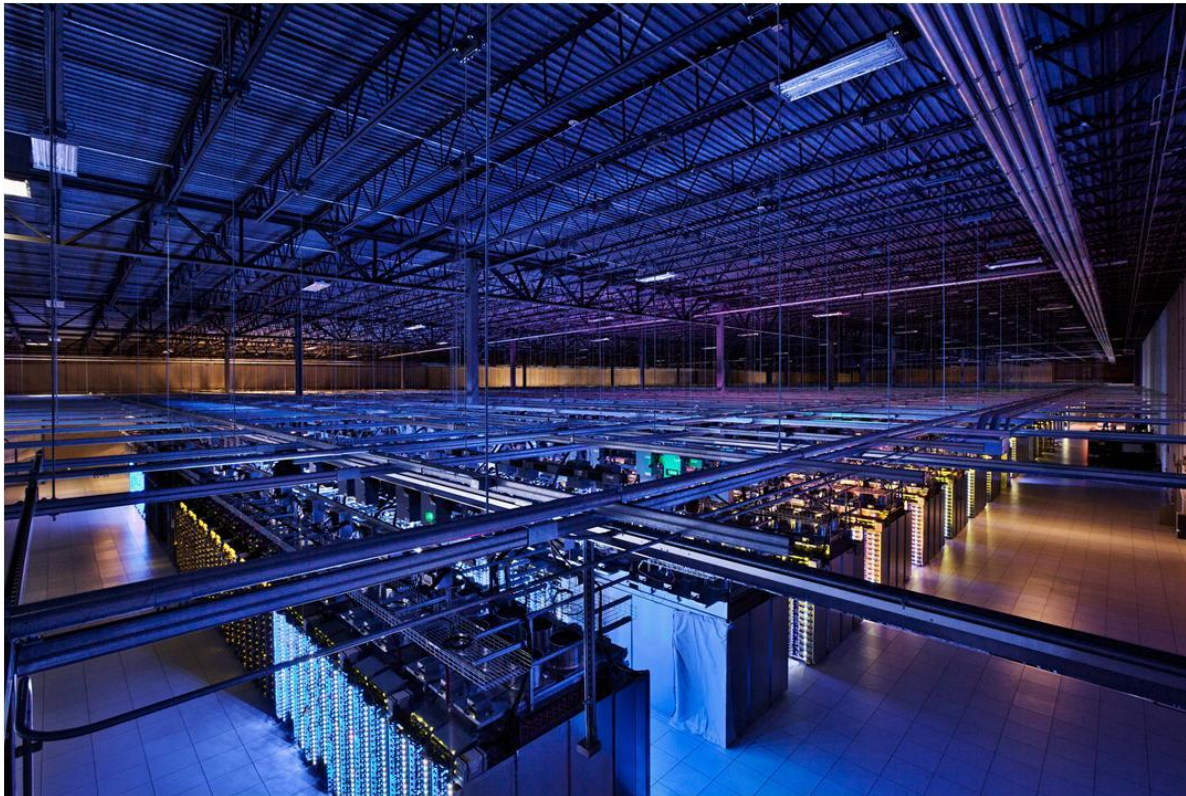


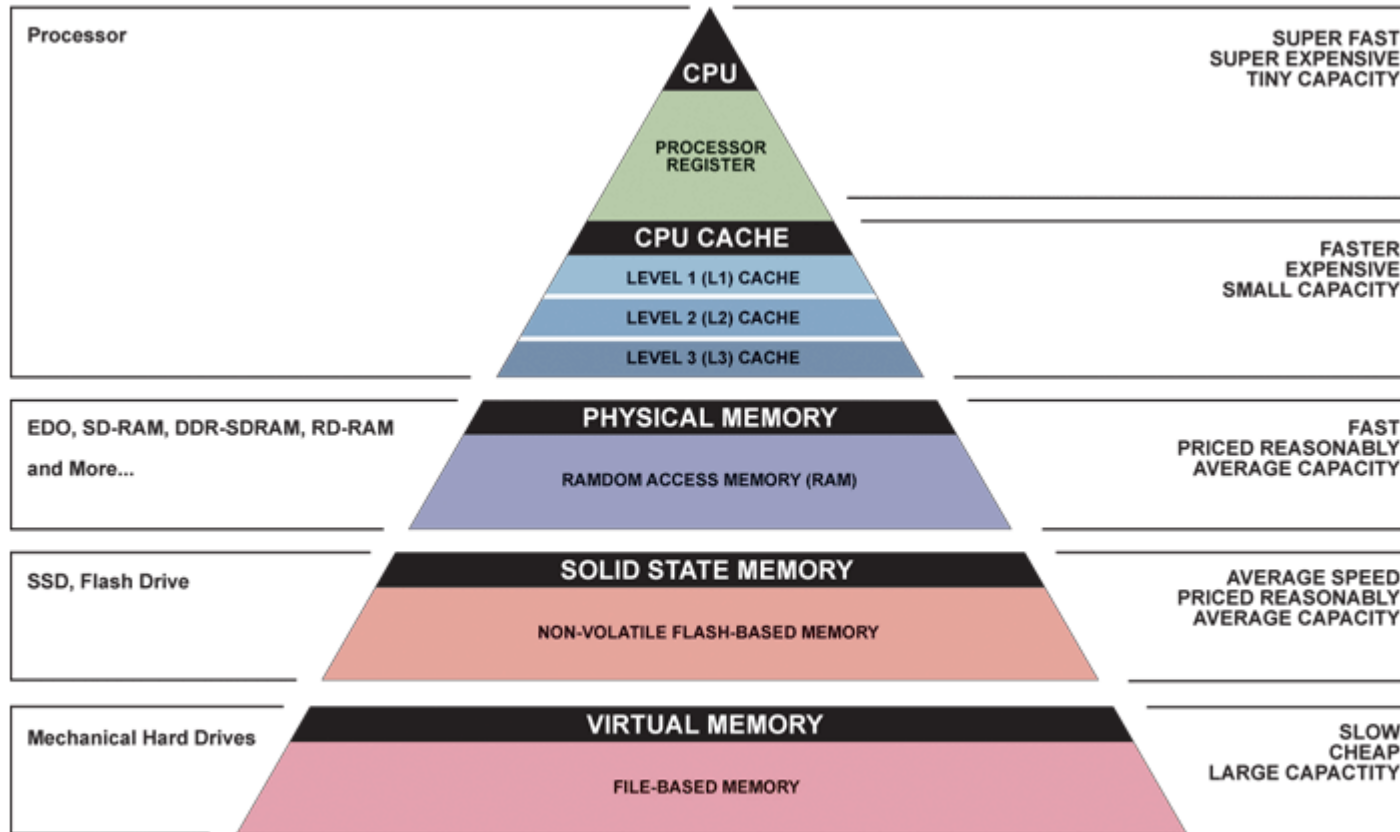
# Large-Scale Data Engineering

Some notes on Access Patterns, Latency,  
Bandwidth



+ Tips for  
practical

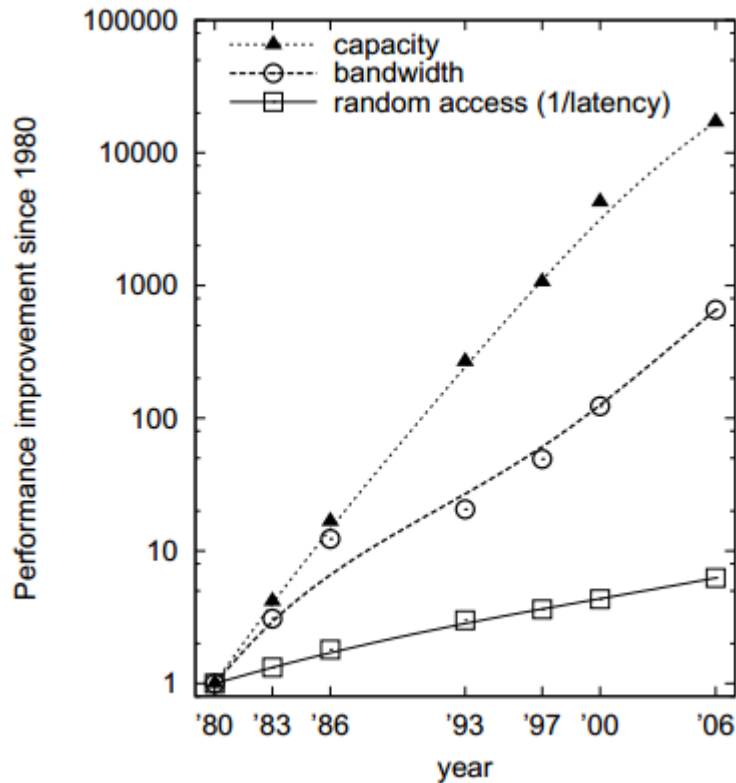
# Memory Hierarchy



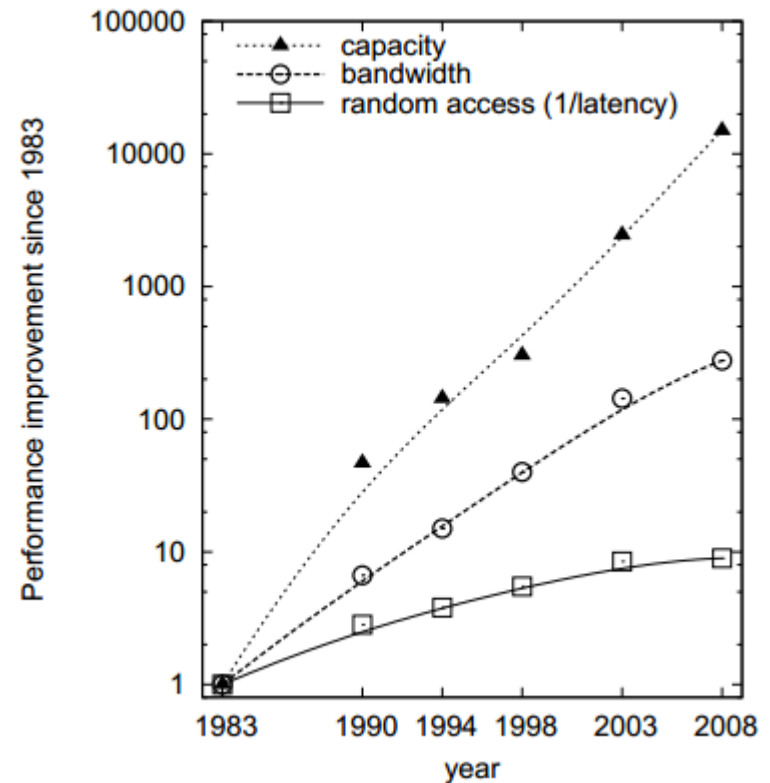
▲ Simplified Computer Memory Hierarchy  
Illustration: Ryan J. Leng



# RAM, Disk Improvement Over the Years



## RAM



## Magnetic Disk

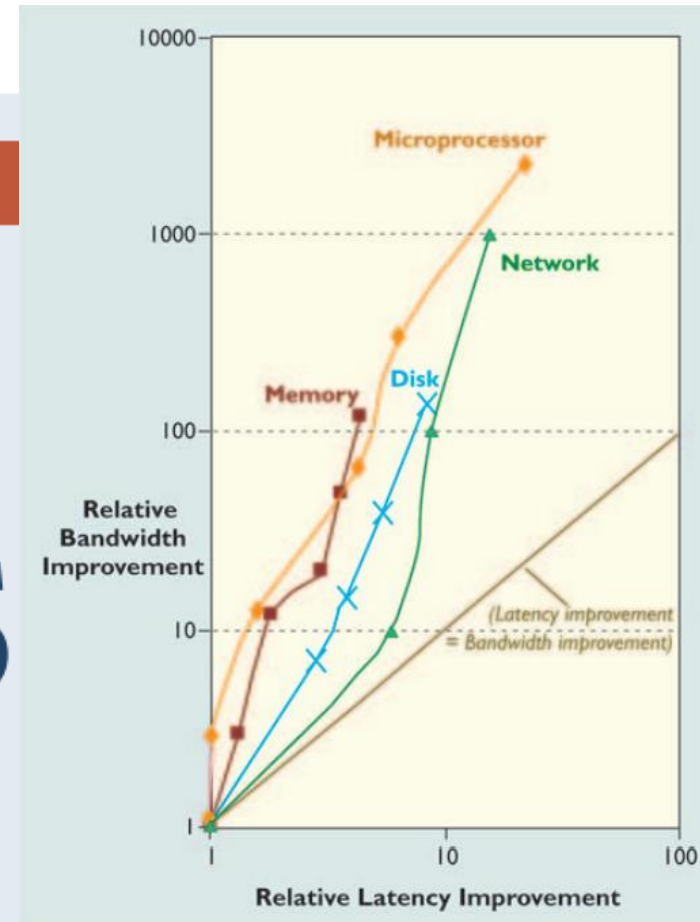
# Latency Lags Bandwidth

- Communications of the ACM, 2004

By David A. Patterson

## LATENCY LAGS BANDWIDTH

*Recognizing the chronic imbalance between bandwidth and latency, and how to cope with it.*



As I review performance trends, I am struck by a consistent theme across many technologies: bandwidth improves much

# Geeks on Latency



jboner / [latency.txt](#)

Created on 31 May 2012

## Latency Numbers Every Programmer Should Know

latency.txt

```

1 Latency Comparison Numbers
2 -----
3 L1 cache reference           0.5 ns
4 Branch mispredict           5 ns
5 L2 cache reference          7 ns      14x L1 cache
6 Mutex lock/unlock           25 ns
7 Main memory reference        100 ns    20x L2 cache, 200x L1 cache
8 Compress 1K bytes with Zippy 3,000 ns
9 Send 1K bytes over 1 Gbps network 10,000 ns  0.01 ms
10 Read 4K randomly from SSD*   150,000 ns  0.15 ms
11 Read 1 MB sequentially from memory 250,000 ns  0.25 ms
12 Round trip within same datacenter 500,000 ns  0.5 ms
13 Read 1 MB sequentially from SSD* 1,000,000 ns  1 ms  4X memory
14 Disk seek                    10,000,000 ns  10 ms  20x datacenter roundtrip
15 Read 1 MB sequentially from disk 20,000,000 ns  20 ms  80x memory, 20X SSD
16 Send packet CA->Netherlands->CA 150,000,000 ns  150 ms
17
18 Notes
19 -----
20 1 ns = 10-9 seconds
21 1 ms = 10-3 seconds
22 * Assuming ~1GB/sec SSD

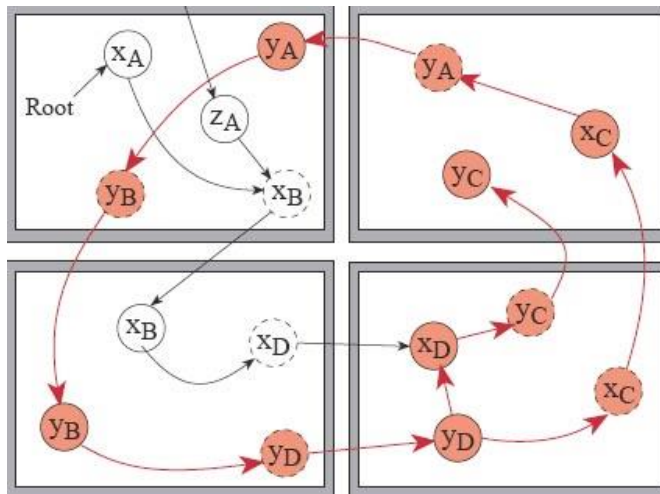
```

# Sequential Access Hides Latency

- Sequential RAM access
  - CPU prefetching: multiple consecutive cache lines being requested concurrently
- Sequential Magnetic Disk Access
  - Disk head moved once
  - Data is streamed as the disk spins under the head
- Sequential Network Access
  - Full network packets
  - Multiple packets in transit concurrently

# Consequences For Algorithms

- Analyze the main data structures
  - How big are they?
    - Are they bigger than RAM?
    - Are they bigger than CPU cache (a few MB)?
  - How are they laid out in memory or on disk?
    - One area, multiple areas?

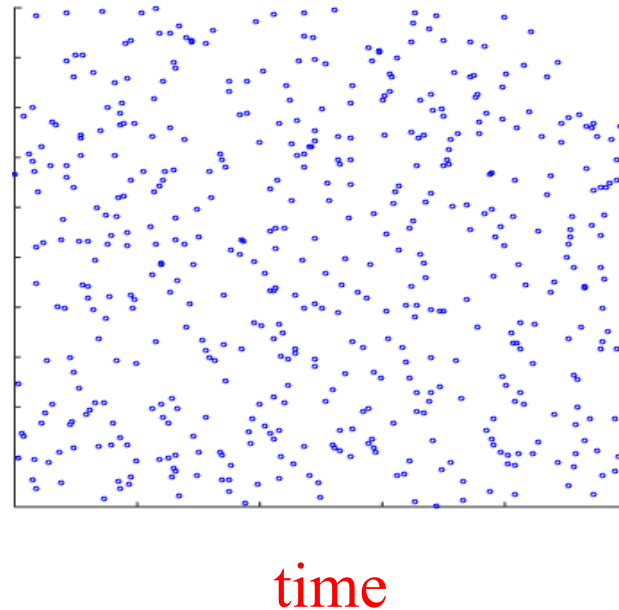
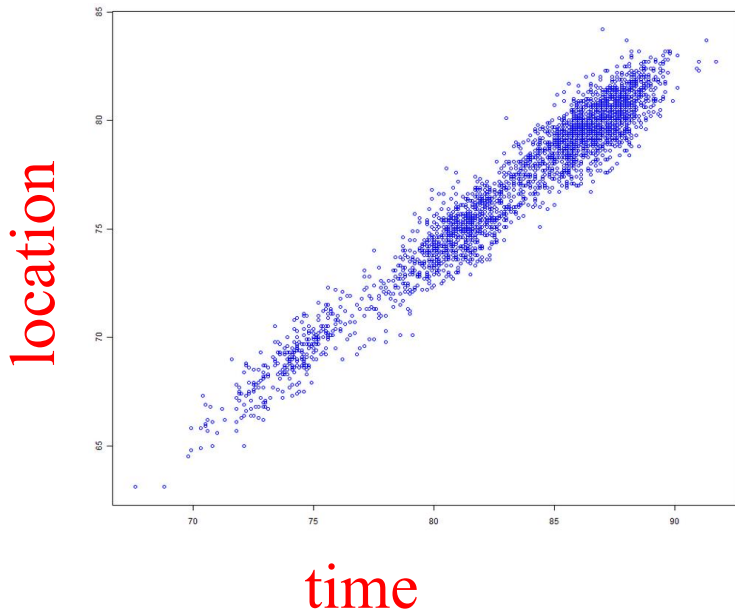


Java Object Data Structure  
vs  
memory pages (or cache lines)



# Consequences For Algorithms

- Analyze your access patterns
  - Sequential: you're OK
  - Random: it better fit in cache!
    - What is the access granularity?
    - Is there temporal locality?
    - Is there spatial locality?



# Storage Layout of a Table

## Basics - Row vs. Column-Stores

### Row-Store Storage

First name	Email	Phone #	Street Address

- Multiple rows are stored per page
- Traditional way for storage

😊 Easy to add a new record

😞 Might read in unnecessary data

### Column Store Storage

First name	Email	Phone #	Street Address

- Stores each column in separate set of disk pages

😊 Only need to read relevant data

😊 Data compression

😞 Tuple writes might require multiple seeks

# Improving Bad Access Patterns

- Minimize Random Memory Access
  - Apply filters first. Less accesses is better.
- Denormalize the Schema
  - Remove joins/lookups, add looked up stuff to the table (but.. makes it bigger)
- Trade Random Access For Sequential Access
  - perform a 100K random key lookups in a large table
    - ➔ put 100K keys in a hash table, then
      - scan table and lookup keys in hash table
- Try to make the randomly accessed region smaller
  - Remove unused data from the structure
  - Apply data compression
  - Cluster or Partition the data (improve locality) ...hard for social graphs
- If the random lookups often fail to find a result
  - Use a Bloom Filter


# Assignment 1: Querying a Social Graph



# LDBC Data generator

- Synthetic dataset available in different scale factors
  - SF100 ← for quick testing
  - SF3000 ← the real deal
- Very complex graph
  - Power laws (e.g. degree)
  - Huge Connected Component
  - Small diameter
  - Data correlations
    - Chinese have more Chinese names*
  - Structure correlations
    - Chinese have more Chinese friends*

← → ↻ | ldbcouncil.org/industry/members


**LDBC**  The graph & RDF benchmark reference


BENCHMARKS » **INDUSTRY** » PUBLIC » DEVELOPER » EVENTS TALKS PUBLICATIONS BLOG


Information about how the LDBC organization works


HOME » **INDUSTRY** » MEMBERS


Companies:


 OPENLINK SOFTWARE  
Making Technology Work For You


 ontotext


 neotechnology  
graphs are everywhere

 \*Sparsity

 bigdata  
by systap

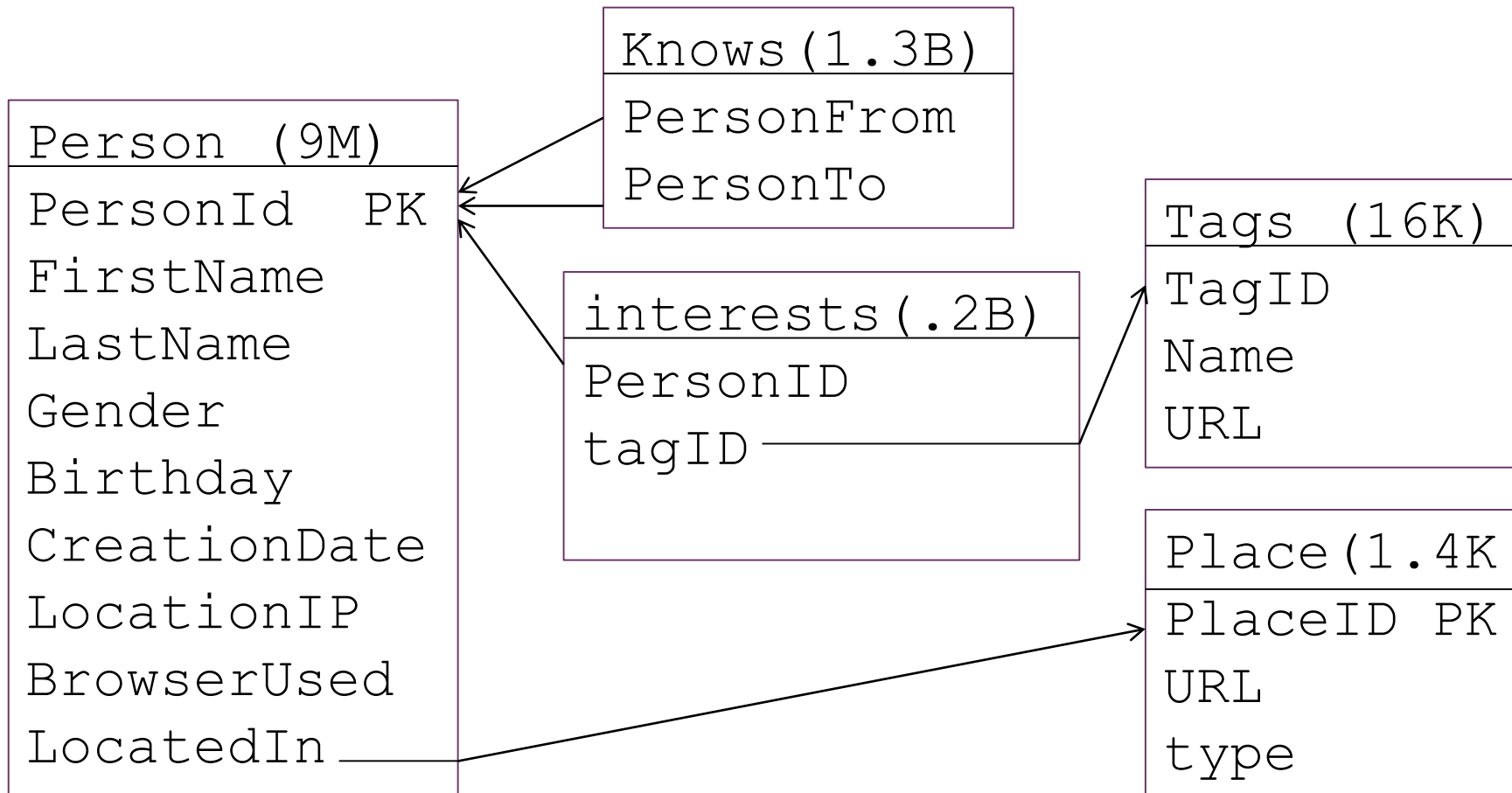
 IBM

 ORACLE  
LABS

 SPARQLcity

# CSV file schema

- See: [http://wikistats.ins.cwi.nl/lsde-data/practical\\_1](http://wikistats.ins.cwi.nl/lsde-data/practical_1)
- Counts for sf3000 (total 37GB)



# The Query

- The marketers of a social network have been data mining the musical preferences of their users. They have built statistical models which predict given an interest in say artists A2 and A3, that the person would also like A1 (i.e. rules of the form: A2 and A3  $\rightarrow$  A1). Now, they are commercially exploiting this knowledge by selling targeted ads to the management of artists who, in turn, want to sell concert tickets to the public but in the process also want to expand their artists' fanbase.
- The ad is a suggestion for people who already are interested in A1 to buy concert tickets of artist A1 (with a discount!) as a birthday present for a friend ("who we know will love it" - the social network says) who lives in the same city, who is not yet interested in A1 yet, but is interested in other artists A2, A3 and A4 that the data mining model predicts to be correlated with A1.

# The Query

*For all persons  $P$  :*

- who have their birthday on or in between  $D1..D2$*
- who do not like  $A1$  yet*

*we give a score of*

- 1 for liking any of the artists  $A2$ ,  $A3$  and  $A4$  and*
- 0 if not*

*the final score, the sum, hence is a number between 0 and 3.*

*Further, we look for friends  $F$ :*

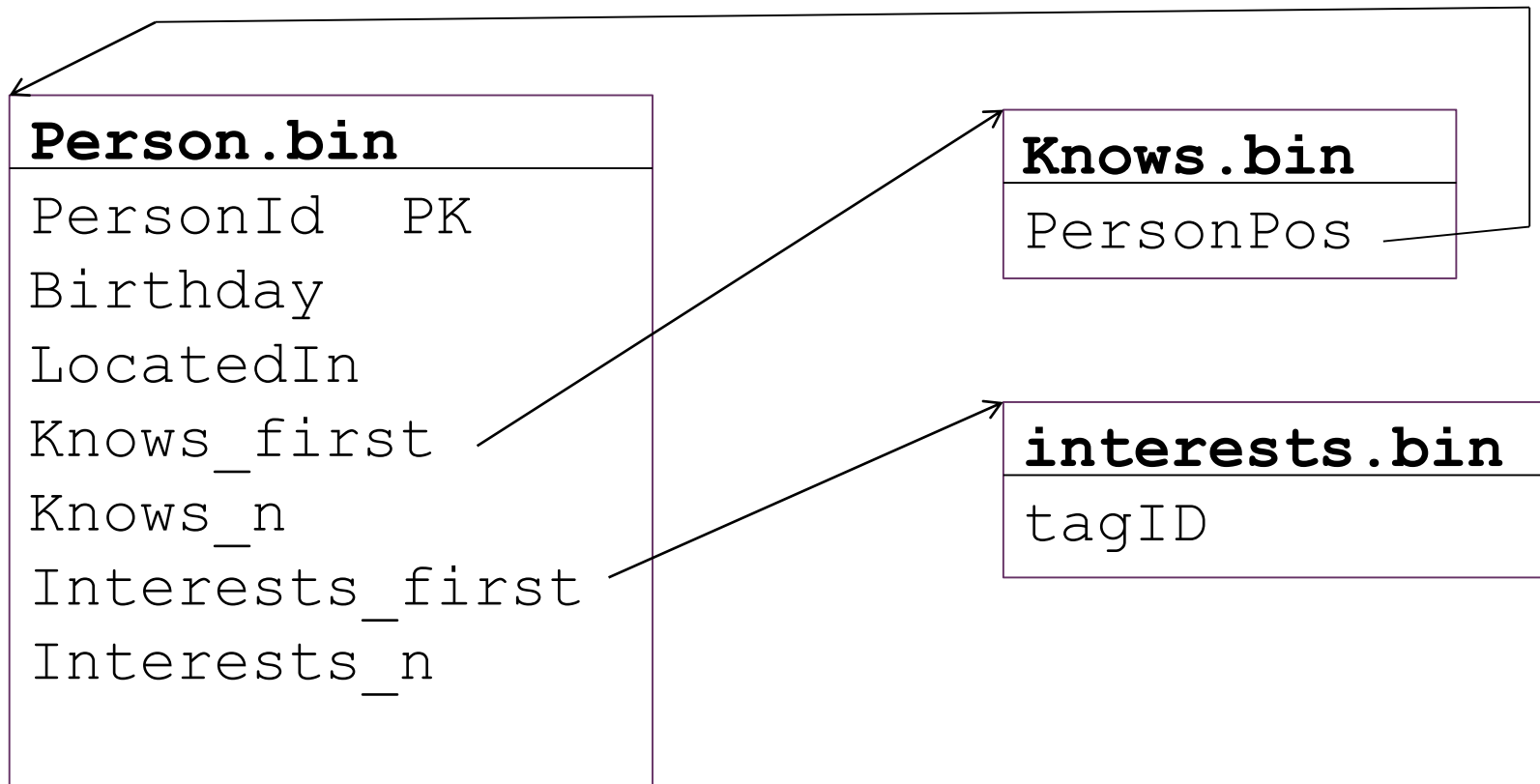
- Where  $P$  and  $F$  who know each other mutually*
- Where  $P$  and  $F$  live in the same city and*
- Where  $F$  already likes  $A1$*

*The answer of the query is a table (score,  $P$ ,  $F$ ) with only scores  $> 0$*



# Binary files

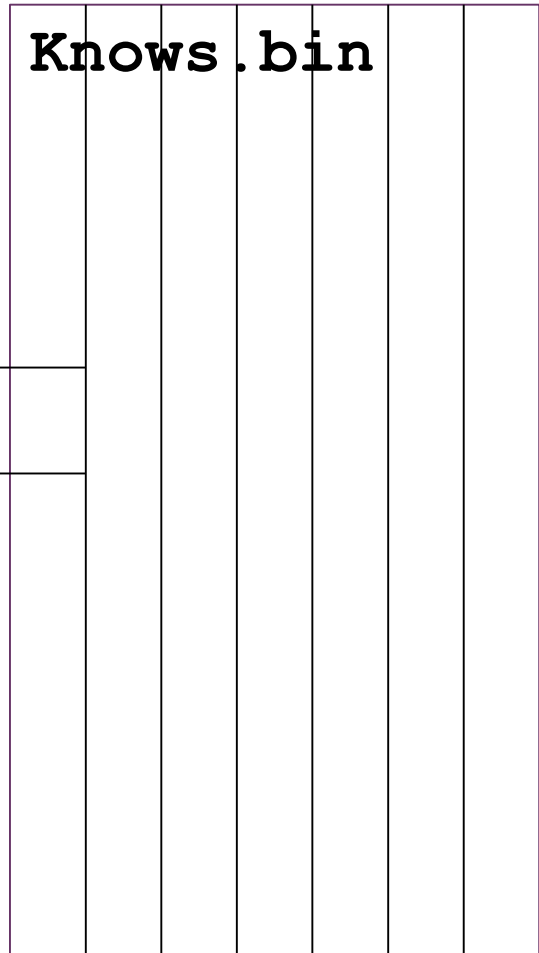
- Created by “loader” program in example github repo
- Total size: 6GB



# What it looks like

- Created by “loader” program in example github repo
- Total size: 6GB

*4bytes*  
*\* 1.3B*



*2bytes*  
*\* 204M*

**Person.bin**

*48bytes*  
*\* 8.9M*

`knows_first`

`knows_n`

# The Naïve Implementation

*The “cruncher” program*

*Go through the persons  $P$  sequentially*

- *counting how many of the artists  $A_2, A_3, A_4$  are liked as the score for those with  $\text{score} > 0$ :*

- *visit all persons  $F$  known to  $P$ .*

*For each  $F$ :*

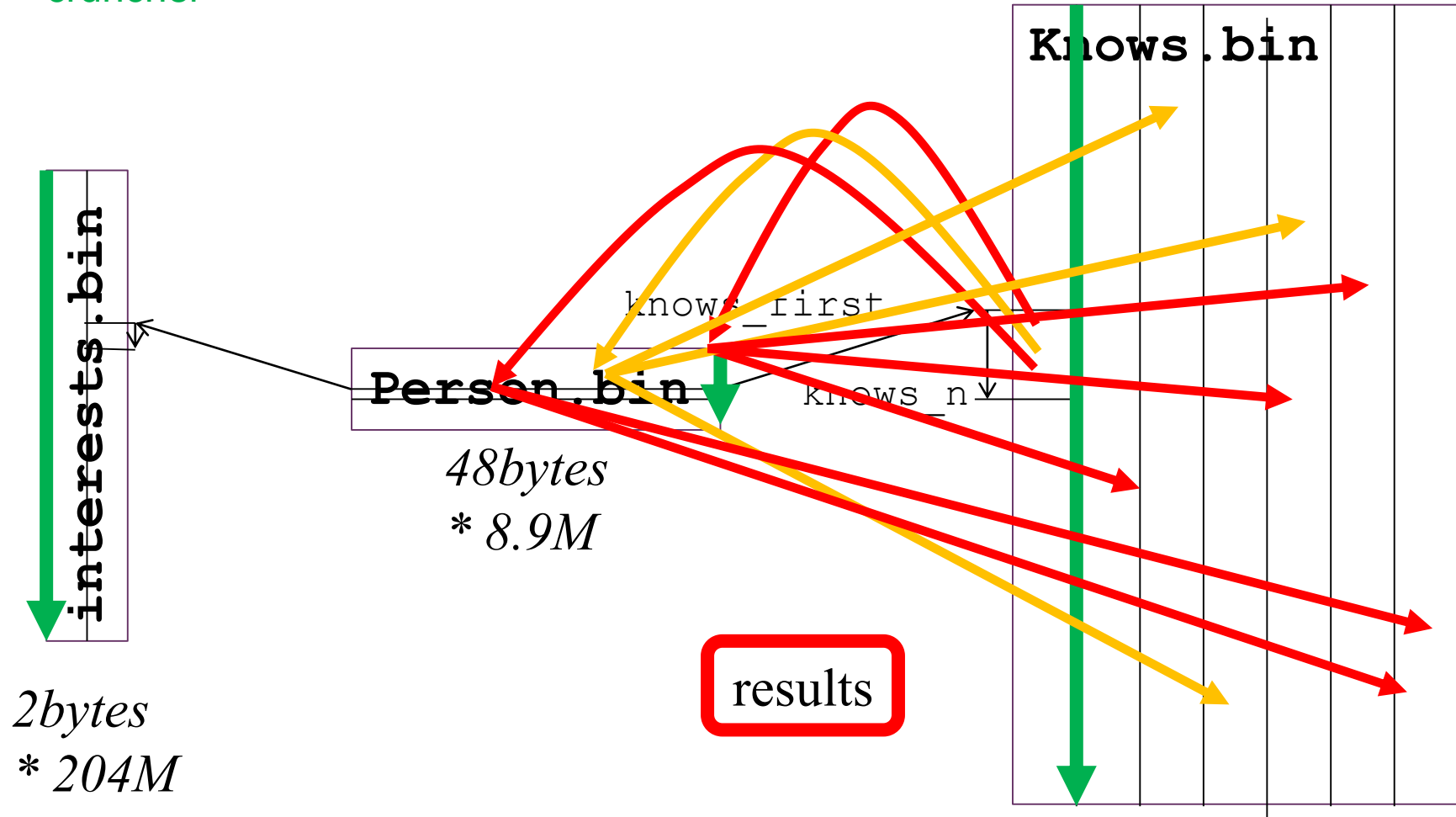
- *checks on equal location*
- *check whether  $F$  already likes  $A_1$*
- *check whether  $F$  also knows  $P$*

*if all this succeeds  $(\text{score}, P, F)$  is added to a result table.*

# Naïve Query Implementation

- “cruncher”

4bytes  
\* 1.3B



# Challenges, questions

For the “reorg” program:

- Can we throw away unneeded data?
- Can we store the data more efficiently?
- Can we put the data in some order to improve access patterns?

For the “query” program:

- Can we move some of the work to the re-org phase?
- Can we improve the access pattern?
  - we trade random access for sequential access?
    - Multiple passes, instead of one?

*We will meet on the leaderboard!*