

scientific data management: not your everyday transaction

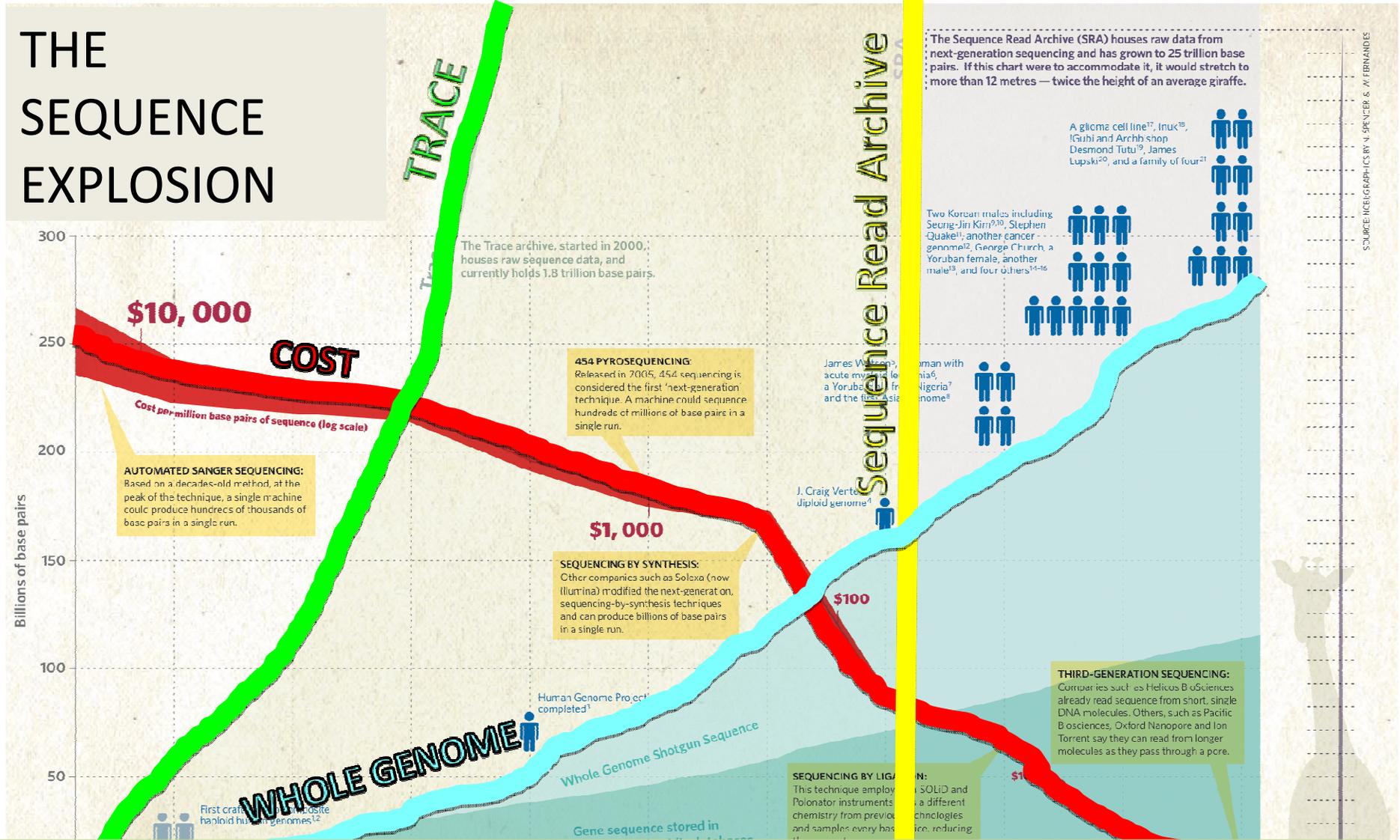
Anastasia Ailamaki

Data-Intensive Applications and Systems (DIAS) Laboratory

School of Computer and Communication Sciences

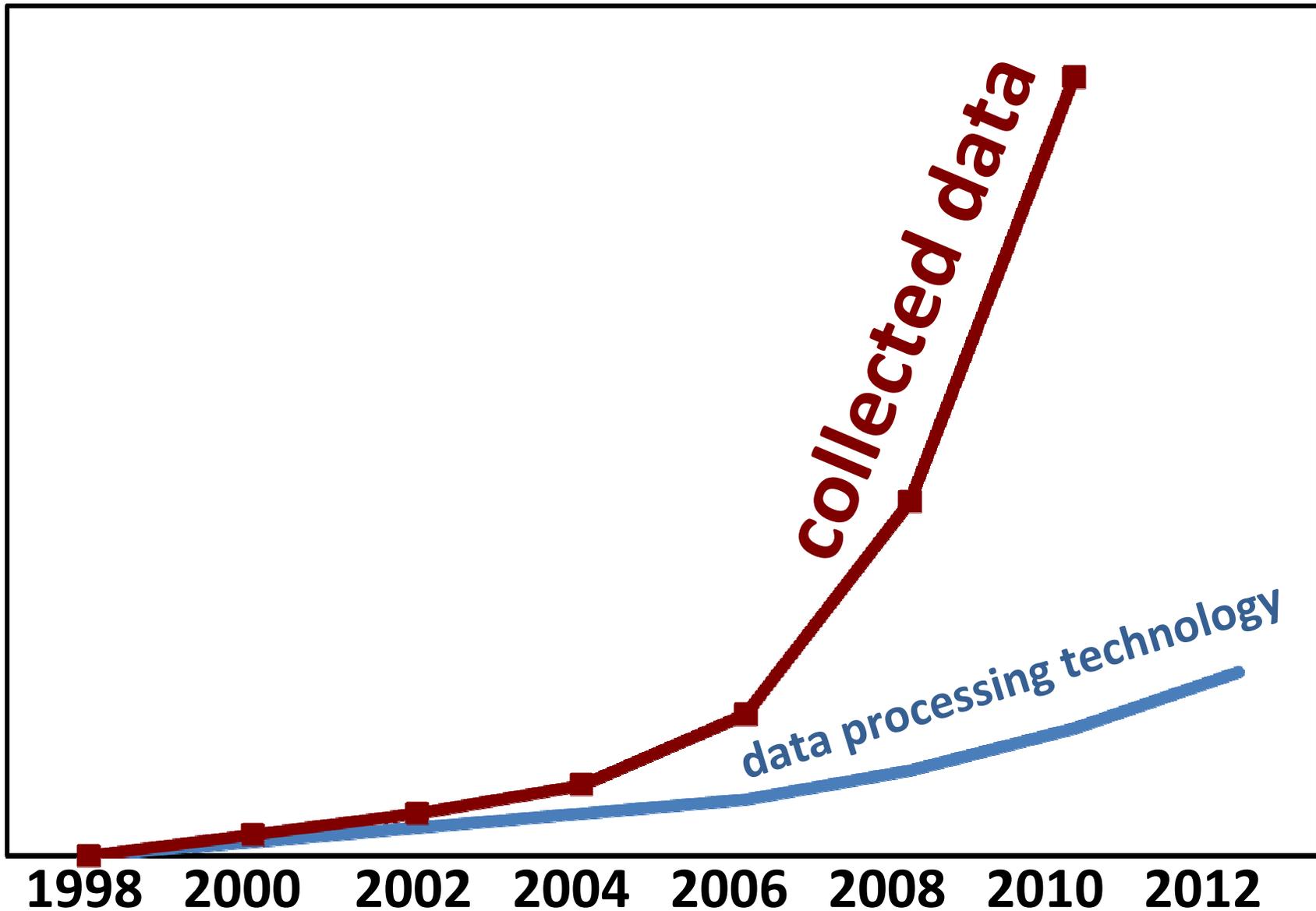


the human genome at ten (nature, 4/2010)



but, benefits hindered by complexity

scientific data grows much faster than technology



scientific data management now

- legacy software
- in main memory of supercomputers
- databases too rigid to use

As data grows, problem changes

- difficult and slow
- some data discarded

bridge CS and domain sciences

meeting domain scientists

1. “Hello, we’re SO HAPPY to meet you. *We have SO MUCH data!* PLEASE come visit!”
2. visit lab, pretty pictures (we have SO MUCH data)
3. “Let’s have lunch!” (we have SO MUCH data)
4. revisit lab, receive promise to get some data
5. ask for data, no reply
6. play DBA (design/normalize schema, design data, write queries, rewrite queries, talk to tech staff)
7. ask for data, receive 2GB
8. repeat (6), then ask again for data, receive 4GB

why collaboration is hard

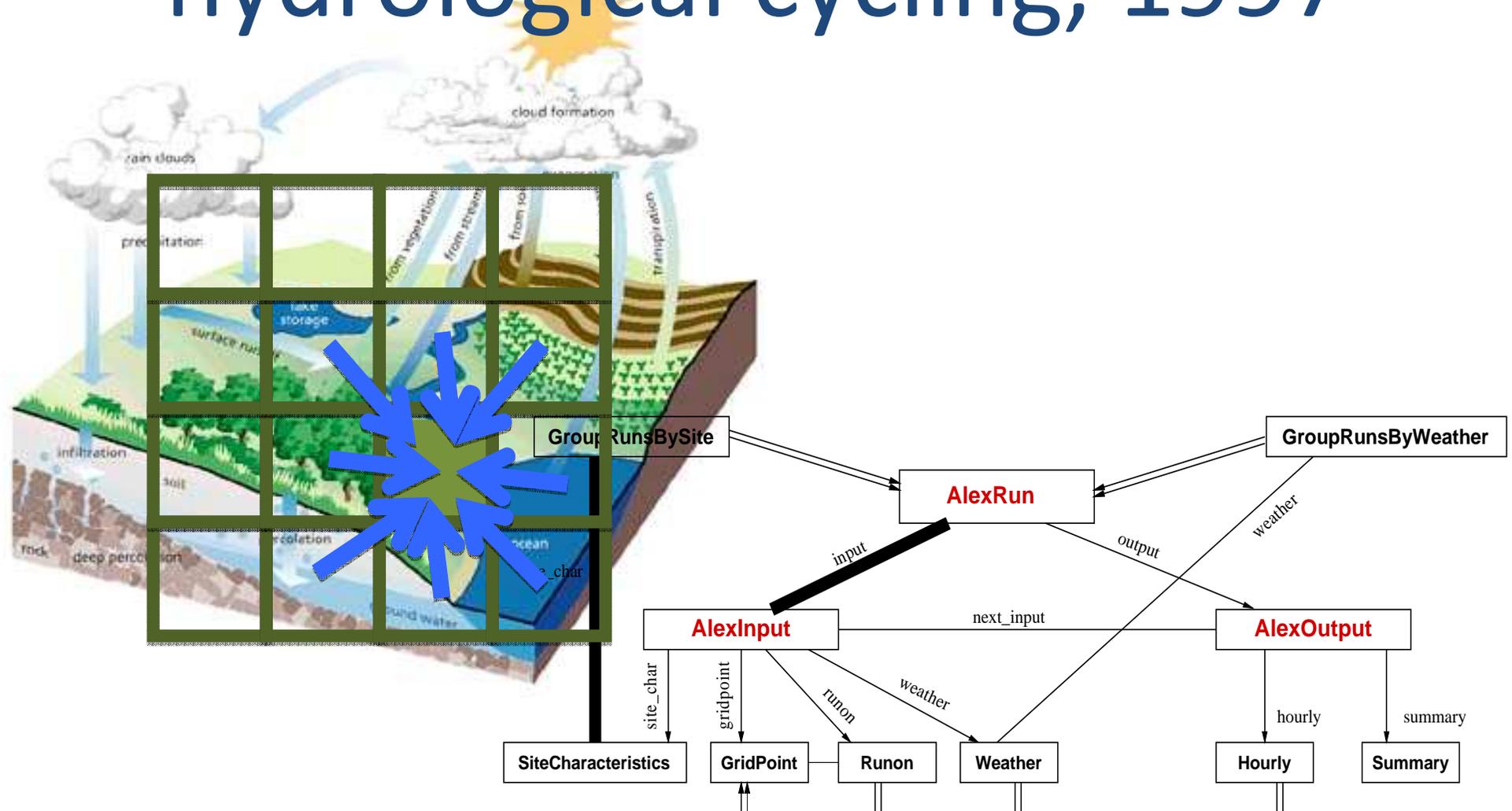
- Data is their achievement
 - They do not understand what we will do with it
 - They are afraid of what we may do with it
 - They think that we will put it on the internet
- They are not sure how we will help them
 - Do not recognize their problems in our demos
- They have been “burned” before

support work builds foundation!

It takes around **18 months** of **discussing** and **learning** about a scientific application and dataset *(while providing DBA services)* until a problem which calls for **true innovation** reveals itself.

ORGANIZING SCIENTIFIC DATA

hydrological cycling, 1997



**data-centric scientific workflow
enactment from within DBMS**

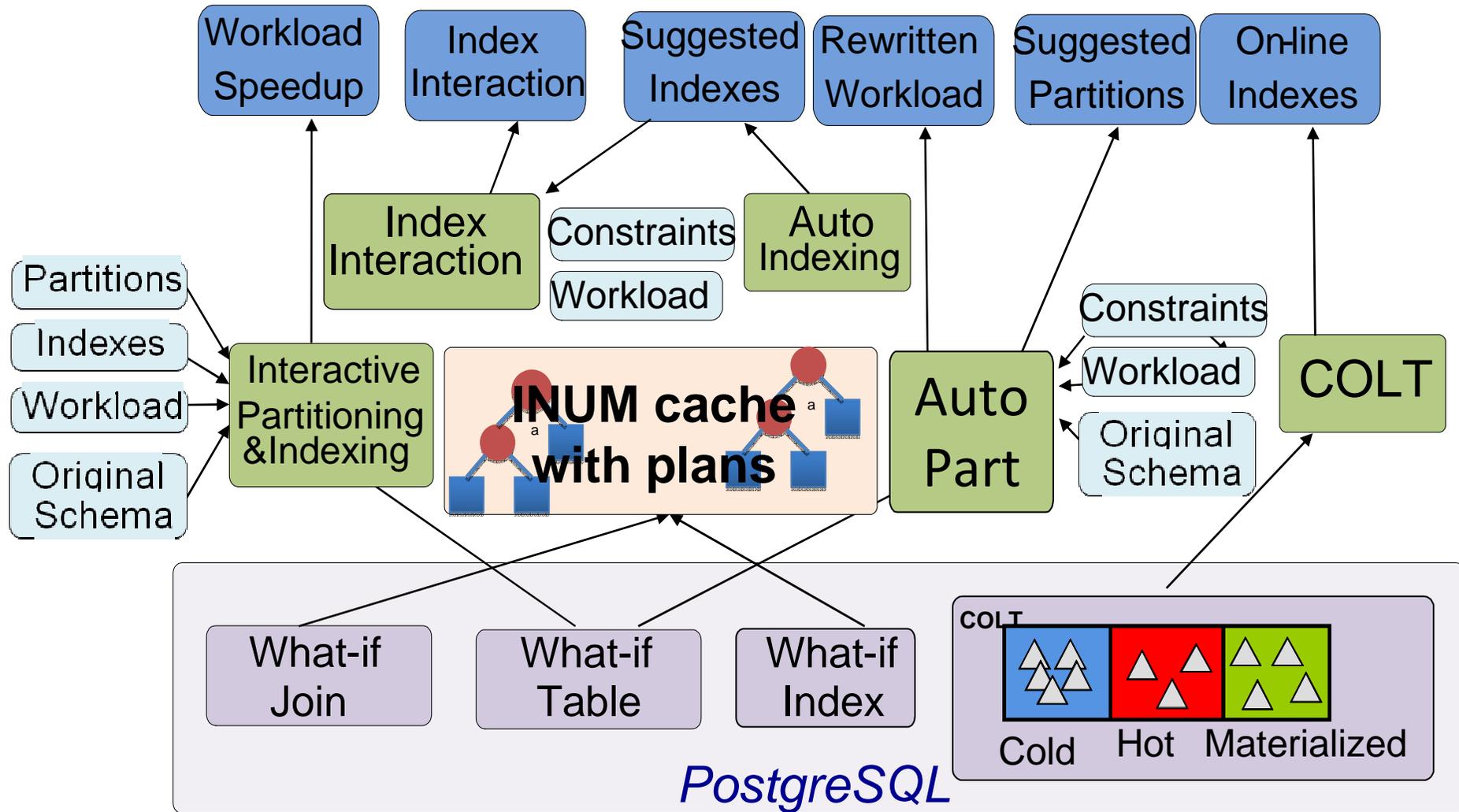
the large synoptic array telescope, 2017

date	time	type	category	Cx	Cy	Cz	...
mon	22:00	star	<i>proto</i>
mon	22:15	star	<i>red giant</i>
mon	22:20	galaxy	<i>spiral</i>
mon	22:27	star	<i>dwarf</i>
mon	23:00	galaxy	<i>elliptical</i>
tue	22:10	galaxy	<i>spiral</i>
tue	22:25	star	<i>proto</i>
...
...



100 billion objects, 20 PB/night

PARINDA DB designer



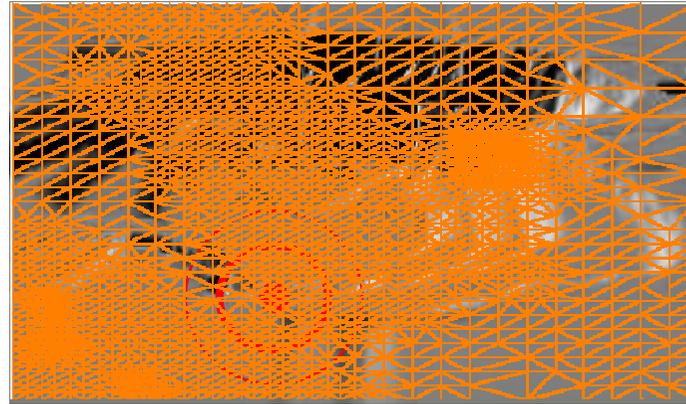
IMPLEMENTING PHYSICAL MODELS

earthquake simulation/analysis

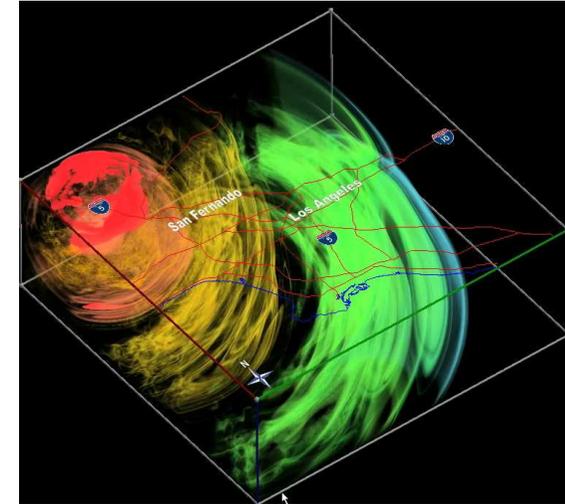
Quake Group [www.cs.cmu.edu/~quake]



Scientist



Simulation Model



Simulation Output

Analys

`fopen('time050.dat')`
`mesh)`

time010

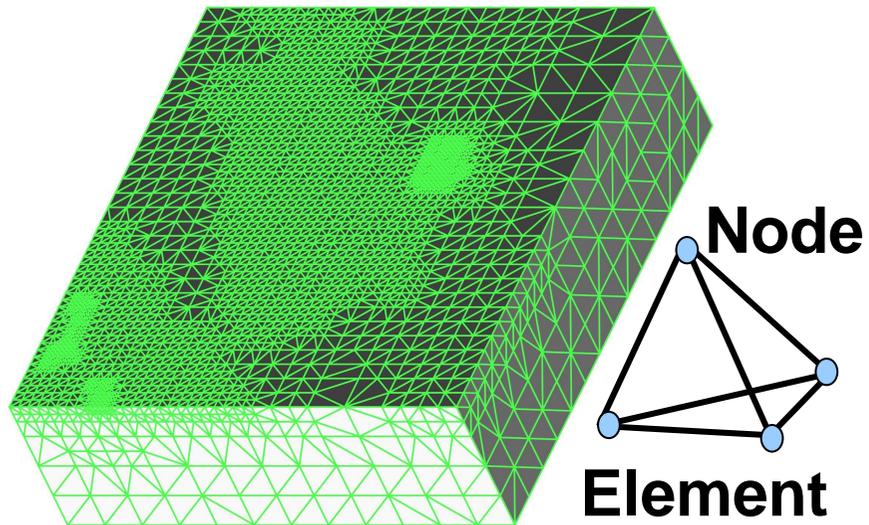
time020

time030

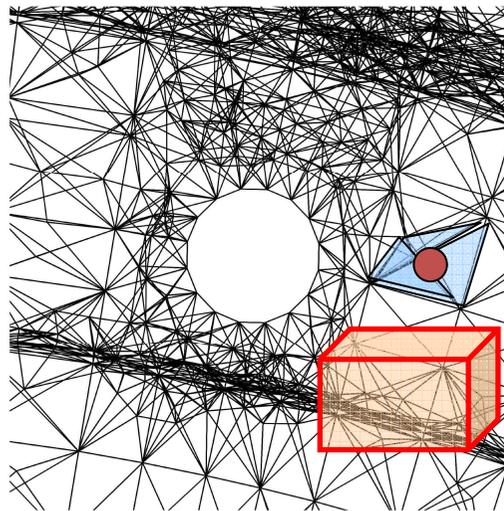


**100GB per time-step, 20000 time-steps
performance? access to complex structures?**

tetrahedral mesh models



- Queries
 - Point
 - Range
 - Feature



Point Query **Q**

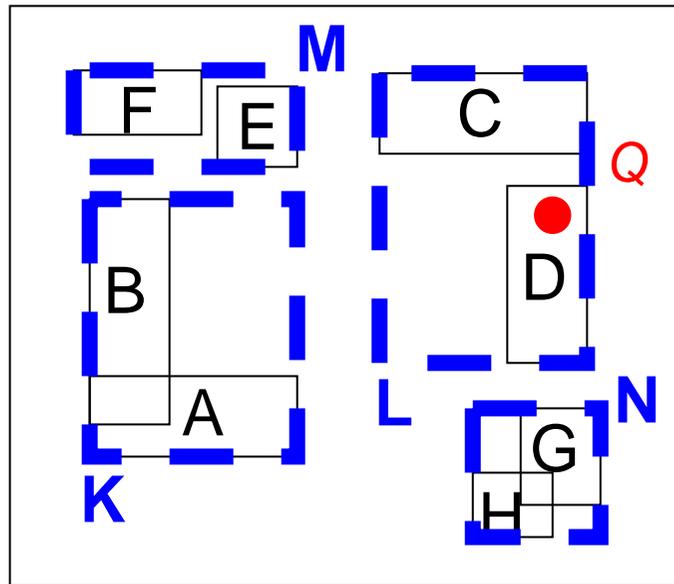
Range Query **R**

- Example: Visualization
 - Show ground velocity at **Q**
 - Draw the temperature of **R**

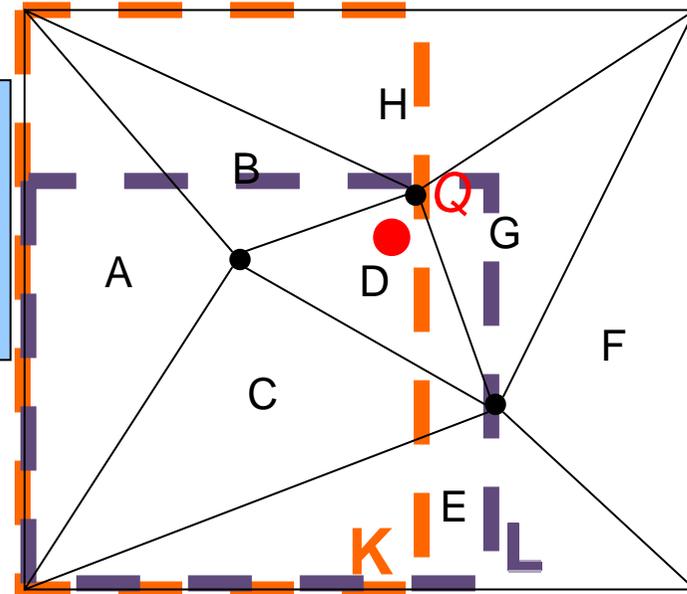
Courtesy Cornell Fracture Group

goal: efficiently process *geometric* queries

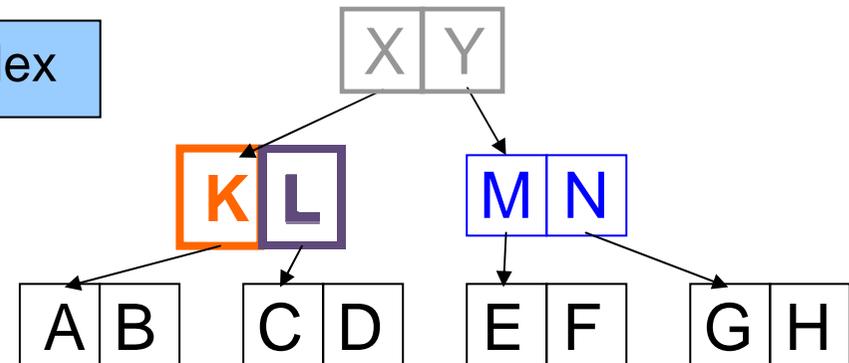
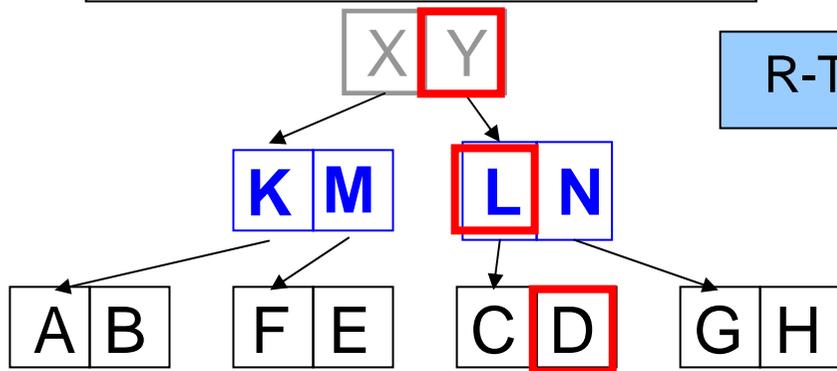
R-Tree indexing



Minimum Bounding Rectangle (MBR)



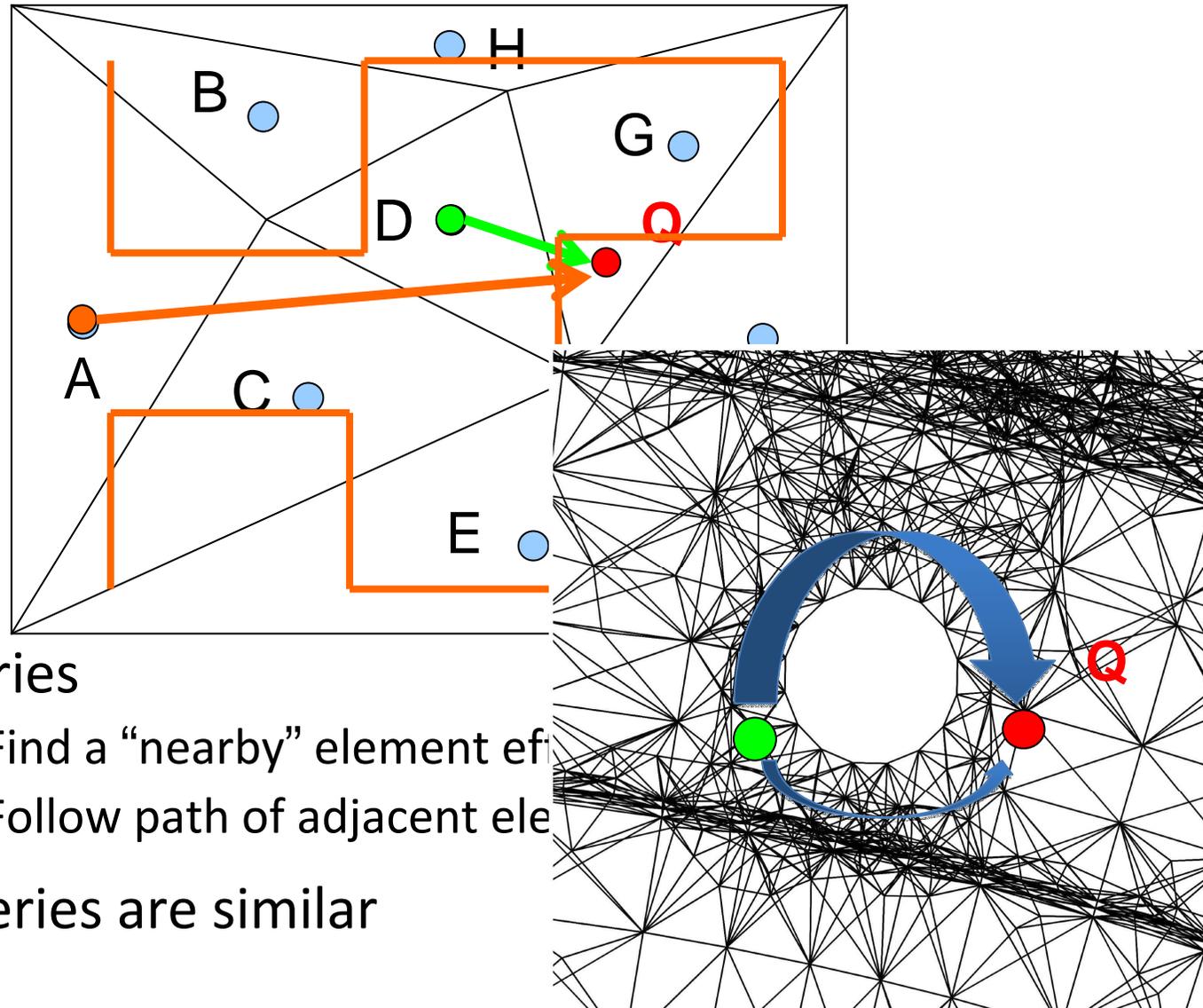
R-Tree Index



Disk page

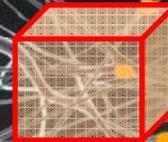
tight mesh connectivity hurts performance

directed local search



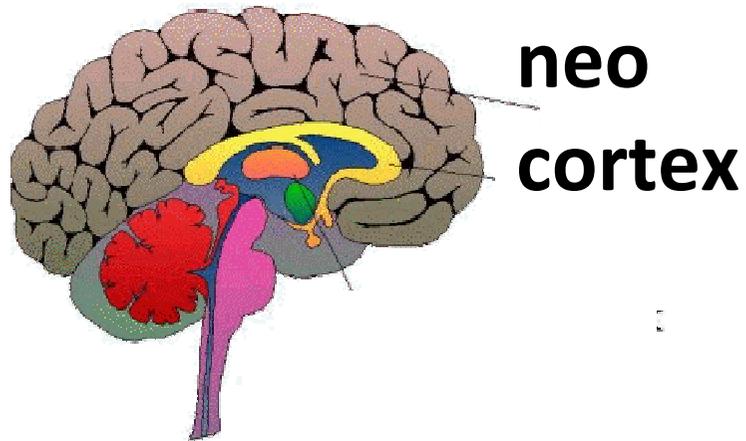
- Point queries
 - Step 1: Find a “nearby” element of
 - Step 2: Follow path of adjacent ele
- Range queries are similar

databasing the brain



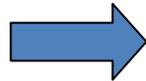
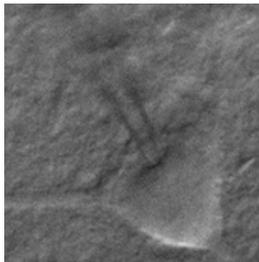
a spatial data management challenge

brain simulation

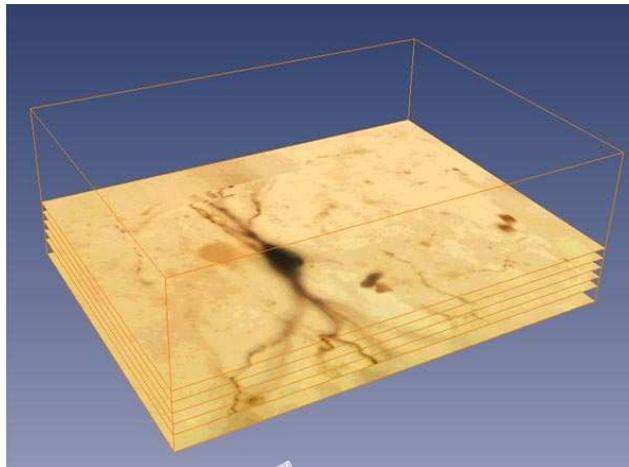


images courtesy of the Blue Brain Project

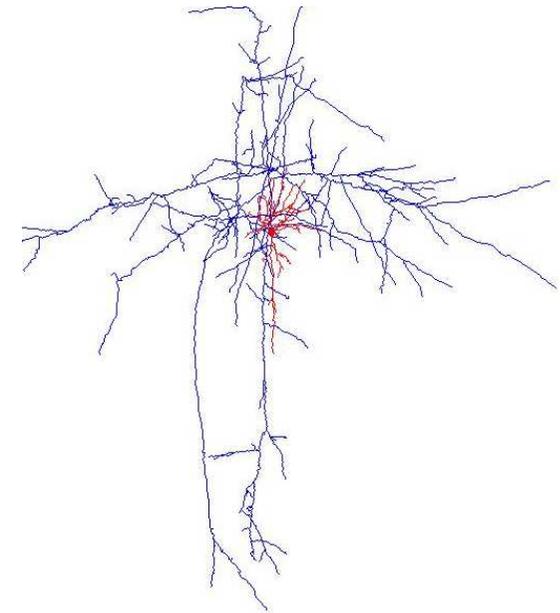
**dye loading &
raster scanning**



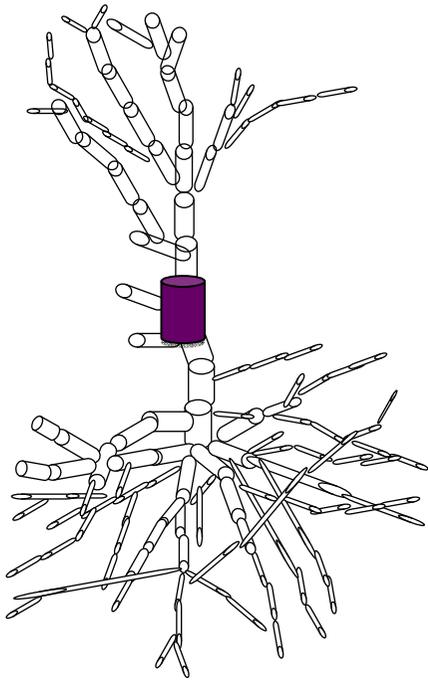
3D reconstruction



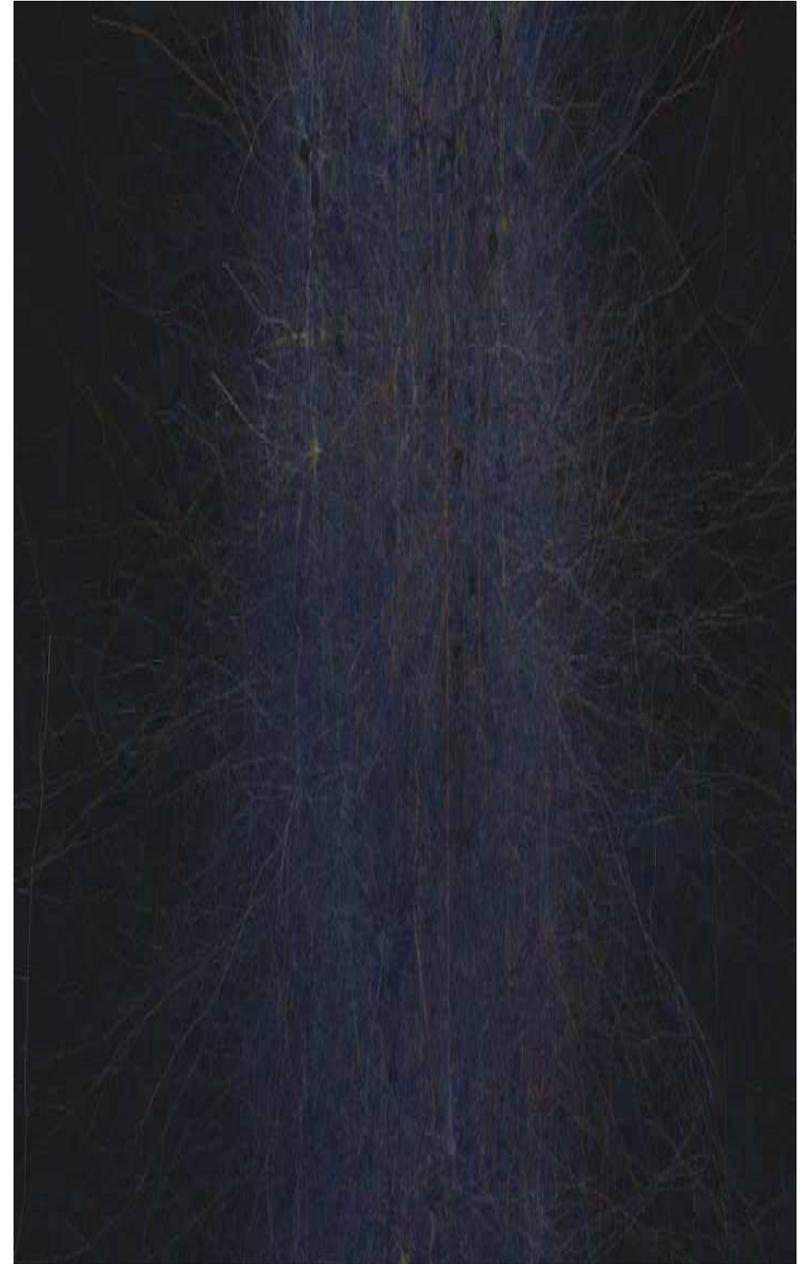
a neuron



morphologies



**single neuron,
modeled with 3D cylinders**



human brain: ~86 billion neurons

brain data deluge

	before	now	future
# of neurons	1692	100K	100B
	1 Layer	10 Columns	Full Brain
segment representation	4.5M 140MB	450M 13.4GB	4.5×10^{14} 14PB
mesh representation	173M 5.8GB	17.3B 580GB	1.7×10^{16} 0.5EB

**molecular representation more fine grained
simulation trace = infinite data**

spatial range



morphometric
analysis

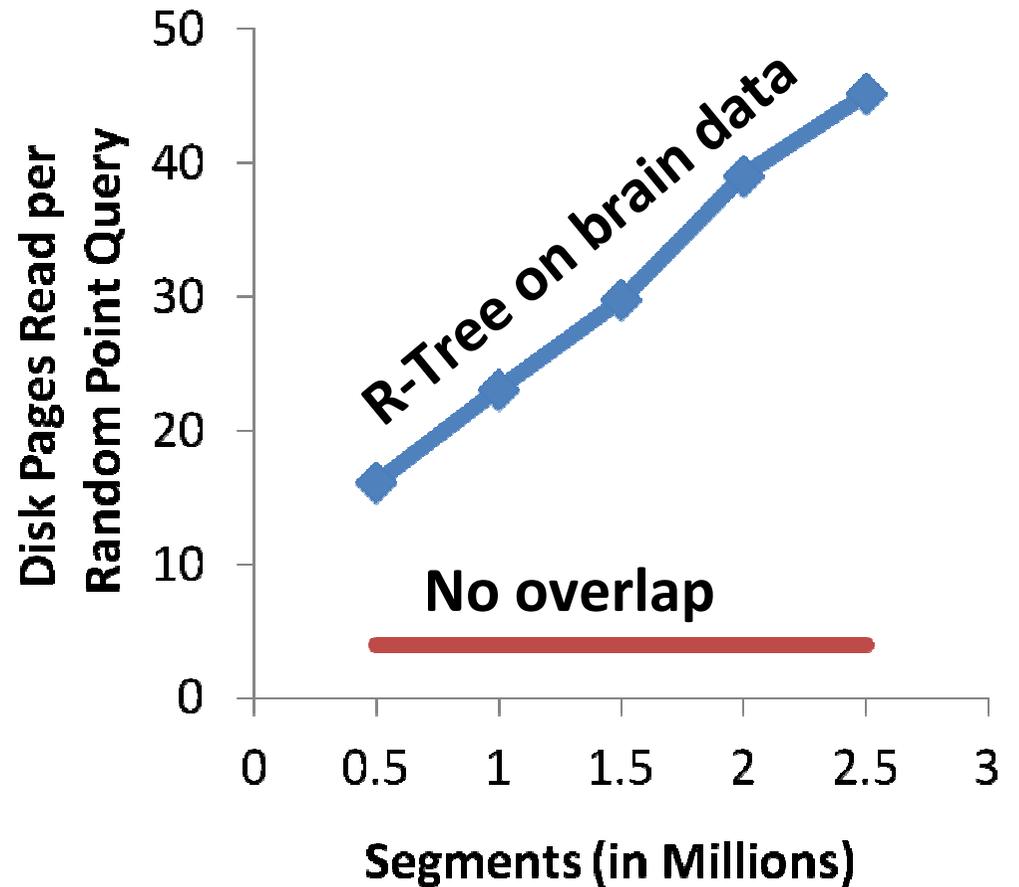
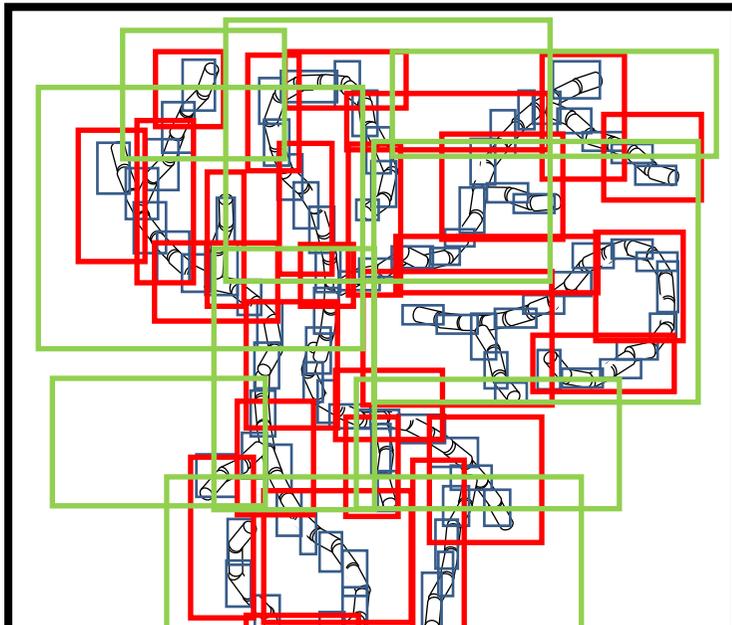
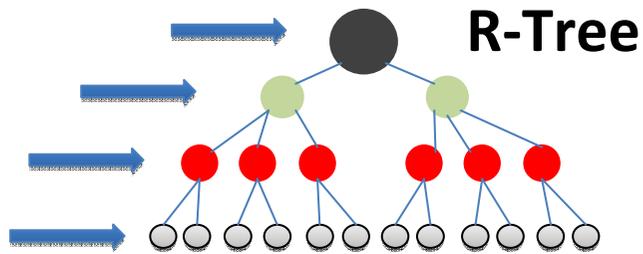
visualization

model
construction

Goal: execute *efficiently* 3D spatial range queries.

- even if data no longer fits into main memory
- even if density of dataset increases

traditional spatial indexing



too much structural overlap

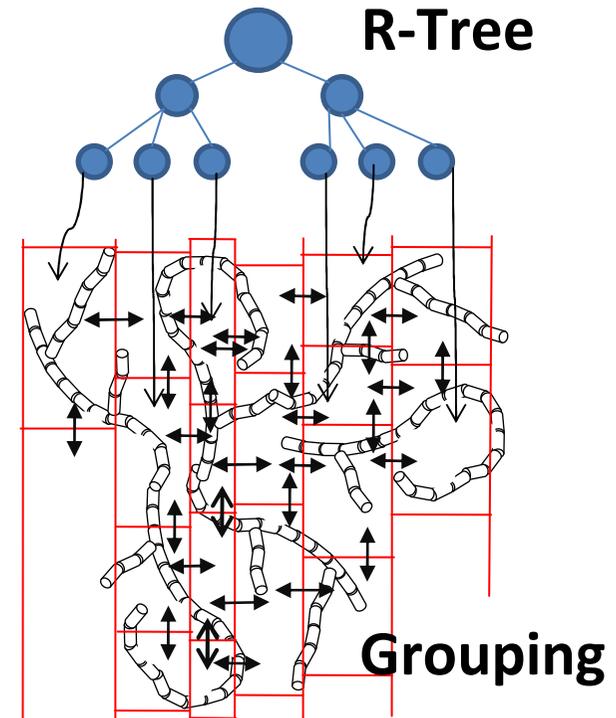
FLAT: insensitive to density

- Indexing

- group spatially close objects on disk pages
- add links between neighboring groups
- use traditional R-Tree to index disk pages

- Querying

- **seed phase**: find random element inside range in R-Tree (not affected by overlap)
- **crawl phase**: use seed element and recursively traverse all neighbors



FLAT indexing

from 10K to 1 million neurons!

SCOUT: moving range queries

Neural tissue density analysis:

User issues stream of queries

I/O too costly

even with spatial index

Predict next query

smart&efficient prefetching

Stream of spatial queries

Neuron branch

Neuron Tissue Sample
(1692 neurons)

query history, density, or content

touch detection

Model Synapses

electrical connections between axons and dendrites

Data Challenge

100K neurons => 5B synapses

30GB addl space to store synapse data

Human Brain => 100B neurons ~PB space

Need efficient spatial proximity queries and precise distance calculation



a major bottleneck in brain simulation

simulation trace analysis

Need *accurate* data statistics to

- Discover and explore neuro-circuit behavior
- Compare to behavior of biological tissue
- Understand plasticity

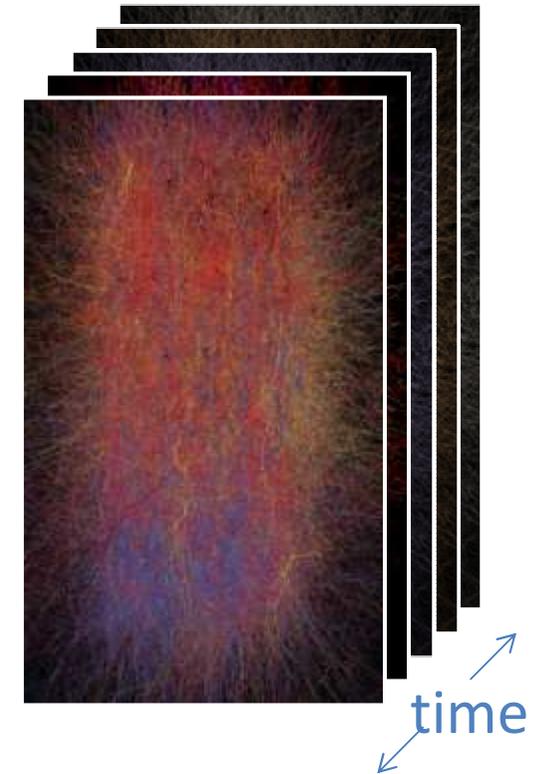
Typical trace file ~0.8TB

for 100K neurons

for only 1 second of simulation

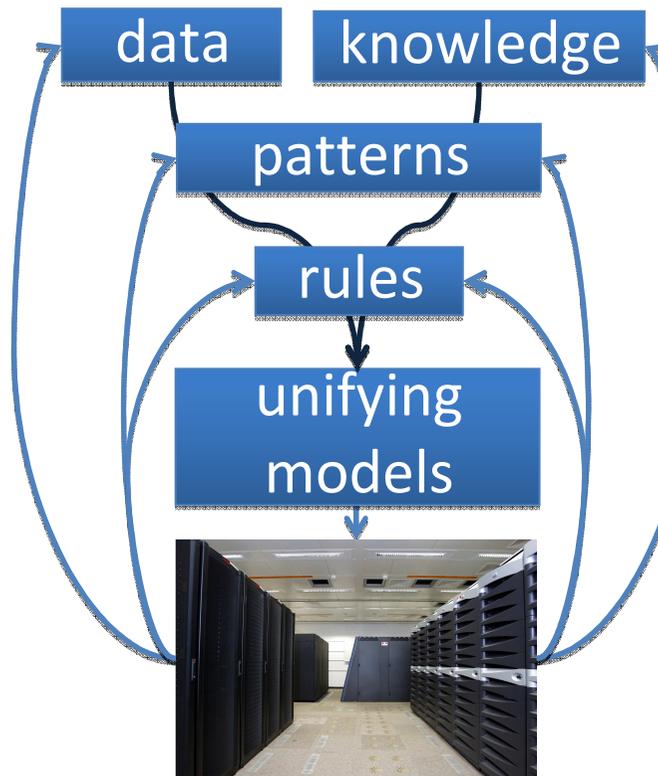
In-memory efficient access method limit use of
complex query analysis

Storage capacity limits longer simulation time



need aggressive spatial compression

vision: the human brain project, 2021



**from molecules to cognition:
a (big) data integration problem**

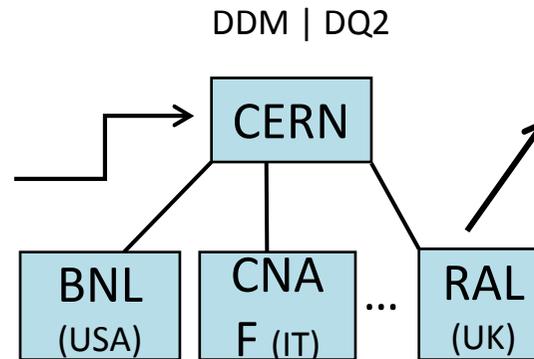
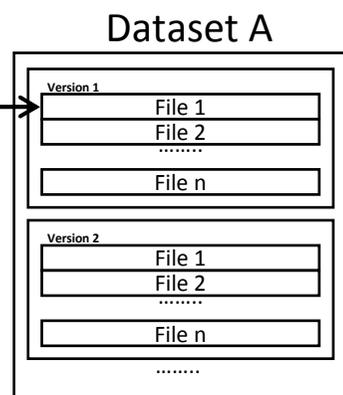
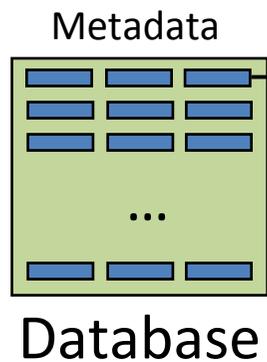
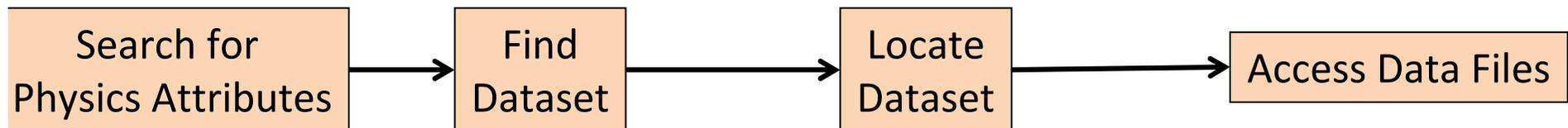
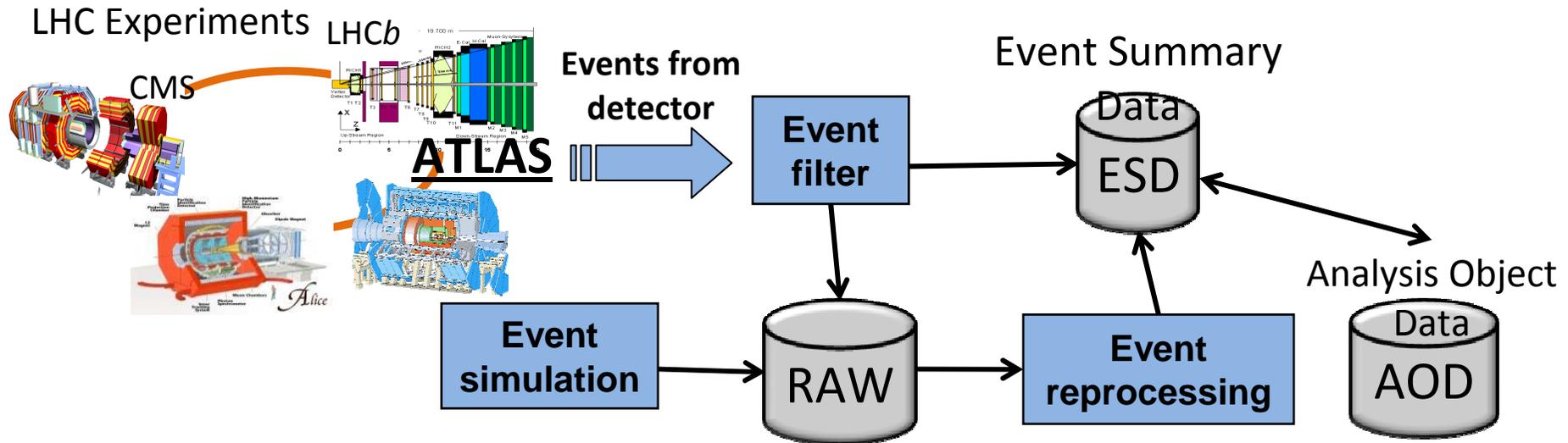
BROADER IMPACT

the CERN large hadron collider, now



27km
100M sensors/detection
40M detections/sec
15 PB/year

ATLAS experiment (simplified)



DB: extract, transform, load, query

time

any alternative
approach?

preparation
"overhead"

... lack of trust in database vendors
... databases "forever owning" the data

NoDB: query, query, query, query

Idea: Queries run **in-situ**, i.e., over raw data files

- ✓ Large collections of files
- ✓ Multiple data formats
 - ✓ Integration with existing tools
- ✓ Changing areas of interest

New technology: fast queries on raw data

lessons learnt

- Be patient
 - Aim at solving the scientist's problems, not ours
 - Go back to the lab and apply findings
- Many solutions necessary, one* does not fit all
 - *query language, data model, data type, index
- Open our minds to build *many* bridges to sciences

key to turn data into information



...an endless source of inspiration

Thank you!



Martha Anderson, Yannis Ioannidis, Miron Livny

Jim Gray, Alex Szalay, Randal Burns, Tanu Malik

Andy Connolly, Bob Nichol, Jeff Gardner

Gerd Heber, Dave O'Hallaron, Julio Lopez

Henry Markram, Felix Schuermann

...and to everyone who collects data