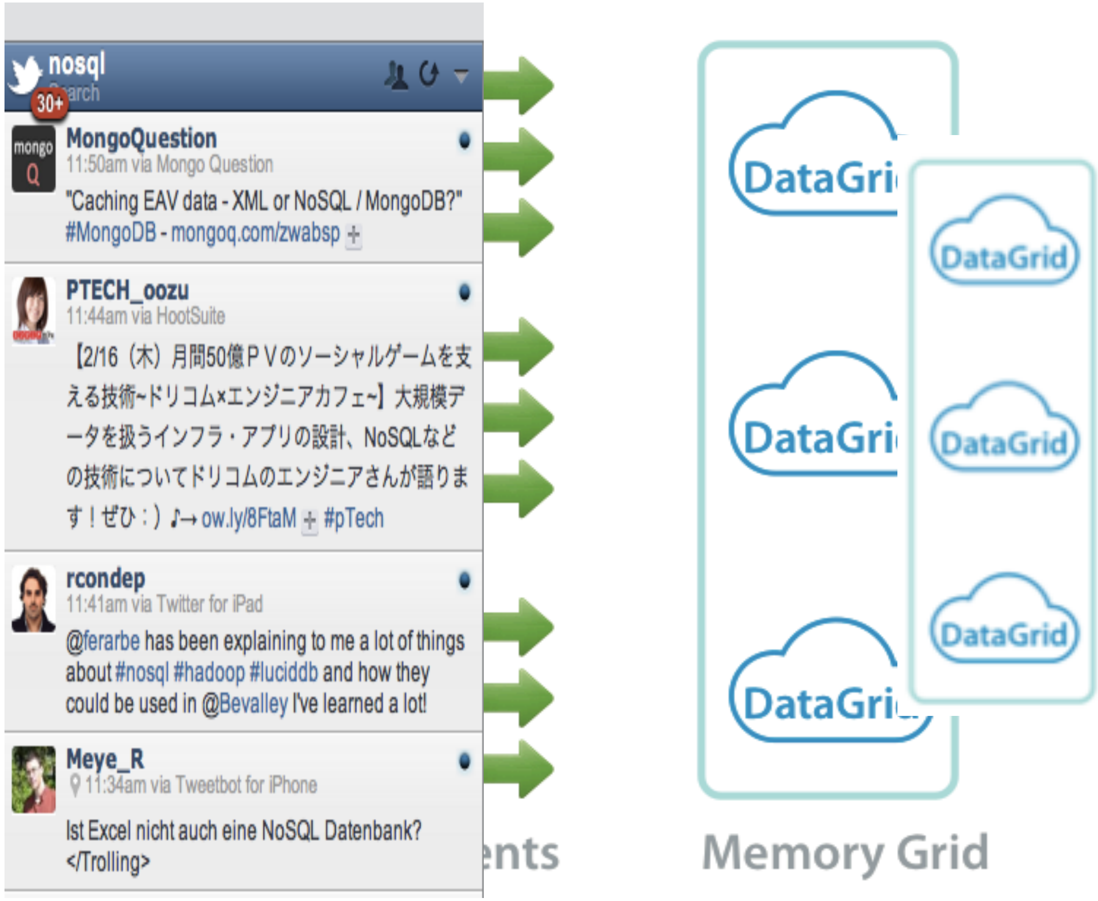


Availability

- Backup node per partition
- Synchronous replication to ensure consistency and no data loss
- On-demand backup to minimizing over provisioning overhead (cost, performance, capacity)



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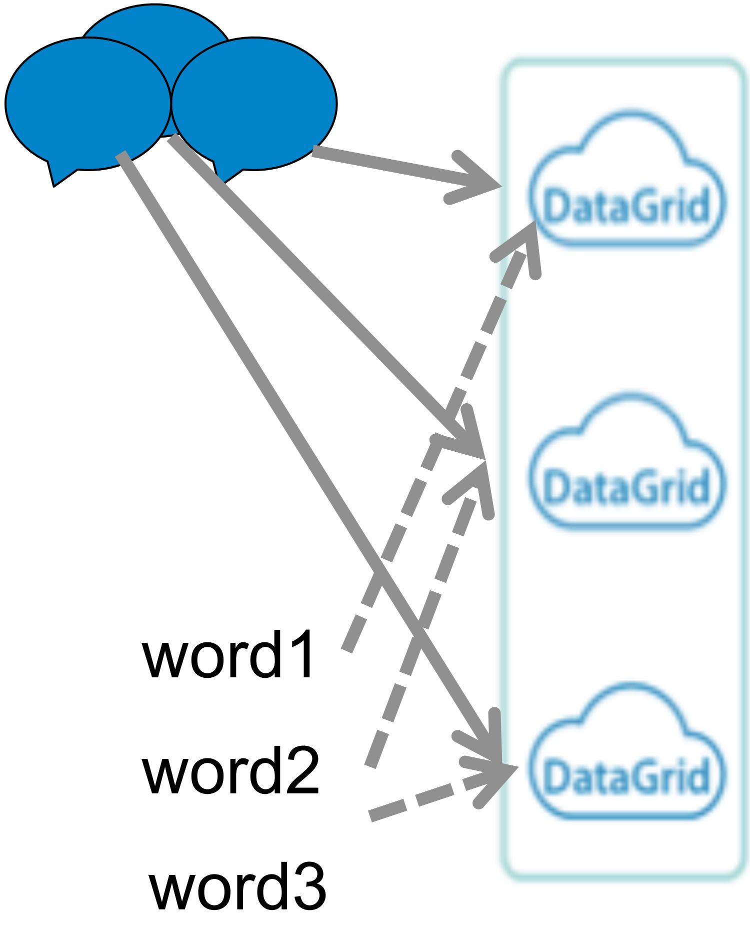
Write Scalability/Performance

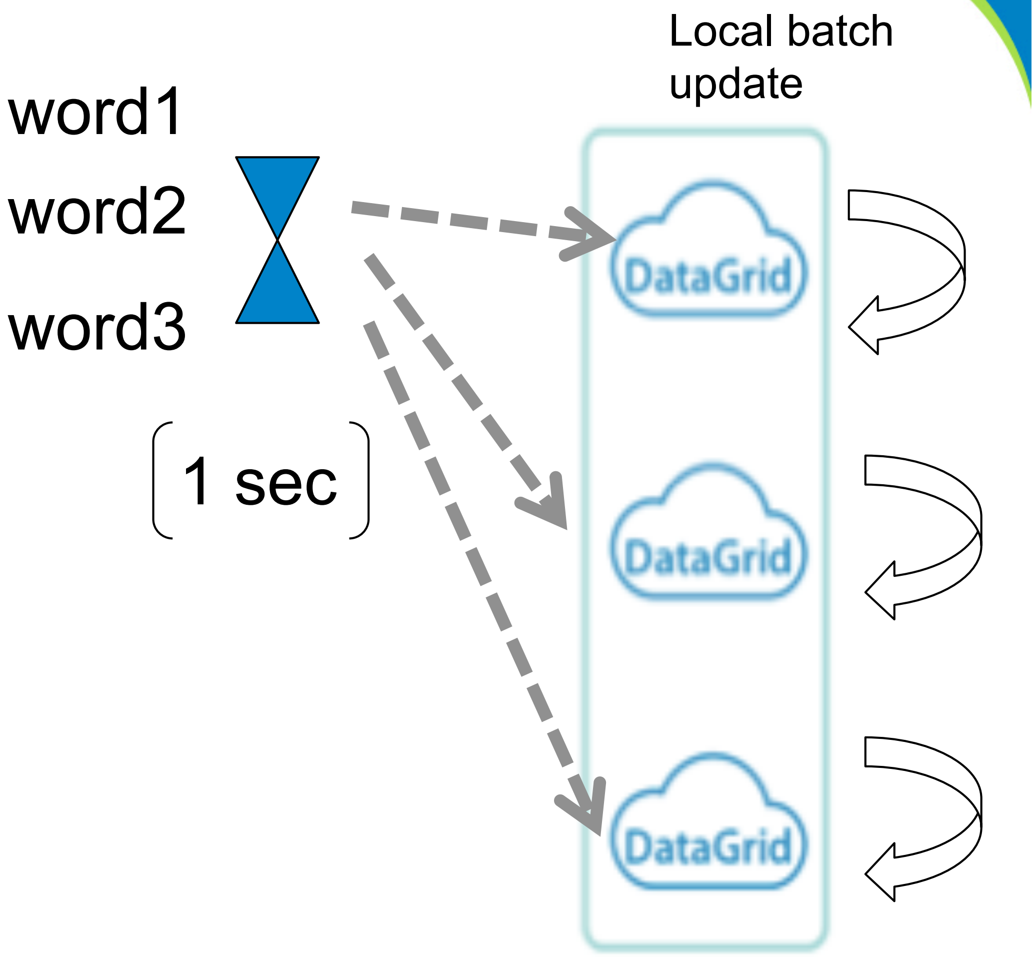
- Partition incoming tweets based on tweet id

- Partition word/count index based on word hash key – all updates to the same index are routed to the same partition.



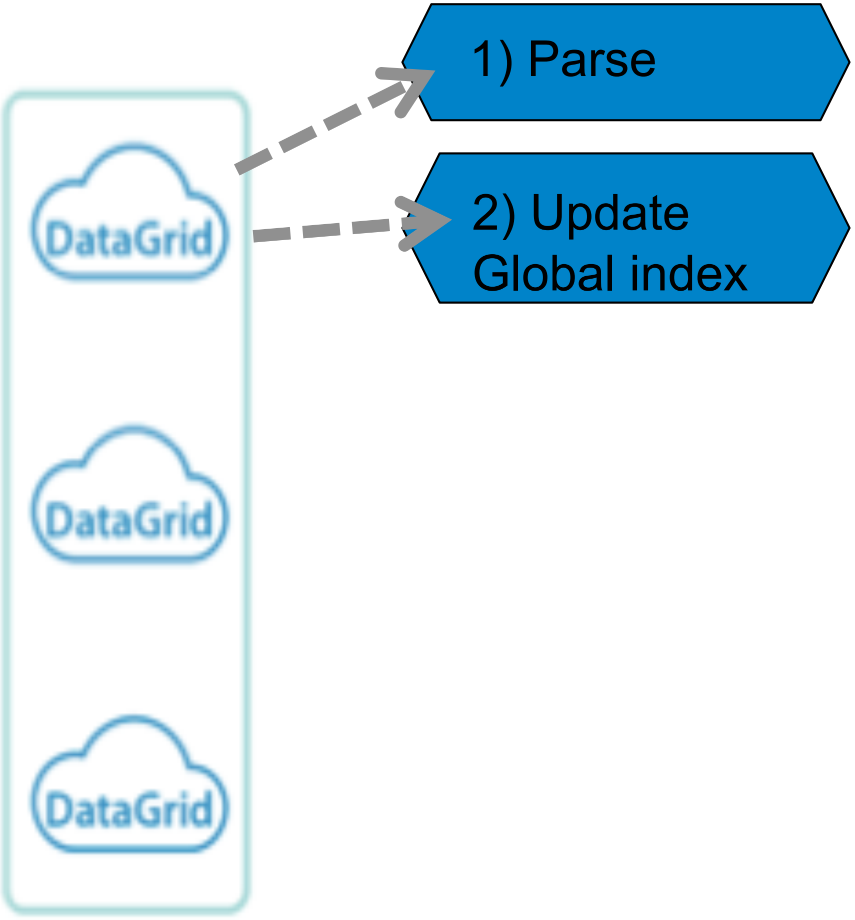
Global index update - optimization

- Use batch write for updating the word/ count index
- Use atomic update to ensure consistency with minimum performance overhead on concurrent updates



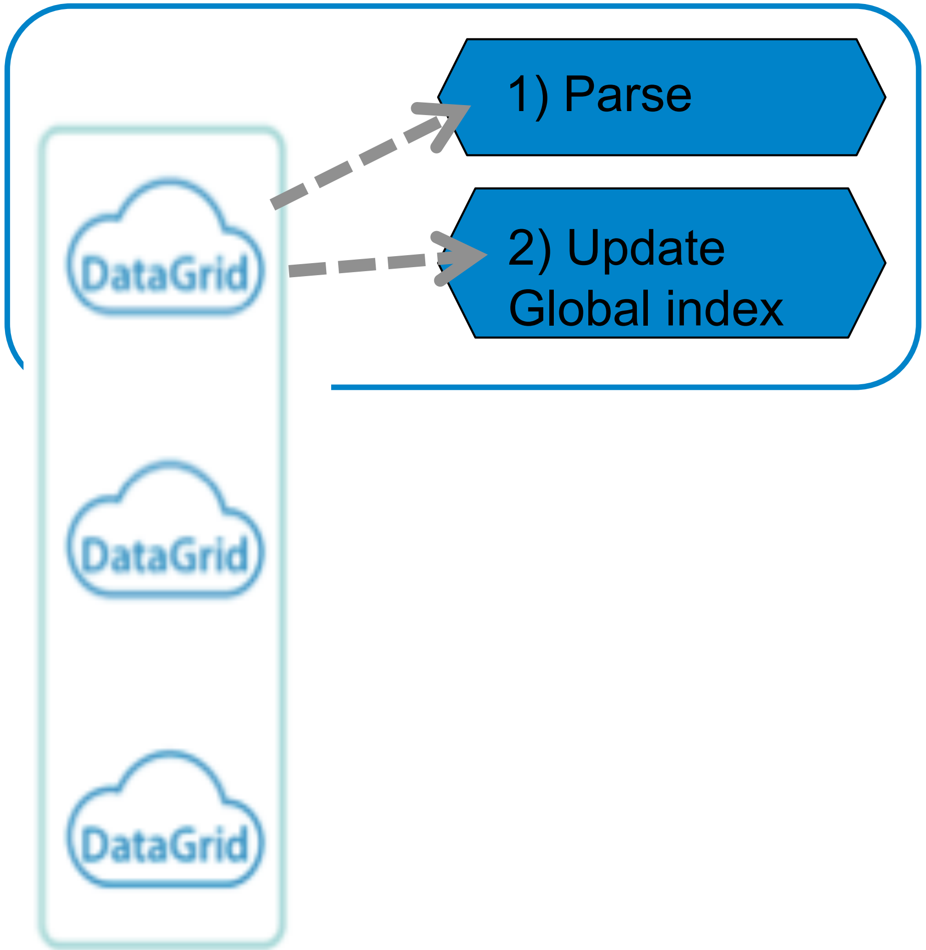
Processing the data

- Use event handlers to process the data as its coming.
- Use shared state to control the flow (order)
- Use FIFO to ensure order
- Use local TX to recover from failure



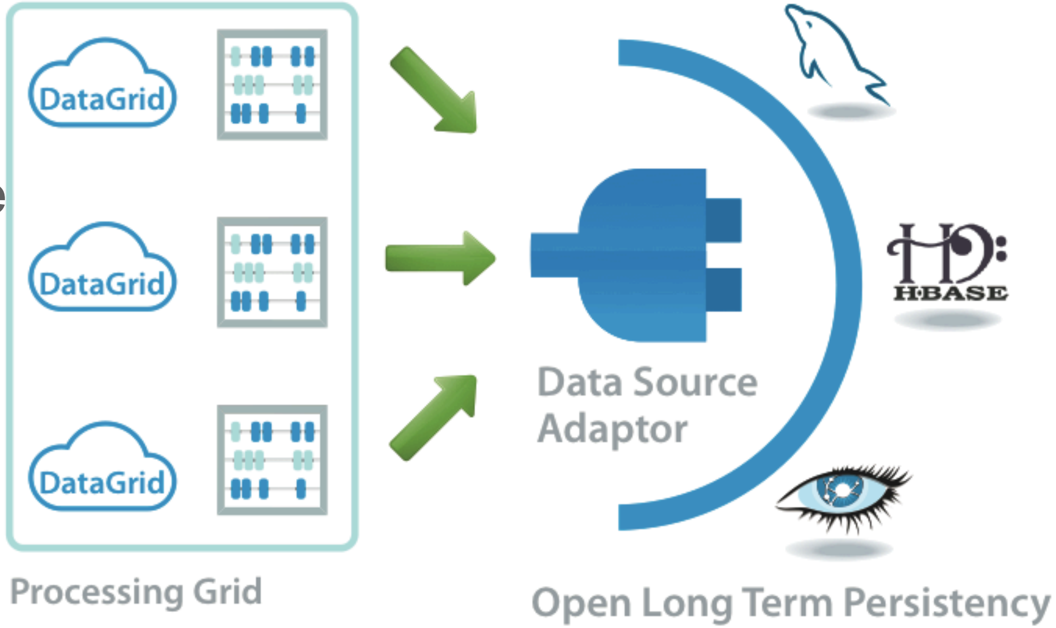
Collocate

- Group event handler and the data into processing-units
  - Minimize latency
  - Simple scaling (less moving parts)
  - Better reliability

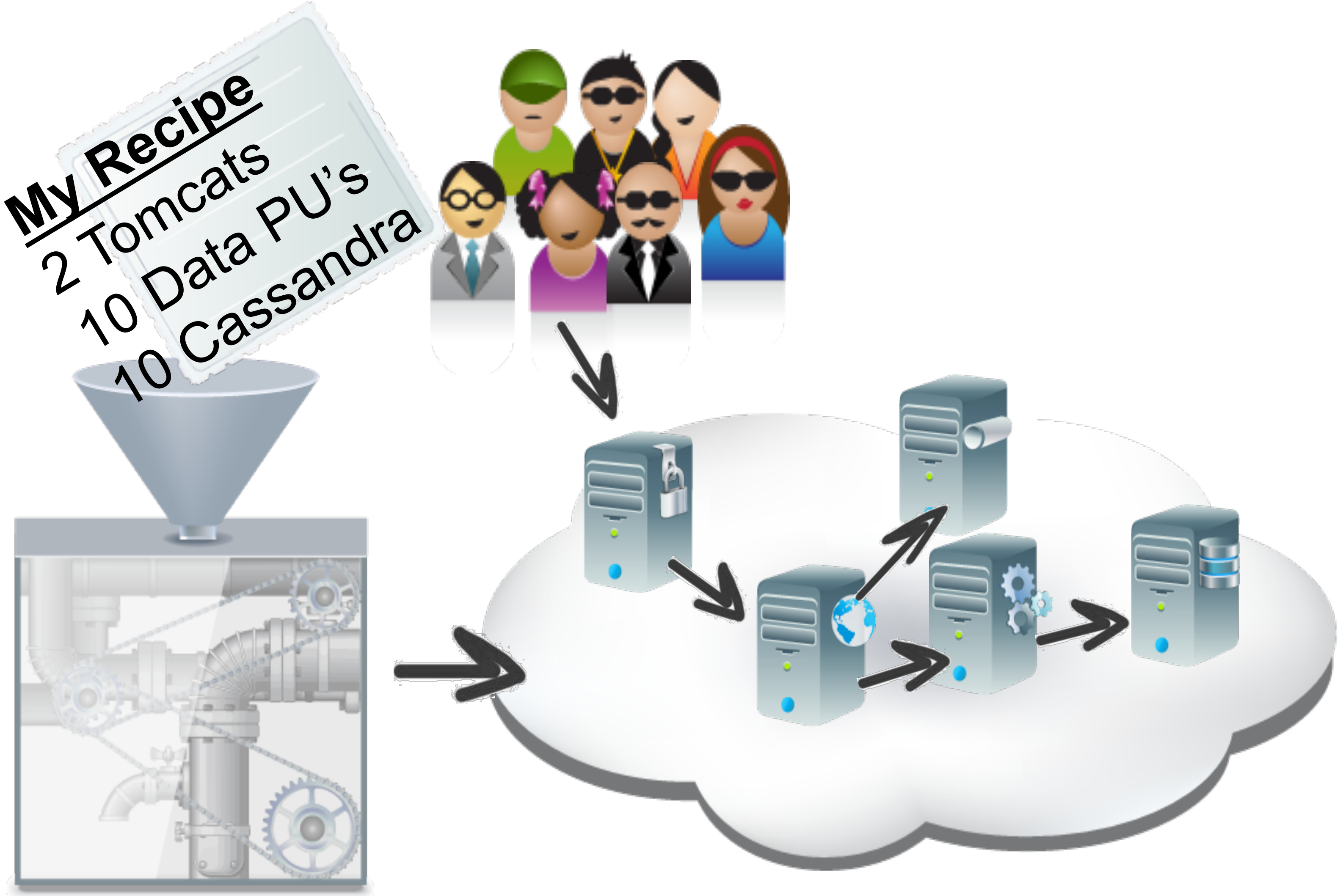


BigData Database for long term data

- Write-behind
  - Batch update to the DB to Minimize disk performance and latency overhead
  - Logs are backed up to avoid data loss between batches
- Plug-in to any DB
  - Use plug-in approach to enable flexibility for choosing the right DB for the JOB

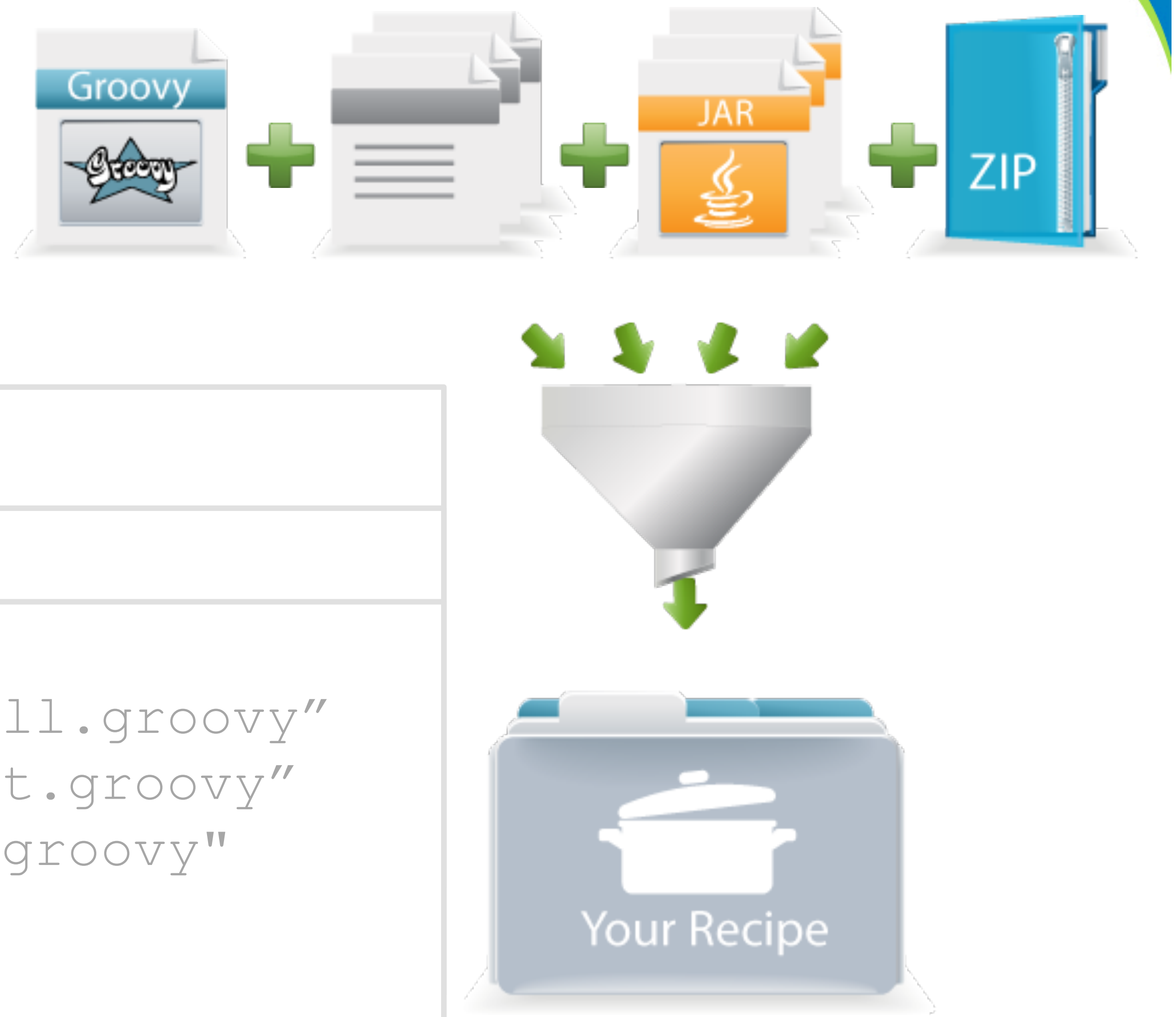


Automation & Cloud enablement



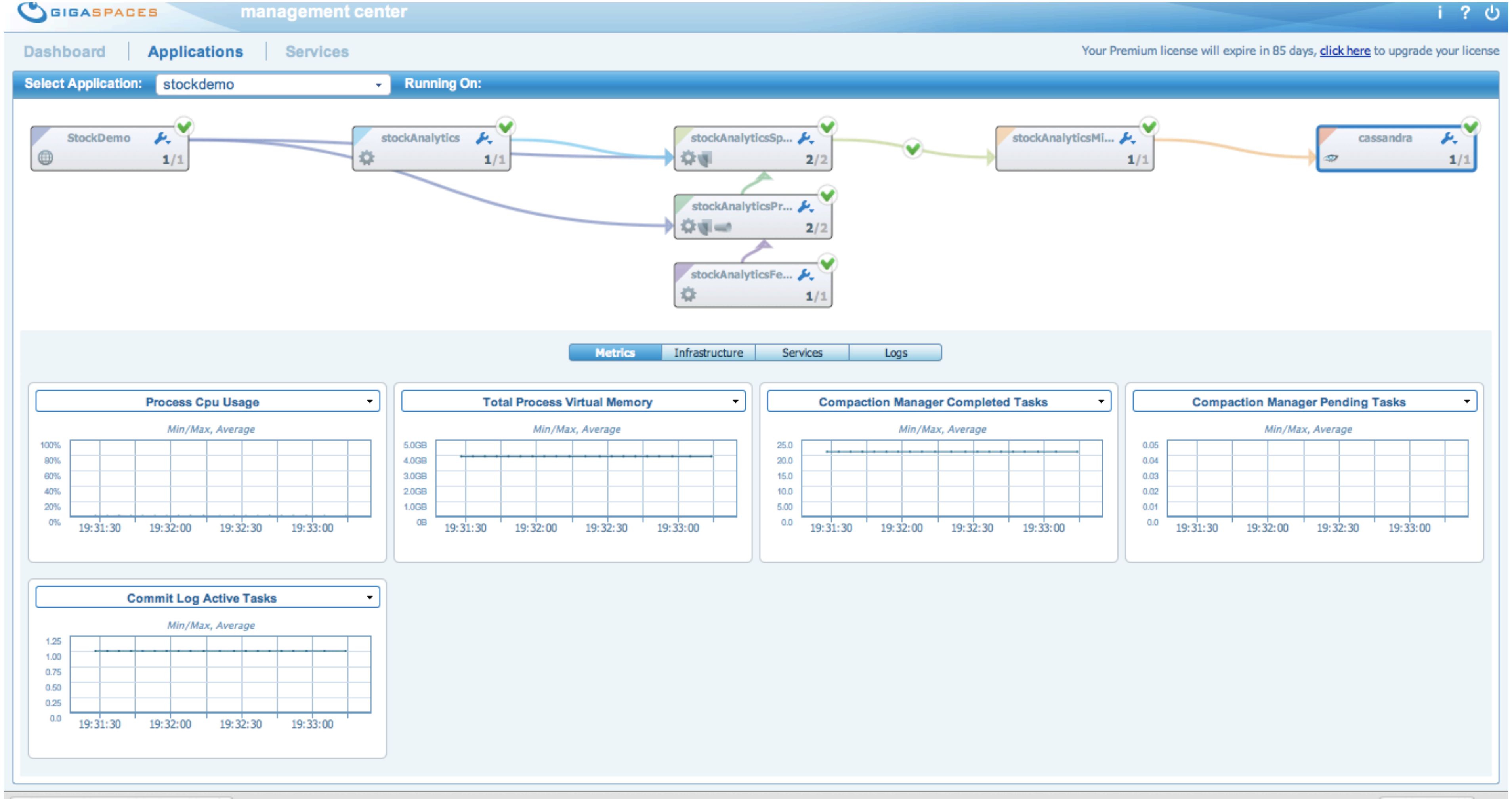
APPLICATION DESCRIPTION THROUGH RECIPES

- ✓ Recipe DSL
- ✓ Lifecycle scripts
- ✓ Custom plug-ins (optional)
- ✓ Service binaries (optional)



```
    application {
         name="simple app"
   service {
     lifecycle{
      init "mysql_install.groovy”
      start "mysql_start.groovy”
      stop "mysql_stop.groovy"
     }
   }

     ..
```

Cloudify Application Management

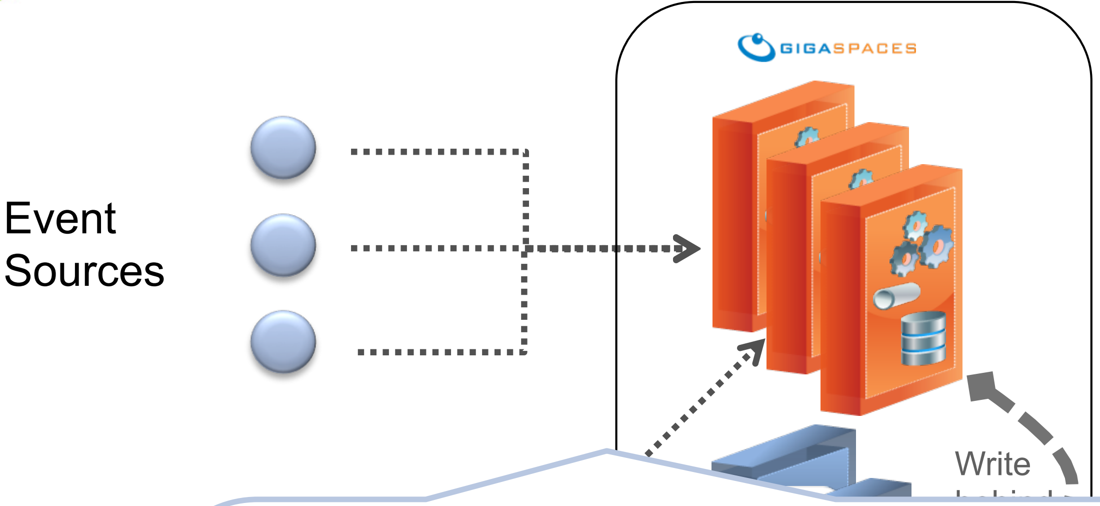


Your Premium license will expire in 85 days, click here to upgrade your license

Select Application: stockdemo

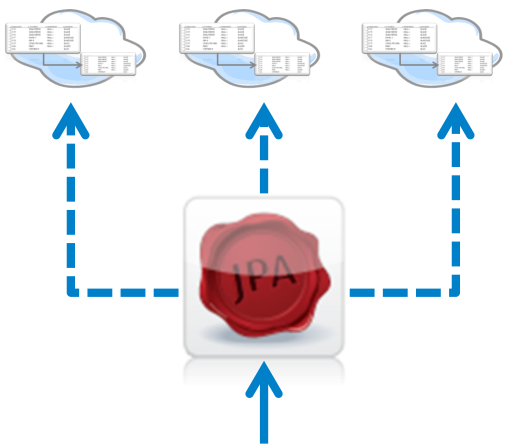
Running On:

Putting it all together



- In Memory Data Grid
- RT Processing Grid
  - Light Event Processing
  - Map-reduce
  - Event driven
  - Execute code with data
  - Transactional

Real Time Map/Reduce

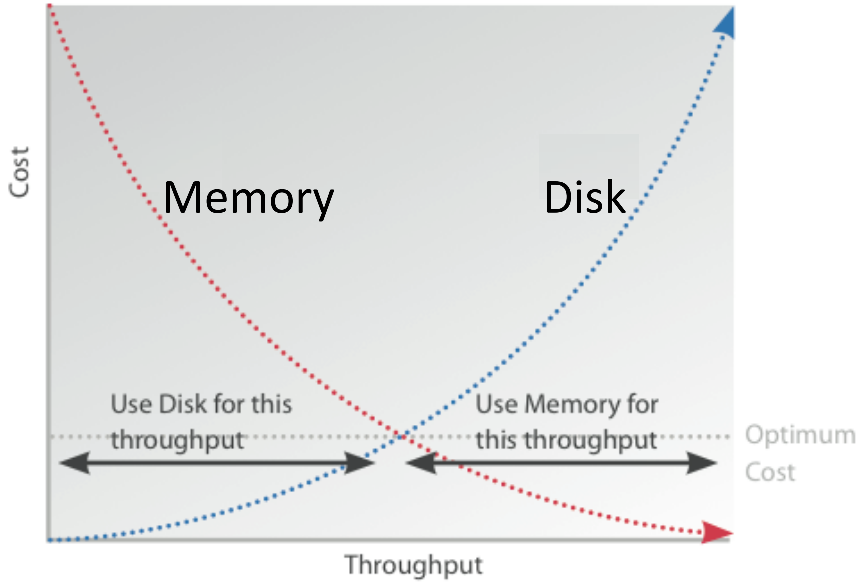


```
Script script = new
StaticScritpt(“groovy”,”println hi; return 0”)

Query q =
em.createNativeQuery(“execute ?”);
q.setParamter(1, script);

Integer result = query.getSingleResult();
```

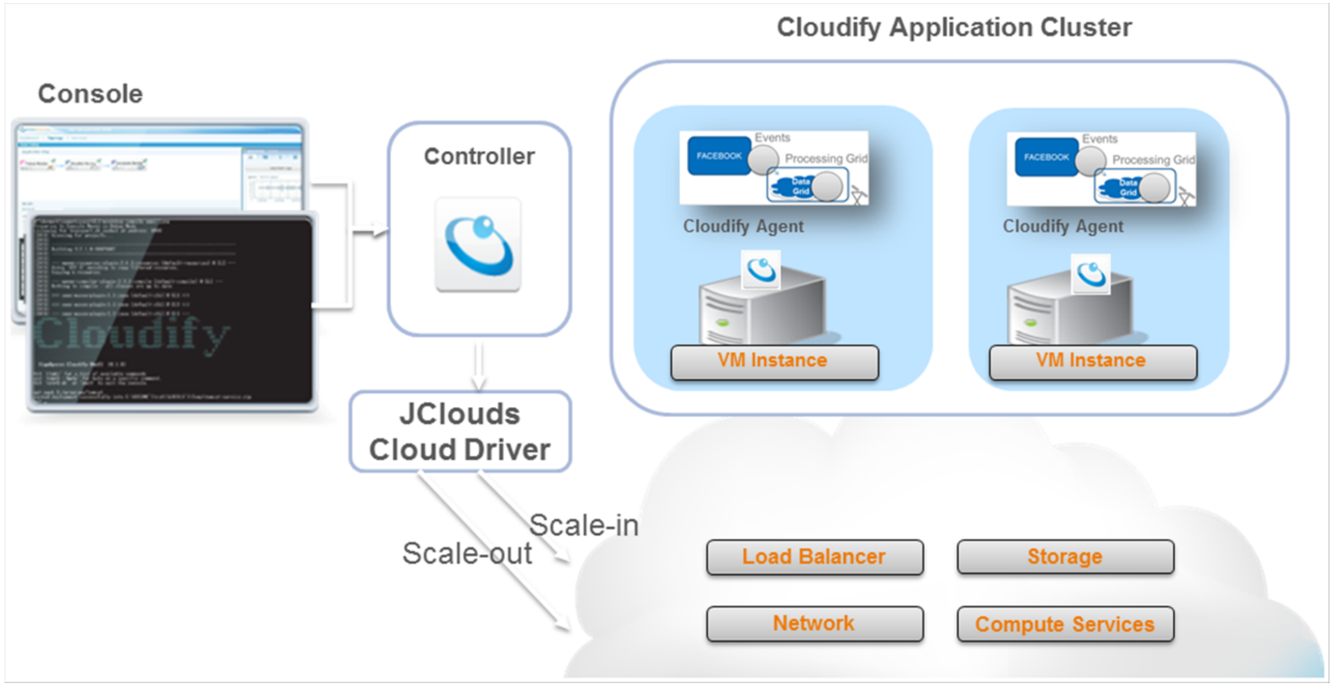
Economic Data Scaling

- Combine memory and disk
  - Memory is **x10, x100** lower than disk for high data access rate (Stanford research)
  - Disk is lower at cost for high capacity lower access rate.
  - Solution:
    - Memory - short-term data,
    - Disk - long term. data

  - Only ~16G required to store the log in memory (500b messages at 10k/h) at a cost of ~32$ month per server.



Economic Scaling



- Automation - reduce operational cost
- Elastic Scaling – reduce over provisioning cost
- Cloud portability (JClouds) – choose the right cloud for the job
- Cloud bursting – scavenge extra capacity when needed

Big Data Predictions

O'REILLY radar

Streaming data processing

Over the next few years we'll see the adoption of scalable frameworks and platforms for handling streaming, or near real-time, analysis and processing. In the same way that Hadoop has been borne out of large-scale web applications, these platforms will be driven by the needs of large-scale location-aware mobile, social and sensor use. –

Edd Dumbill O'REILLY

Summary

Big Data Development Made Simple:

Focus on your business logic, Use Big Data platform for dealing scalability, performance, continues availability,..

Its Open: Use Any Stack : Avoid Lockin

Any database (RDBMS or NoSQL); Any Cloud, Use common API's & Frameworks.

All While Minimizing Cost

Use Memory & Disk for optimum cost/performance .
Built-in Automation and management - Reduces operational costs
Elasticity – reduce over provisioning cost

THANK YOU!

@natishalom
http://blog.gigaspaces.com