

# Scaling from **Big Data** to *Fast Data*

Emerging Challenges from  
eScience and eEngineering

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COMAD, 2013, Ahmedabad





# How do you react when the *next big thing* is here?

- Bah, humbug!
- Me too, Me too
- Hmm, lets examine this...



mcswhispers.wordpress.com



/bit.ly/1etUwra



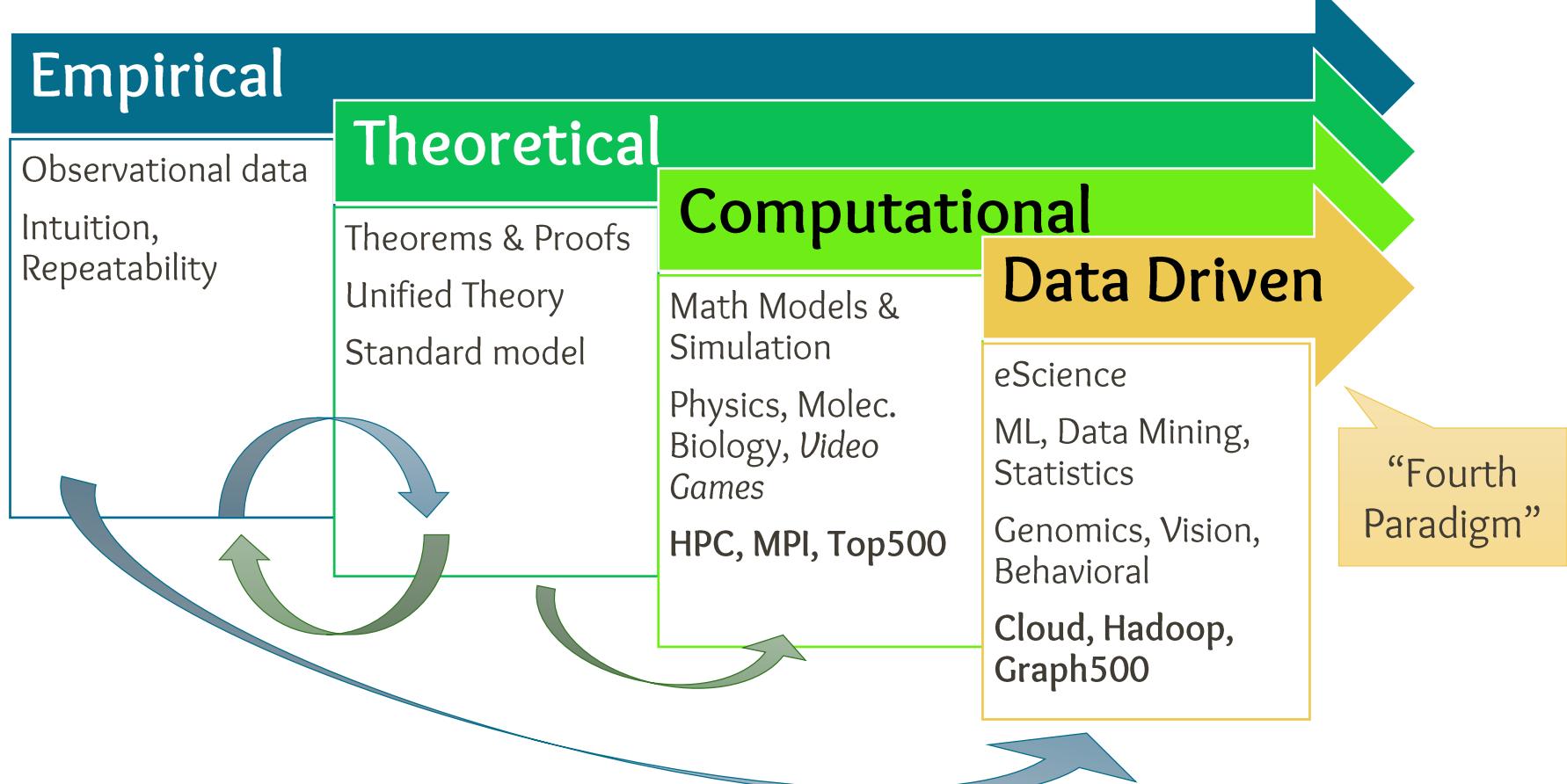
# Bah, humbug!

- There are enough of these around...too many to list



# “Big Compute, Big Data, Big Science”<sup>†</sup>

- The way science is done has evolved



<sup>†</sup>Title from Robert Harrison (Stony Brook/Brookhaven Lab)'s HiPC 2013 Keynote



# Easing into eScience

IISc  
SERC  
M.Tech.  
Comput'nal  
Science



The Data Grid JNCA,  
2000

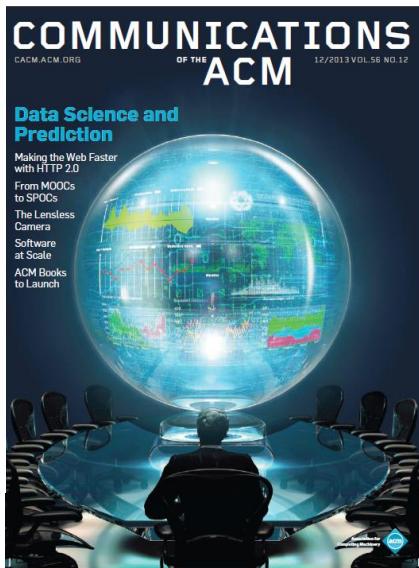


IU Informatics PhD, 2006

**Towards**  
Data Intensive  
Scientific  
Discoveries!



4Pl.in, 2013



Dec, 2013



4 Sept, 2008



Wired, July 2008



# The Obligatory 3D's

- **Volume**
  - Sheer size of data. Storage, mgmt., bandwidth
- *Velocity*
  - Realtime processing, ephemeral, latency
- **Variety**
  - Complexity, linked data analysis, compute+I/O
- Not exclusive dimensions, but useful
- Helps shape some of the interesting eScience and eEngineering activity



# Volume | Pan-STARRS Sky Survey, 2008

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“Me Too”



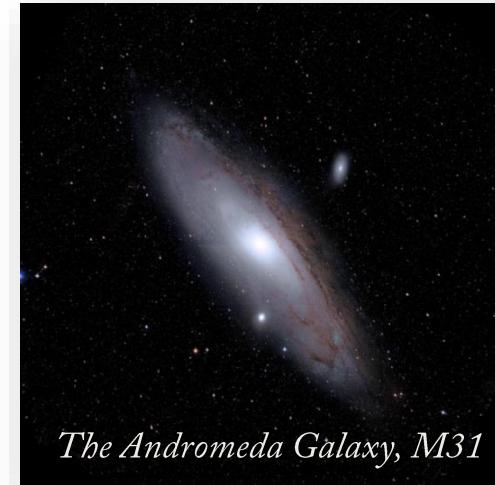
[bit.ly/Jbwv9O](http://bit.ly/Jbwv9O)



# Pan-STARRS Sky Survey

[www.ps1sc.org](http://www.ps1sc.org)

- Discover & characterize Earth-approaching objects that might pose a danger to our planet.
- One of the largest telescopes
  - **1.4 Gigapix** camera world's largest!
- Scan **2/3<sup>rds</sup>** of sky, **3** times/month
  - 1 PB of images, **30 TB** of processed data/year
  - 150 M detections / night
  - 5.5 Billion objects, **350 Billion** detections



*The Andromeda Galaxy, M31*

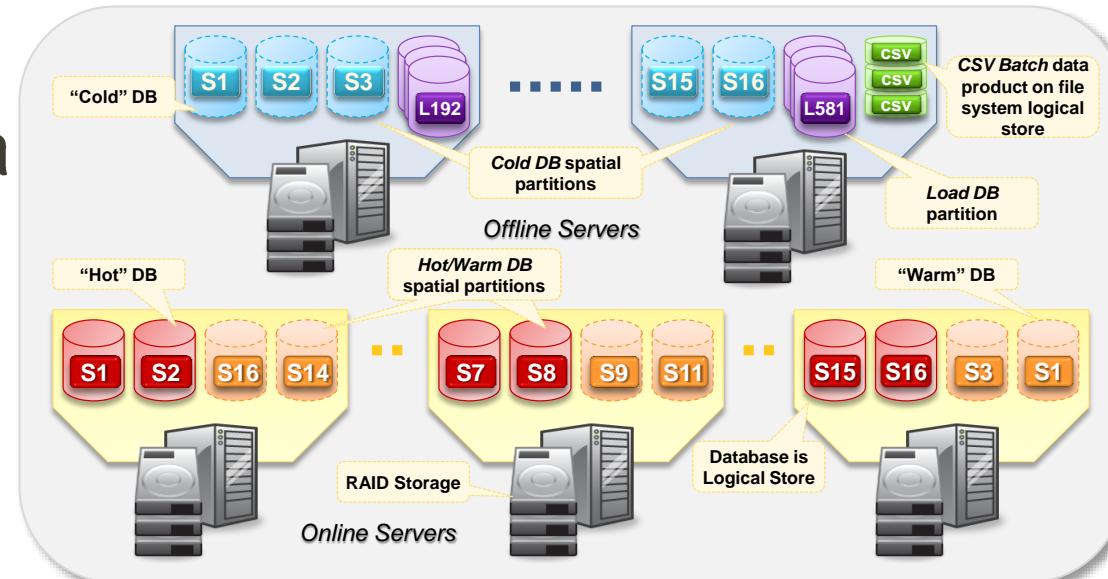
*Dome of PS1 telescope at Haleakala*





# HW & DB Architecture

- HW/SW/DB layout co-design
- GrayWulf commodity cluster for scale out <sup>†</sup>
  - Amdahl's ratios: I/O BW= 0.5, Memory=1.04
- Distributed MSSQL Databases
  - CASJobs auto, query generation
  - “MyDB” local scratch DB of results

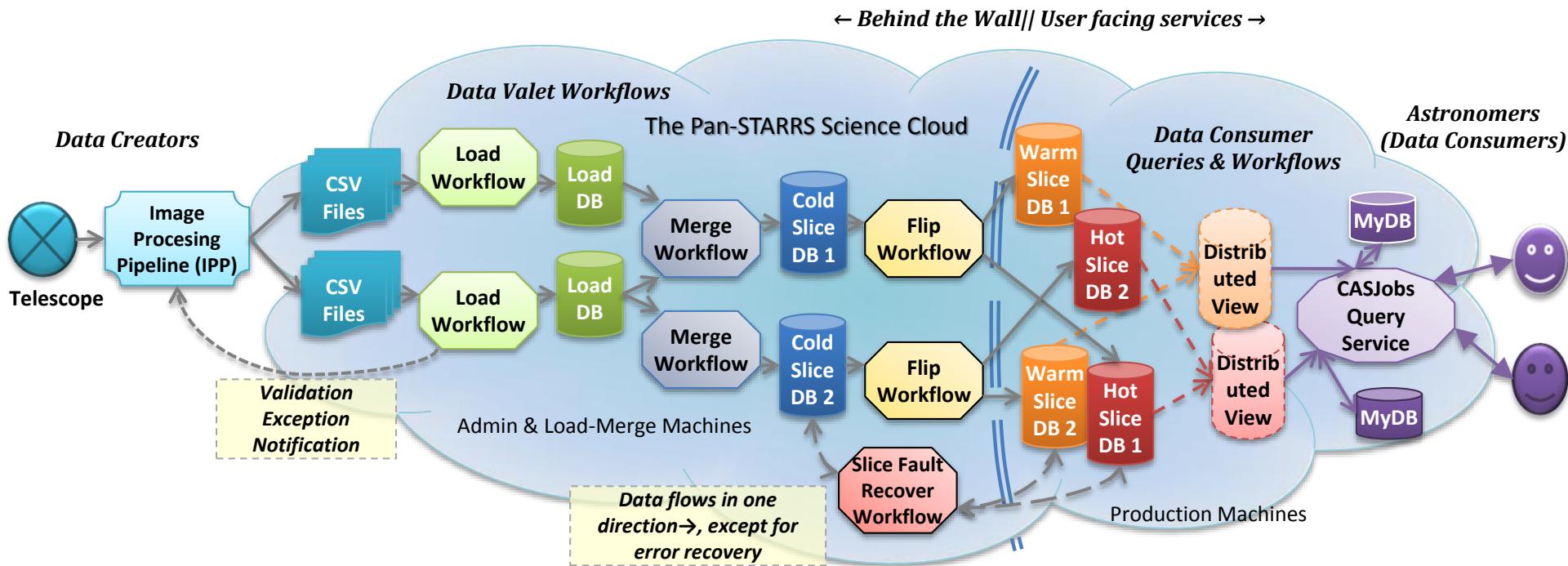


<sup>†</sup>SC 2008 Storage Challenge Award



# Scientific Data Ingest Pipeline

- Reduce time to science ready data
  - Once every 6 months → once/week, 10x data
- Ensure performance: *Relax ACID* on distributed DB
- Ensure *resilience* & externalize *consistency*





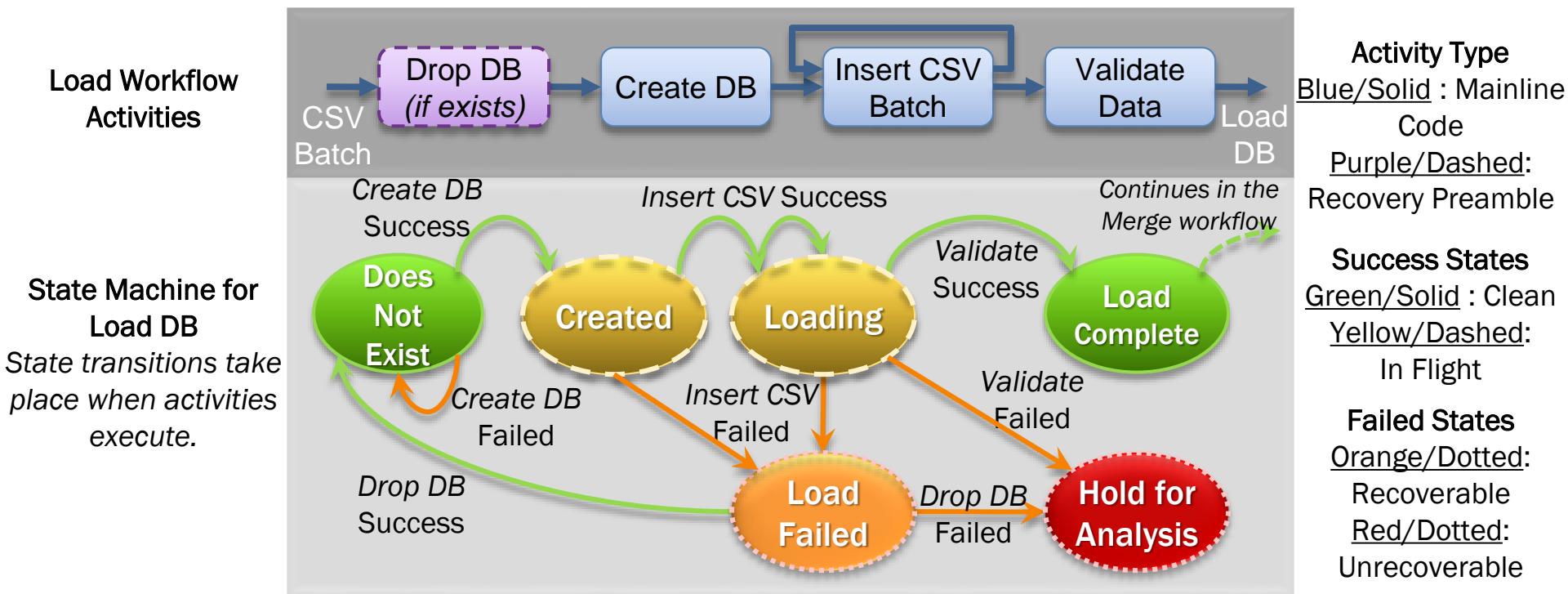
# Transactional ETL Workflows

- Well defined, Well tested workflows
  - Run repeatedly, impact cumulative
- Granular, Reusable workflows
  - Separate policy from mechanism
- Workflows as **Data State Machines**
  - *Data containers* have states
  - *Workflows & tasks* cause state transitions
- Leverage **provenance** as transaction log



# WF Recovery Baked into Design

- Faults are a fact of life in distributed sys.
  - Handling faults a *routine* action
  - Mitigate I/O cost, ease manageability





# Using Provenance for Resilience

1. Re-Execute Idempotent Recovery
  - Rerun without side-effects
2. Resume Idempotent Recovery
  - Allow a “goto” at the start
3. Recover & Resume
  - Tasks to rollback to initial state. Reduce to #3
4. Independent Recovery
  - Complex faults, global sync, manual oversight



# Velocity | The Los Angeles Smart Grid, 2011

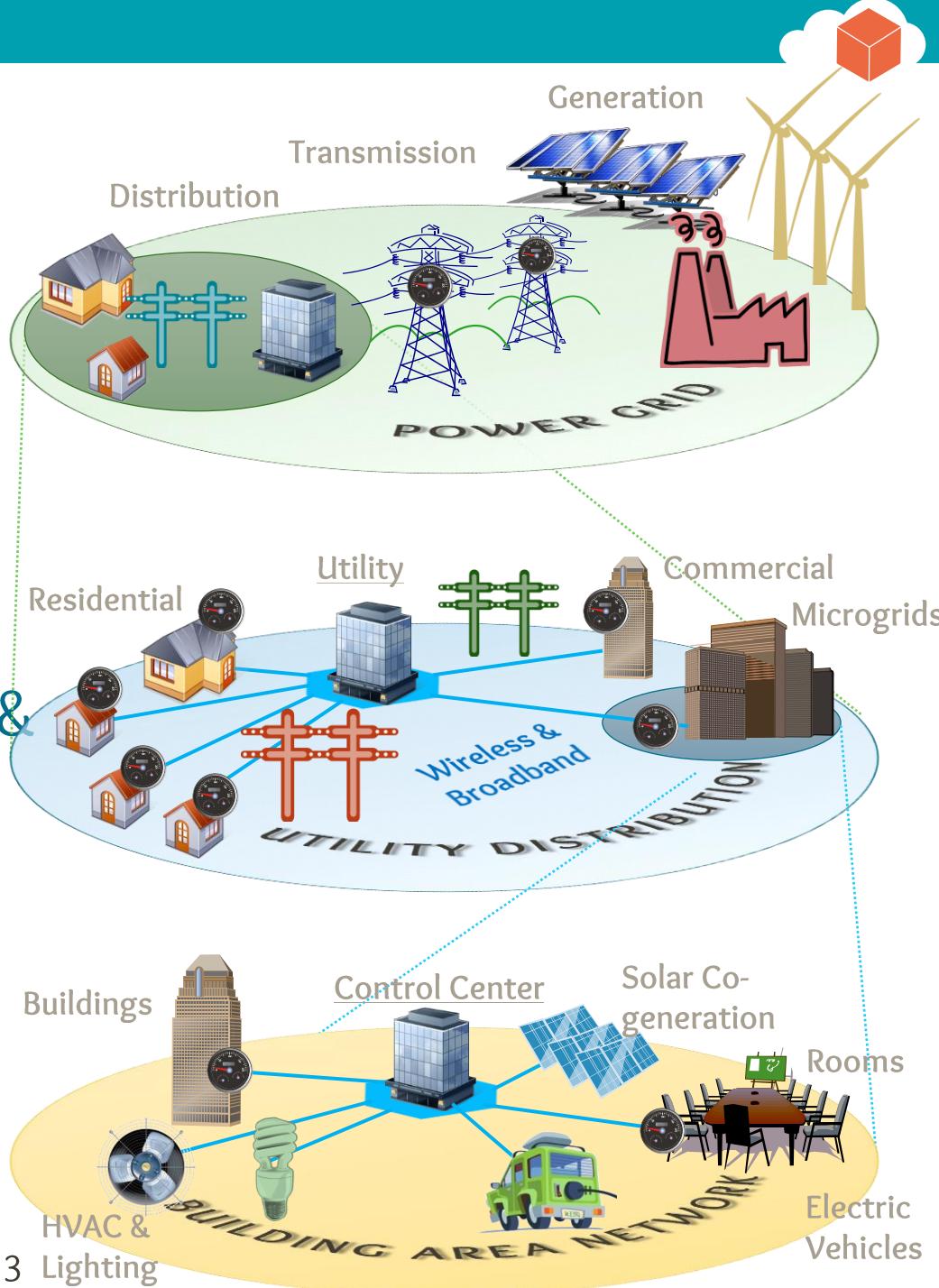
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“Hmmm, lets examine this...”



# Smart Grids: *The Cyber Physical Sys.*

- Integration of Renewables
- Advanced Instrumentation
- Bi-directional communication
- Real-time data acquisition & control
- Self-contained 'Micro Grids'...like USC
- *LADWP: largest US public utility*



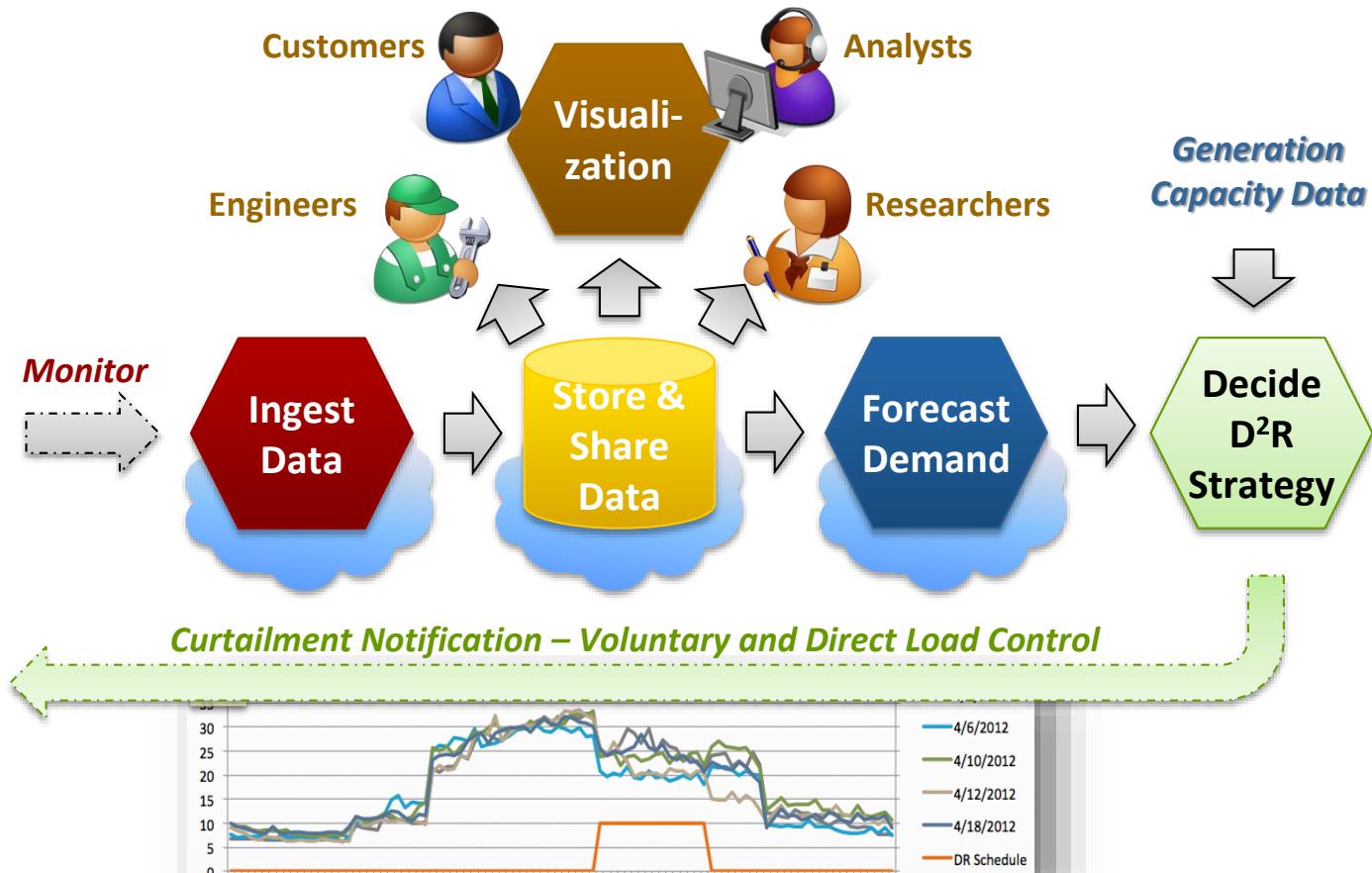
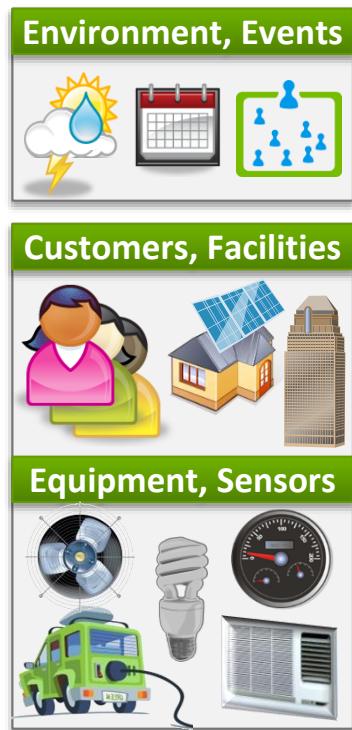
Cloud-based software platform for data-driven smart grid management, Simmhan, et al, CiSE, 2013



# Dynamic Demand Response (D<sup>2</sup>R)

*Reduce consumer demand for electricity during periods of peak usage to relieve stress on power grid*

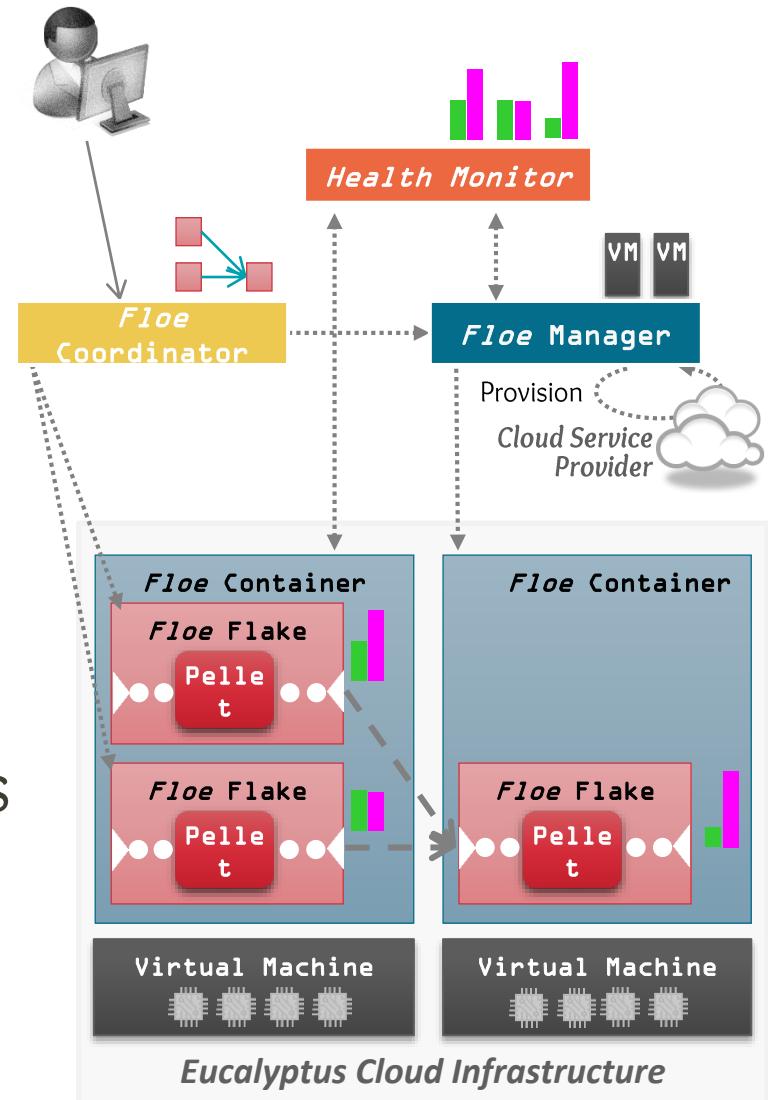
**When → By How Much → How/Whom ... Predict, Adapt, Evolve**





# Information Integration of Big Data

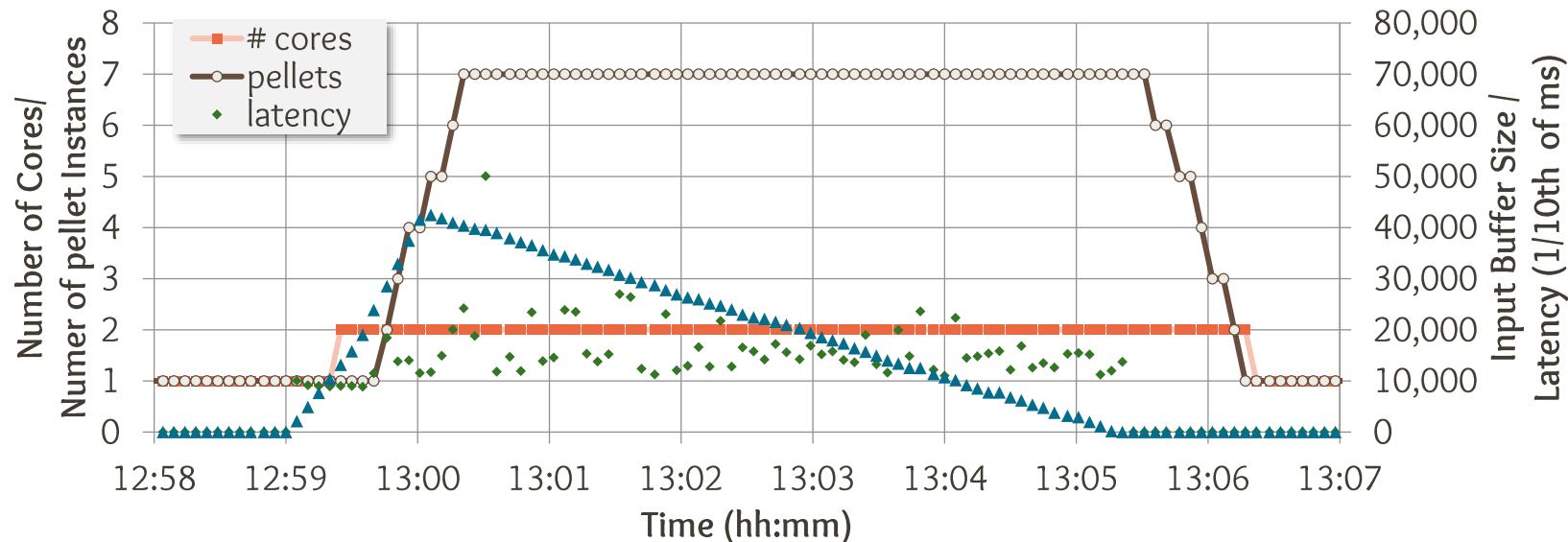
- Real-time data streams
  - ~50,000 Sensors
  - 1/15min intervals
- Semantic Information Ingest Pipeline
  - Normalize Heterogeneous Data
  - Ease data access in a complex environment
- Scale to thousands of customers
  - *Floe: Continuous Dataflow Engine for Elastic Execution on Clouds*





# Elastic Scaling Up & Out on VMs

- Ensure latency target is met
  - Add/remove # of cores allocated per VM
  - Add/remove VMs allocated per dataflow
- Initial placement on independent VMs
- Decentralized VM-local scaling algorithm





# Runtime Adaptation QoS Trade-off

- Allow alternate tasks with differential QoS
  - E.g. high rez model w/ high cost & utility vs. low rez model
  - Logically independent, no app. side effects
  - **Meet throughput** goal, Maximize **value**
- Heuristic runtime adaptation algorithm
  - Thru'put skew of  $\epsilon$  triggers adaptation
  - Estimate local+downstream impact
  - Incremental +/- 1 core/VM per timestep



# Semantic CEP for D2R

- **Complex Event Processing (CEP)**
  - Detect event patterns from data streams
- **Semantic CEP:** Use domain semantics for higher abstraction in pattern specification
  - E.g. Find offices with *airflow* greater than 200
  - Predict energy spikes, energy leaks
- Go forward and back in time

```
SELECT ?event
FROM OPCStream
WHERE {?event evt:hasEventSource ?src .
?src ee:hasLocation ?loc .
?loc rdf:type bd:Office .
?src rdf:type ee:AirflowSensor .
?event.value > 200 }
```

DEBS 2014  
Challenge



# Variety | Computational Biology, etc., 2013

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“Hmmm, lets examine this...

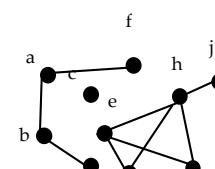
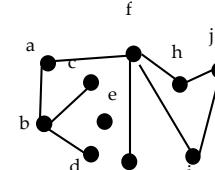
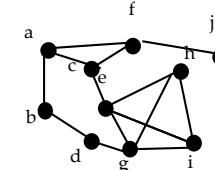
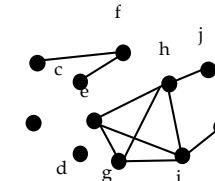




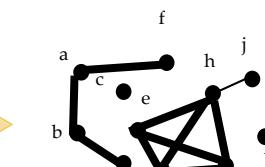
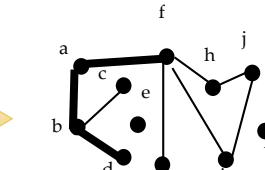
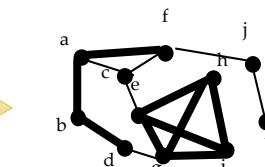
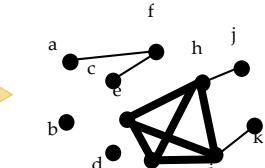
# Graph Collections in Systems Bio.

- Co-expression networks
  - Recurrent correlation behavior between gene
  - Over time (lifespan), Across space (cancer patients)
- Modelled as a graph series
  - Same topo, different values
- Find frequent clusters

Coexpression Networks



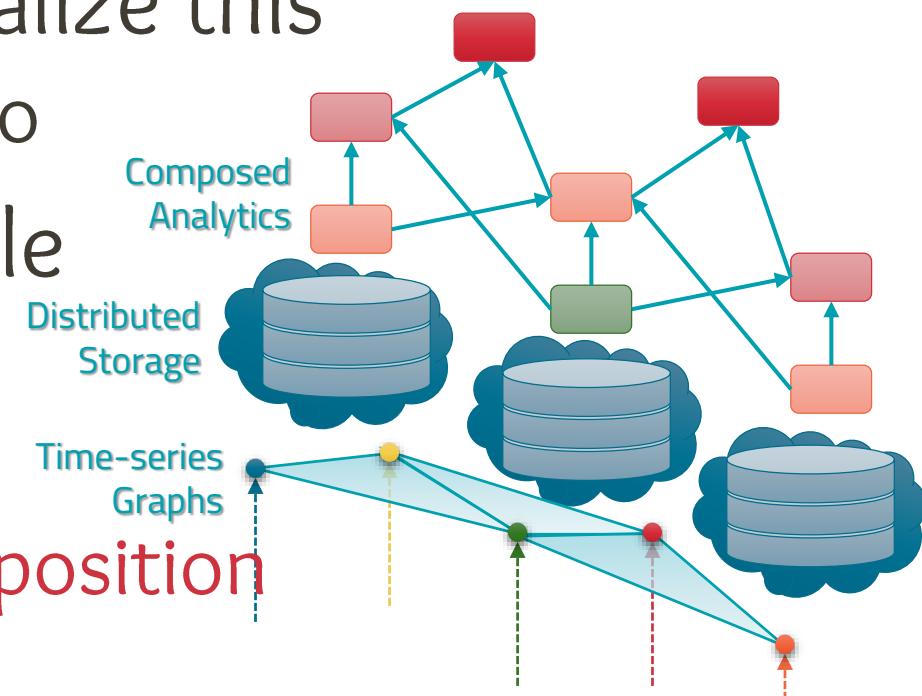
Recurrent Patterns





# Dynamic & Timeseries Graphs

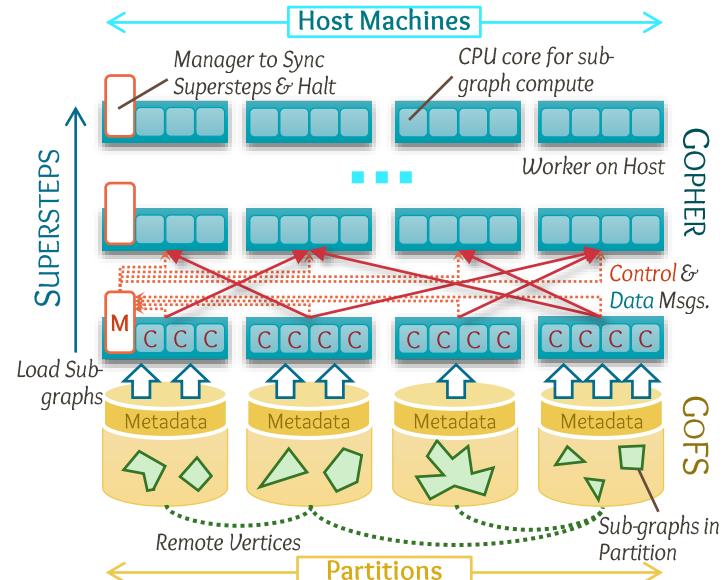
- Graph (time)series are common in CPS
  - Static Road N/W, Variable traffic flows in time
  - Power grid N/W, Power loads on vertices
- Dynamic graphs generalize this
  - Topology can change too
- Abstractions for scalable analytics on TS graphs
  - Efficient storage model
  - Intuitive & efficient composition





# GoFFish Software Platform

- **GoFS**: Distributed Graph-oriented File Sys.
- **Gopher**: Compose sub-graph centric analytics
- Targeted at distributed commodity H/W
- Sub-graph & TS aware distributed storage
  - APIs for *SG Iteration, Filtering and Projection*
  - *Temporal Instance Packing*
  - *SG Binning & Caching*

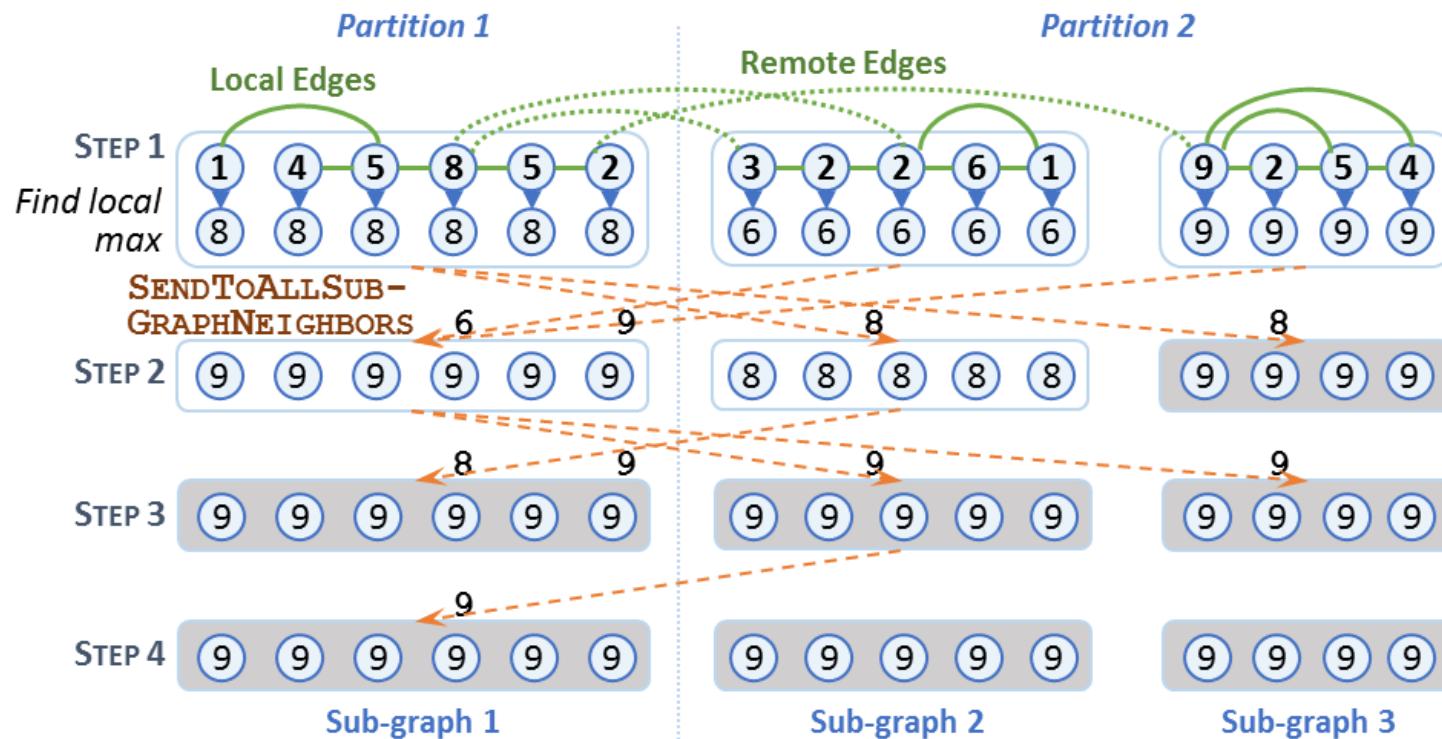


Scalable Analytics over Distributed Time-series Graphs using GoFFish, Simmhan, et al, (under review)



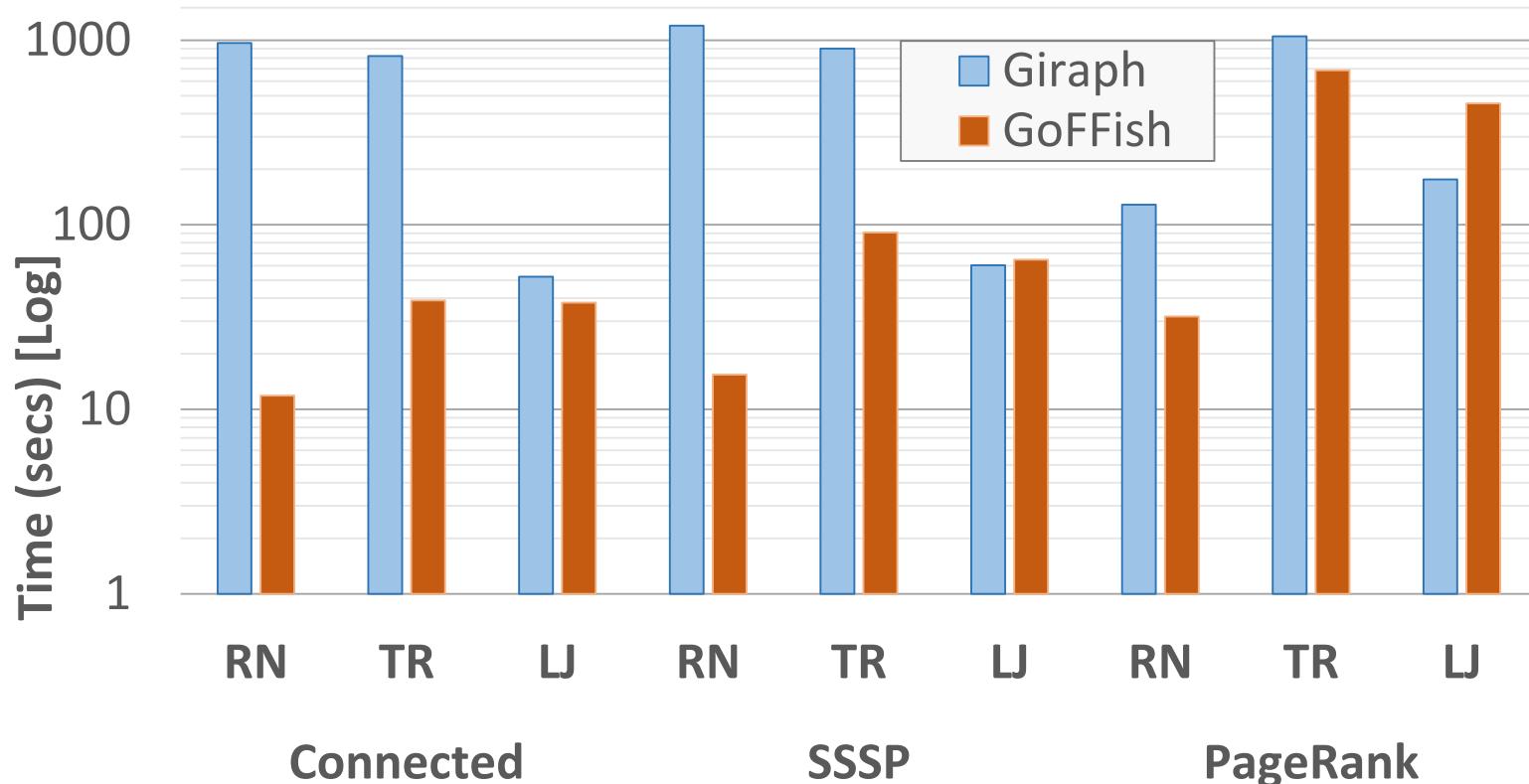
# Sub-graph centric programming

- Logic defined for sub-graphs (>Google Pregel)
- Bulk Synchronous Parallel exec of supersteps
- Message passing between SG's in superstep



# Results vs. Apache Giraph

CA Road (2M/2.7M), Traceroute (19M/23M),  
Live Journal (5M/68M)



GoFFish: A Sub-Graph Centric Framework for Large-Scale Graph Analytics, Simmhan, et al, ArXiv 2013



# To Conclude

- eScience has been focussing on “Big Data” for a while
  - There is some credence to the hype
- Novel applications are coming up
  - Scientific apps are a vanguard
- Platforms for analytics on dynamic & interconnected data are vital
  - Internet of Things, anyone?
- ***We need you @ SERC, IISc!***
  - Application deadline for MSc/PhD is **Mar, 2014**



# Thank You!

## Questions?

### Acknowledgements

Catharine van Ingen, Roger Barga, Alex Szalay, Jim Heasley, Viktor Prasanna, Alok Kumbhare, Charith Wickramaarachchi, Soonil Nagarkar, Santosh Ravi, Raghu Raghavendra, Shel Swenson & Jasmine Zhou

