



Lectuer-1 Big Data Systems(SEZG522)

Slides: Courtesy:.Prof. Anindya





First Semester

2022-23

Course Contents

- 1. Introduction to Big Data and data locality
- 2. Parallel and Distributed Processing
- 3. Big Data Analytics and Big Data Systems
- 4. Consistency, Availability, Partition tolerance and Data Lifecycle
- 5. Distributed Systems Programming
- 6. Hadoop Ecosystem Technologies
- 7. NoSQL Databases
- 8. Big Data on Cloud
- 9. Amazon storage services
- 10. In-memory and streaming Spark

Books

- 1. Seema Acharya and Subhashini Chellappan. *Big Data and Analytics*. Wiley India Pvt. Ltd. Second Edition
- 2. DT Editorial Services. *Big Data Black Book*. DreamTech. Press. 2016
- 3. Kai Hwang, Jack Dongarra, and Geoffrey C. Fox. *Distributed* and Cloud Computing: From Parallel Processing to the Internet of Things. Morgan Kauffman 2011.
- 4. Additional Readings(As mentioned in the handout)

Evaluation Components

	Name	Type			Day, Date, Session, Time	
Evaluation Component	(Quiz, Lab, Project, Mid term exam, End semester exam, etc)	Closed book.	Weightage	Duration		
EC – 1	Quiz 1	Online	5%	10-15 minutes	To be announced	
	Assignment-1	Take Home	10%	To be decided	To be announced	
	Assignment-2	Take Home	15%	To be decided	To be announced	
EC – 2	Mid Semester Test	Open Book	30%	2 hours	25/09/2022(AN)	
EC - 3	Comprehensive Examination	Open book	40%	2 hours	27/11/2022(AN)	

Lecture -1 Contents

Motivation

- Why do modern Enterprises need to work with data
- What is Big Data and data classification
- Scaling RDBMS

What is a Big Data System

- Characteristics
- Design challenges

Architecture

- High level architecture of Big Data solutions
- Technology ecosystem
- Case studies

Why locality of reference and storage organisation matter

Example of a data-driven Enterprise: A large online retailer

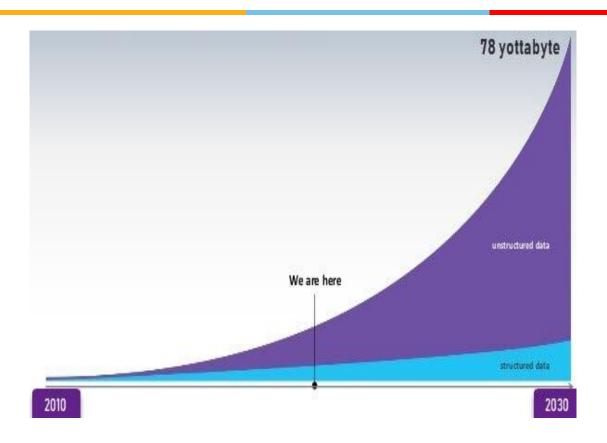


- What data is collected
 - Millions of transactions and browsing clicks per day across products, users
 - Delivery tracking
 - Reviews on multiple channels website, social media, customer support
 - Support emails, logged calls
 - Ad click and browsing data
 - **–** ...
- Data is a mix natural language text, logs, events, videos and images *etc*.

- What is this data used for
 - User profiling for better shopping experience
 - Operations efficiency metrics
 - Improve customer support experience, support training
 - Demand forecasting
 - Product marketing
 - **–** ...
- Data is the only way to create competitive differentiators, retain customers and ensure growth

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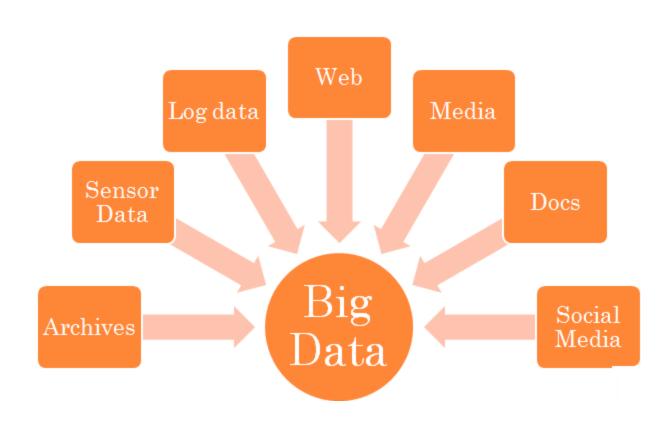
Data Volume Growth



- Facebook: 500+
 TB/day of
 comments,
 images, videos
 etc.
- NYSE: 1TB/day of trading data
- A Jet Engine: 20TB / hour of sensor / log data

Source: What is big data?

Variety of Data Sources



Data Classification



Structured

Databases

 Semistructured

XML

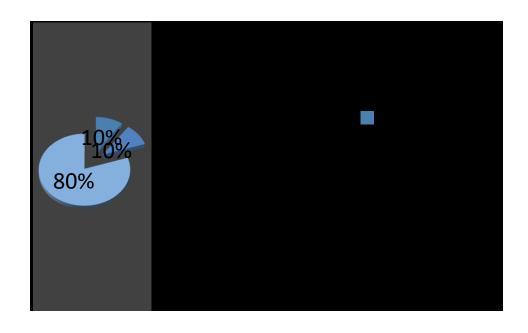
• Unstructur ed

Web pages Images

- Structured data is metrics, events that can be put in RDBMS with fixed schema
- Semi-structured data are XML, JSON structure where traditional RDBMS have support with varying efficiency but needs new kind of NoSQL databases
- New applications produce unstructured data which could be natural language text and multi-media content



Data Usage Pattern



Higher demand now of analysing unstructured data to glean insights

Examples

- analysis of social media
 content for sentiment analysis
- analysis of unstructured text content by search engines on the web as well as within enterprise
- analysis of support emails,
 calls for customer satisfaction
- NLP / Conversational AI for answering user questions from backend data

Structured Data

- Data is transformed and stored as per pre-defined schema
- Traditionally stored in RDBMS
- CRUD operations on records
- ACID semantics
 (Atomicity, Consistency, Isolation, Durability)
- Fine grain security and authorisation
- Known techniques on scaling RDBMS more on this later
- Typically used by Systems of Record, e.g. OLTP systems, with strong consistency requirements and read / write workloads

```
TABLE Employee (
emp_id int PRIMARY KEY,
name varchar (50),
designation varchar(25),
salary int,
dept_code int FOREIGN KEY
```

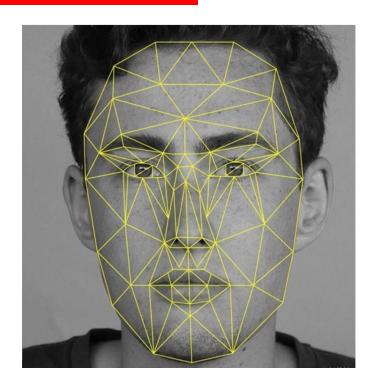


- No explicit data and schema separation
- Models real life situations better because attributes for every record could be different
- Easy to add new attributes
- XML, JSON structures
- Databases typically support flexible ACID properties, esp consistency of replicas
- Typically used by Systems of Engagement, e.g. social media

```
"title": "Sweet fresh strawberry",
"type": "fruit",
"description": "Sweet fresh strawberry",
"image": "1.jpg",
"weight": 250,
"expiry": 30/5/2021,
"price": 29.45,
"avg rating": 4
"reviews": [
             { "user" : "p1", "rating": 2,
          "review": " ..... " }, ....
```

Unstructured Data

- More real-life data
 - video, voice, text, emails, cha ts, comments, reviews, blogs
- There is some structure that is typically extracted from the data depending on the use case
 - image adjustments at pixel structure level
 - face recognition from video
 - tagging of features extracted in image / video
 - annotation of text

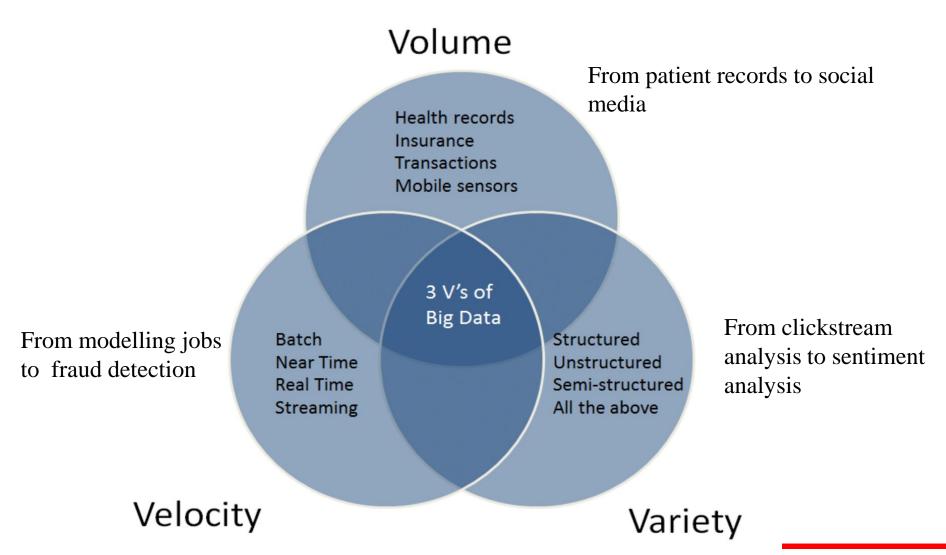


What can we do with it?

- Data mining
 - Association rule mining, e.g. market basket or affinity analysis
 - Regression, e.g. predict dependent variable from independent variables
 - Collaborative filtering, e.g. predict a user preference from group preferences
- NLP e.g. Human to Machine interaction, conversational systems
- Text Analytics e.g. sentiment analysis, text categorization
- Noisy text analytics e.g. spell correction

Defining Big Data



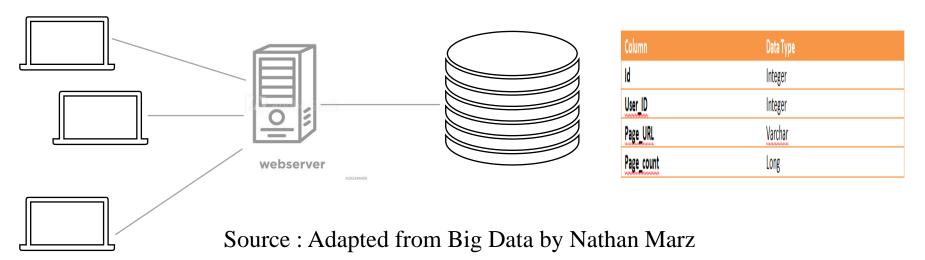


Isn't a traditional RDBMS good enough?



Example Web Analytics Application

- Designing an application to monitor the page hits for a portal
- Every time a user visiting a portal page in browser, the server side keeps track of that visit
- Maintains a simple database table that holds information about each page hit
- If user visits the same page again, the page hit count is increased by one
- Uses this information for doing analysis of popular pages among the users



Scaling with Intermediate Layer

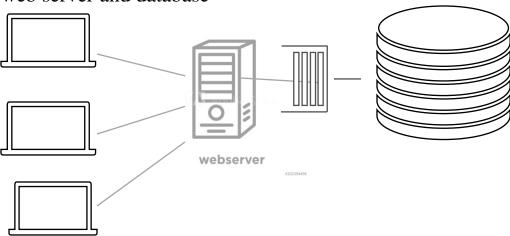
Using a queue

Portal is very popular, lot of users visiting it

- Many users are concurrently visiting the pages of portal
- Every time a page is visited, database needs to be updated to keep track of this visit
- Database write is heavy operation
- Database write is now a bottleneck!

Solution

- Use an intermediate queue between the web server and database
- Queue will hold messages
- Message will not be lost





Scaling with Database Partitions

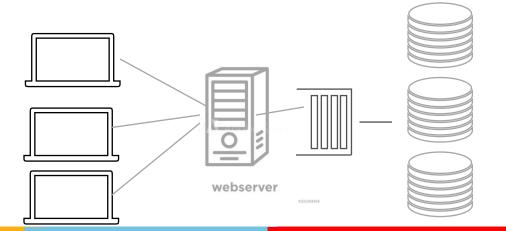
Using Database shards

Application is too popular

- Users are using it very heavily, increasing the load on application
- Maintaining the page view count is becoming difficult even with queue

Solution

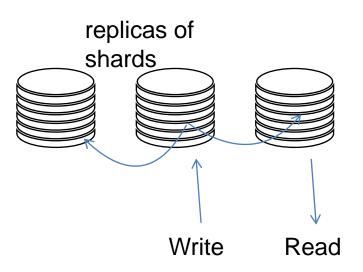
- Use database partitions
- Data is divided into partitions (shards) which are hosted on multiple machines
- Database writes are parallelized
- Scalability increasing
- Also complexity increasing!



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Issues with RDMS

- With too many shards some disk is bound to fail
- Fault tolerance needs shard replicas so more things to manage
- Complex logic to read / write because need to locate the right shard human errors can be devastating
- Keep re-sharding and balancing as data grows or load increases
- What is the consistency semantics of updating replicas? Should a read on a replica be allowed before it is updated?
- Is it optimised when data is written once and read many times or vice versa?

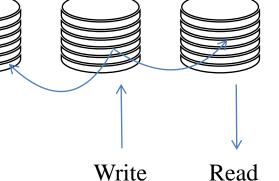


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Contd..

- Not all BigData use cases need strong ACID semantics, esp Systems of Engagement
 - Becomes a bottleneck with many replicas and many attributes - need to optimise fast writes and reads with less updates
- Fixed schema is not sufficient ... as application becomes popular more attributes need to be captured and DB modelling becomes an issue.
 - Which attributes are used depends on the use case.

replicas of shards in a social site DB



```
"title": "Sweet fresh strawberry",
"type": "fruit",
"description": "Sweet fresh strawberry",
"image": "1.jpg",
"weight": 250,
"expiry": 30/5/2021,
"price": 29.45,
"avg_rating": 4
"reviews": [
{ "user": "p1", "rating": 2, "review": " ..... " }, ....
```

want to add field applicable to some products

- Very wide de-normalized attribute sets
- Data layout formats column or row major - depends on use case
 - What if we query only few columns? Do I need to touch the entire row in storage layer?
- Expensive to retain and query long term data - need low cost solution

what if a JSON had 1000+ attributes demographic records for millions of users

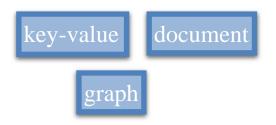
Characteristics of Big Data Systems



- Application does not need to bother about common issues like sharding, replication
 - Developers more focused on application logic rather than data management
- Easier to model data with flexible schema
 - Not necessary that every record has same set of attributes
- If possible, treat data as immutable
 - Keep adding timestamped versions of data values
 - Avoid human errors by not destroying a good copy

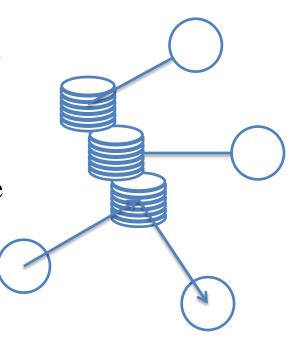
replicated / partitioned storage







- Application specific consistency models
 - a reader may read a replica that's has not been updated yet as in "read preference" options in MongoDB
 - e.g. comments on social media
- Handles high data volume, at very fast rate coming from variety of sources because immutable writes are faster with flexible consistency models
 - Keep adding data versions with timestamp
 - Replica updates can keep happening in the background



- Built as distributed and incrementally scalable systems
 - add new nodes to scale as in a Hadoop cluster
- Options to have cheaper long term data retention
 - long term data reads can have more latency and can be less expensive to store on commodity hardware, e.g. Hadoop file system (HDFS)
- Generalized programming models that work close to the data
 - e.g. Hadoop map-reduce that runs tasks on data nodes



Challenges in Big Data Systems

- Latency issues in algorithms and data storage working with large data sets
- Basic design considerations of Distributed and Parallel systems reliability, availability, consistency
- What data to keep and for how long depends on analysis use case
- Cleaning / Curation of data
- Choose the right technologies from many options, including open source, to build the Big Data System for the use cases

- Programming models for analysis
- Scale out for high volume
- Cloud is the cost effective way long term but need to host Big Data outside the Enterprise
- Data privacy and governance
- Skilled coordinated teams to build/maintain Big Data Systems and analyse data

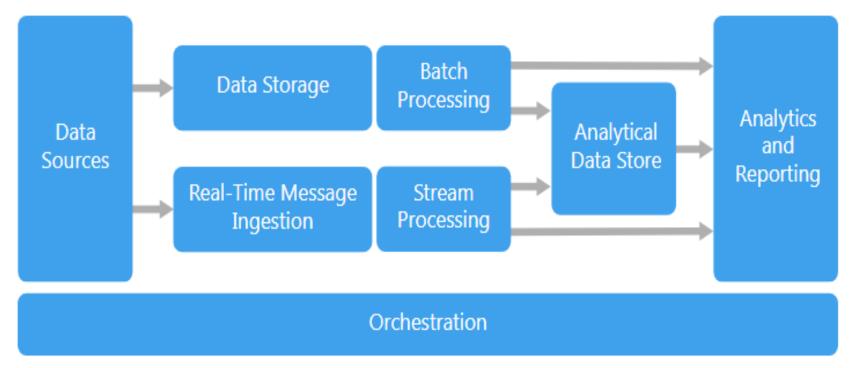
Types of Big Data Solutions

- 1. Batch processing of big data sources at rest
 - ✓ Building ML models, statistical aggregates
 - ✓ "What percentage of users in US last year watched shows starring Kevin Spacey and completed a season within 4 weeks or a movie within 4 hours"
 - ✓ "Predict number of US family users in age 30-40 who will buy a Kelloggs cereal if they purchase milk"
- 2. Real-time processing of big data in motion
 - ✓ Fraud detection from real-time financial transaction data
 - ✓ Detect fake news on social media platforms
- 3. Interactive exploration with ad-hoc queries
 - ✓ Which region and product has least sales growth in last quarter



Big Data Architecture Style

• Designed to handle the ingestion, processing, and analysis of data that is too large or complex for traditional database systems.



Source: Microsoft Big Data Architecture

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Big Data Systems Components

1. Data sources

 One or more data sources like databases, docs, files, IoT devices, images, video etc.

2. Data Storage

- Data for batch processing operations is typically stored in a distributed file store that can hold high volumes of large files in various formats.
- Data can also be stored in keyvalue stores.



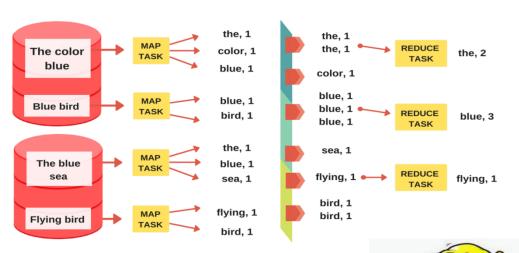


e.g. social data



e.g. medical images





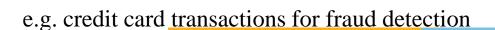
e.g. search scans on unindexed docs

3. Batch processing

- Process data files using long-running parallel batch jobs to filter, sort, aggregate or prepare the data for analysis.
- Usually these jobs involve reading source files, processing them, and writing the output to new files.

4. Real-time message ingestion

 Capture data from realtime sources and integrate with stream processing. Typically these are in-memory systems with optional storage backup for resiliency.



medologo



5. Stream processing

Real-time in-memory filtering, aggregating or preparing the data for further analysis. The processed stream data is then written to an output sink. These are mainly in-memory systems. Data can be written to files, database, or integrated with an API.



e.g. fraud detection logic

6. Analytical data store

Real-time or batch processing can be used to prepare the data for further analysis. The processed data in stored in a structured format to be queried using analytical tools. The analytical data store used to serve these queries can be a relational data warehouse or BigData warehouse like Hive. There may be also NoSQL stores such as MongoDB, HBase.







e.g. financial transaction history across clients for spend analysis



e.g. weekly management report



7. Analysis and reporting

The goal of most big data solutions is to provide insights into the data through analysis and reporting. These can be various OLAP, search and reporting tools.

8. Orchestration and ETL

Most big data solutions consist of repeated data processing operations, encapsulated in workflows, that transform source data, move data between multiple sources and sinks, load the processed data into an analytical data store, or push the results straight to a report or dashboard. To automate these workflows, you can use an orchestration technology such Azure Data Factory, Apache Oozie or Sqoop.

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Technology Ecosystem

Keep meta-da parallel tasks	ta for ^{in-me} of stre	mory proces eaming data	ssing DWH	Key-valu	e Indexed	l Data prep	Complex processi	X Process	ata Manage ing workflows
Coordination: Zookeeper	In-memory processing: Spark	Stream processing: Storm, Kafka, Spark-S	SQL over Hadoop: Hive	NoSQL: HBASE, MongoDB	Search: Solr	ETL: Flume, Sqoop	Machine Learning: Spark MLlib	Scripting: Pig	Scheduler: Oozie
Coord	Resource management and basic map-reduce: Yarn for Hadoop* nodes								
		Storage: HDFS							
Manage m									

Locality of Reference

- Big Data Systems need to move large volumes of data
 - e.g. browse and stream content on Netflix or answer analytical queries on e-commerce transaction data in Amazon
- Is there a way to reduce latency of data requests using locality of reference in the data and request origin



Levels of Storage

Data Location – Memory vs Storage vs Network

- Computational Data is stored in primary memory aka memory
- Persistent Data is stored in secondary memory aka Storage
- Remote data access from another computer's memory or storage over network





Numbers Everyone Should Know

L1 cache reference	0 .	.5 ns
Branch mispredict	5	ns
L2 cache reference	7	ns
Mutex lock/unlock	25	ns
Main memory reference	100	ns
Compress 1K bytes with Zippy	3,000	ns
Send 2K bytes over 1 Gbps network	20,000	ns
Read 1 MB sequentially from memory	250,000	ns
Round trip within same datacenter	500,000	ns
Disk seek	10,000,000	ns
Read 1 MB sequentially from disk	20,000,000	ns
Send packet CA->Netherlands->CA	150,000,000	ns

Reference: http://www.cs.cornell.edu/projects/ladis2009/talks/dean-keynote-ladis2009.pdf

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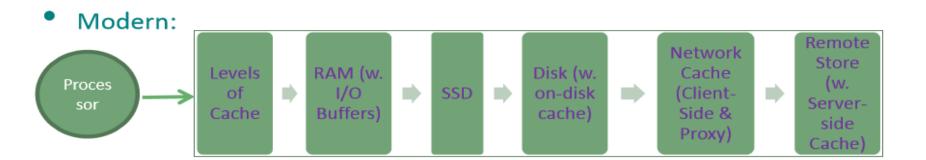
Memory Hierarchy

- A memory hierarchy amortizes cost in computer architecture:
 - fast (and therefore costly) but small-sized memory to
 - large-sized but slow (and therefore cheap) memory

Classic:

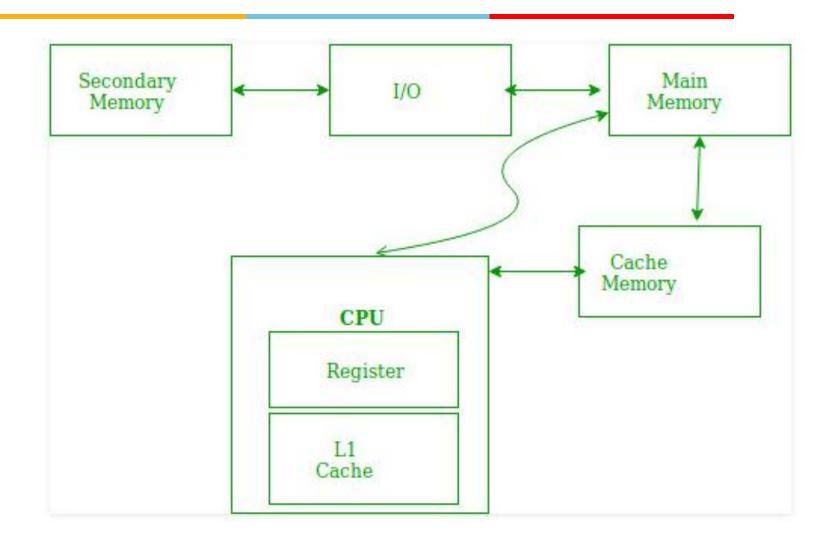
In a BigData search, recent Solr indexed data can be a cache for long term HDFS data.





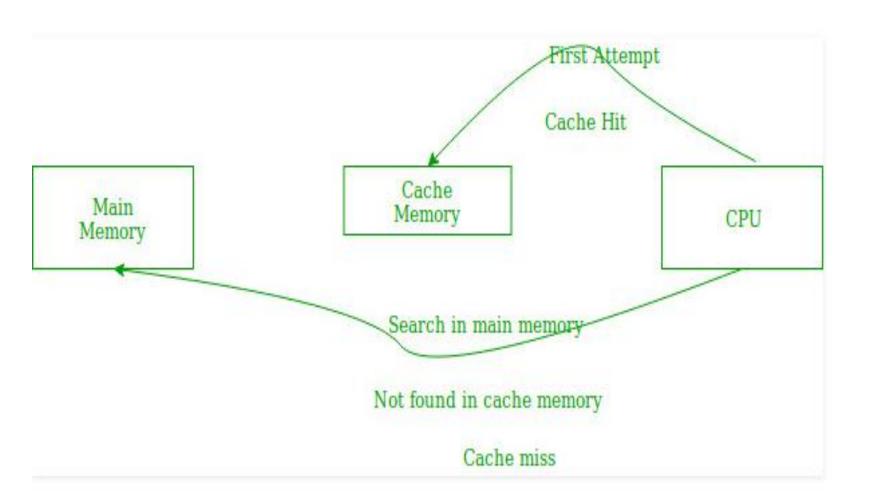


Memory Hierarchy Access



Memory Hierarchy: Cache hit/miss





Cache Performance

Hit Ratio - The performance of the cache

- Cache hit
 - When CPU refers to memory and find the data or instruction within the Cache Memory
- Cache miss
 - If the desired data or instruction is not found in the cache memory and CPU refers to the main memory to find that data or instruction

• One can generalise this to any form of cache e.g. movie request from user to nearest Netflix content cache

Access Time of Memories

•Average access time of any memory system consists of two levels:

Cache Memory Main Memory

•If Tc is time to access cache memory and Tm is the time to access main memory and h is the cache hit ration, then

Tavg = Average time to access memory
Tavg =
$$h * Tc + (1-h) * (Tm + Tc)$$



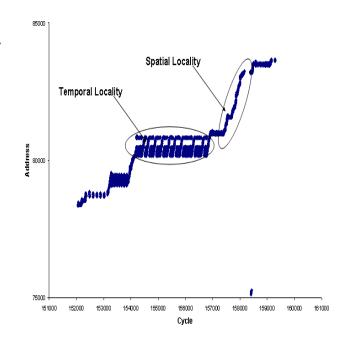
Data reference empirical evidence

- Programs tend to reuse data and instructions they have used recently.
- 90/10 rule comes from empirical observation: "A program spends 90% of its time in 10% of its code"
- Implication:
 - Predict with reasonable accuracy
 what instructions and data a program will use in the near future based on the recent past

Principle of Locality of Reference (LoR)



- 1. The locus of data access and hence that of memory references is small at any point during program execution
- 2. It is the tendency of a processor to access the same set of memory locations repetitively over a short period of time
- 3. Locality is a type of predictable behavior that occurs in computer systems
- 4. Systems that exhibit strong locality of reference are great candidates for performance optimization through the use of techniques such as the caching, prefetching for memory and advanced branch predictors at the pipelining stage of a processor core.



Locality of Reference - Temporal locality



t = x:

- Data that is accessed (at a point in program execution) is likely to be accessed again in the near future:
- i.e. data is likely to be repeatedly accessed in a short span
 of time during execution
 void swap(int x, int y)
- Examples
 - 1. Instructions in the body of a loop
 - 2. Parameters / Local variables of a function / procedure
 - 3. Data (or a variable) that is computed iteratively e.g. a cumulative sum or product
 - 4. Another user in Netflix in same region will watch the same episode soon
 - 5. A recent social media post will be viewed soon by other users

Locality of Reference - Spatial locality



• Data accessed (at a point in program execution) is likely located adjacent to data that is to be accessed in near future:

data accessed in a short span during execution is likely to be within a small region (in memory)

Examples

A linear sequence of instructions

Elements of an Array (accessed sequentially)

Another user's query will reuse part of the data file brought in for current user's query

```
int sum_array_rows(int
marks[8]){
    int i, sum = 0;
    for (i = 0; i < 8; i++)
        sum = sum + marks[i];
    return sum;
}</pre>
```

Memory hierarchy and locality of reference



- A memory hierarchy is effective only due to locality exhibited by programs (and the data they access)
- Longer the range of execution time of the program, larger is the locus of data accesses
- Need to have cache replacement strategies because increasing cache size will also increase access time and increase cost
 - Least Recently Used (LRU) is a typical cache entry replacement strategy
 - This is an example of temporal locality

Contd..

LOR leads to memory hierarchy at two main interface levels:

- Processor Main memory
 - Introduction of caches
 - Unit of data transfer is blocks (# of cache lines)
- Main memory Secondary memory (storage)
 - Virtual memory (paging systems)
 - Unit of data transfer is pages (page size is 4 or 8 KB)

Fetching larger chunks of data enables spatial locality



LoR and data structure choices

In Java, the following 2 classes are available in util package

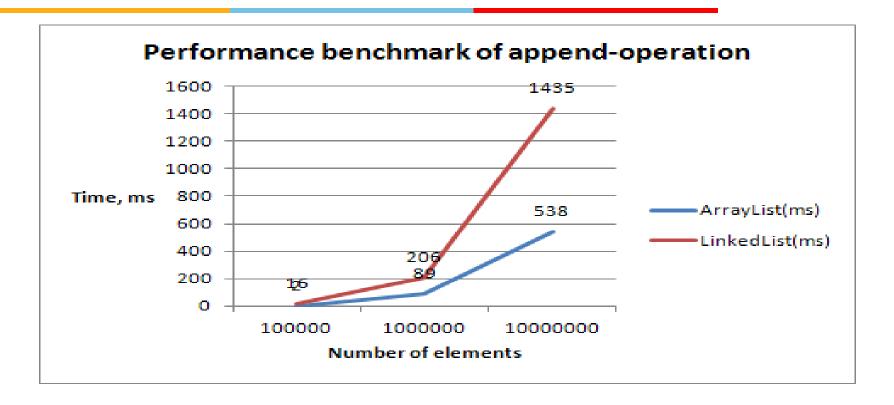
- LinkedList<Integer> QuizMarks a dynamic list of objects
- ArrayList<Integer> QuizMarks a dynamic array of objects
- Which is a better data structure to use for sequential access performance?

Test

- Append a single element in a loop N times to the end of a LinkedList.
 Repeat with ArrayList.
- Take average for 100 runs.
- The time complexity of the operation on both collections is the same.

Which one works faster?





• Analysis - sequential access in arrays is faster than on linked lists on many machines, because they have a very good spatial <u>locality of reference</u> and thus make good use of data caching.

Locality Example : Matrices addition



Consider matrices and an operation such as the addition of two matrices:

Elements M[i,j] may be accessed either row by row or column by column

Option 1: Add columns within each row

Option 2: Add rows within each column

Both options have same time complexity. Why is one faster?

Locality Analysis

M[I][J]	J=0	J=1	J=2	J=3
I=0	W[0]	W[1]	W[2]	W[3]
	miss	hit	hit	hit
I=1	W[4]	W[5]	W[6]	W[7]
	Miss	Hit	Hit	hit
I=2	W[8]	W[9]	W[10]	W[11]
	miss	hit	hit	hit
I=3	W[12]	W[13]	W[14]	W[15]
	miss	hit	hit	hit

Locality Analysis

M[I][J]	J=0	J=1	J=2	J=3
I=0	W[0]	W[1]	W[2]	W[3]
	miss	miss	miss	miss
I=1	W[4]	W[5]	W[6]	W[7]
	Miss	miss	miss	miss
I=2	W[8]	W[9]	W[10]	W[11]
	miss	miss	miss	miss
I=3	W[12]	W[13]	W[14]	W[15]
	miss	miss	miss	miss

Big Data: Storage organisation matters



- We need to build a prediction model of sales for various regions
- There are many attributes for a region and "total sales" is the metric used
- Suppose the database is "columnar" (Column major data organisation)
 - Will exhibit high spatial locality and hit rate because data blocks will fetch blocks of total sales column and not other unnecessary columns
 - Will improve speed of modelling logic
- Columnar storage is common in most Big Data Systems to run analysis and queries that focus on specific attributes at a time for searching, aggregating, modelling etc.

Summary

- Why modern Enterprises and new age applications are data-centric
- Challenges with existing data systems
- Advantages and challenges with Big Data systems
- High level architecture and technology ecosystem
- Some real applications using the tech stack
- Data locality of reference and why it is useful for Big Data Systems

THANK YOU