From Data Series Indexing to Big Data Series Analytics

Themis Palpanas

Paris Descartes University
French University Institute

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References 1

- papers
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    - http://www.mi.parisdescartes.fr/~themisp/publications/vldb19-lernaeanhydra.pdf
  - **The Lernaean Hydra of Data Series Similarity Search: An Experimental Evaluation of the State of the Art.** PVLDB 2019
    - http://www.mi.parisdescartes.fr/~themisp/publications/vldb19-lernaeanhydra.pdf
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  - **Massively Distributed Time Series Indexing and Querying.** TKDE 2018
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References 2

- papers
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  - **Coconut: A Scalable Bottom-Up Approach for Building Data Series Indexes.** PVLDB 2018
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  - **Comparing Similarity Perception in Time Series Visualizations.** VIS 2018
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    - http://www.mi.parisdescartes.fr/~themisp/publications/sofsem16-bisem.pdf
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  - **Indexing for Interactive Exploration of Big Data Series**. SIGMOD 2014
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  - **Beyond One Billion Time Series: Indexing and Mining Very Large Time Series Collections with iSAX2+**. KAIS 2014
    - http://www.mi.parisdescartes.fr/~themisp/publications/kais14-isax2plus.pdf
  - ***i*SAX 2.0: Indexing and Mining One Billion Time Series**. ICDM 2010
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References

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  - **ULISSE**
    - http://helios.mi.parisdescartes.fr/~mlinardi/ULISSE.html
  - **DPiSAX**
    - https://github.com/DPiSAX/DPiSAX.github.io
  - **ADS**
    - https://github.com/zoumpatianos/ADS
  - **iSAX2+**
    - http://www.mi.parisdescartes.fr/~themisp/isax2plus/

- data series toolbox
  - **DSStat**
    - https://github.com/zoumpatianos/DSStat

- demos
  - **Coconut Palm**
    - http://users.ics.forth.gr/~kondylak/Coconut_Palm/Coconut_Palm.html
  - **RINSE**
    - http://daslab.seas.harvard.edu/rinse/

Acknowledgements

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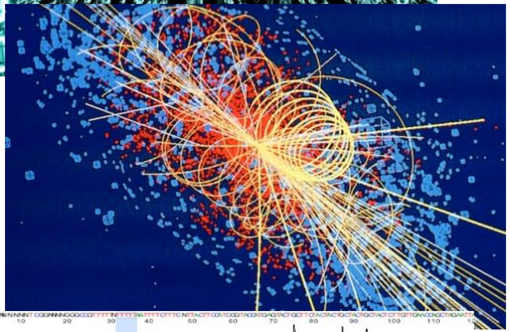
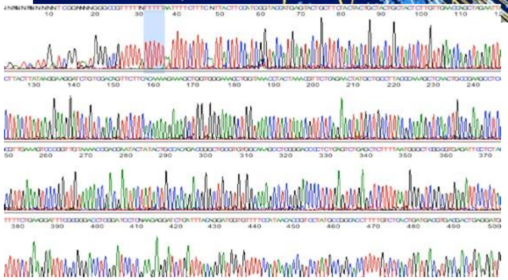
Executive Summary



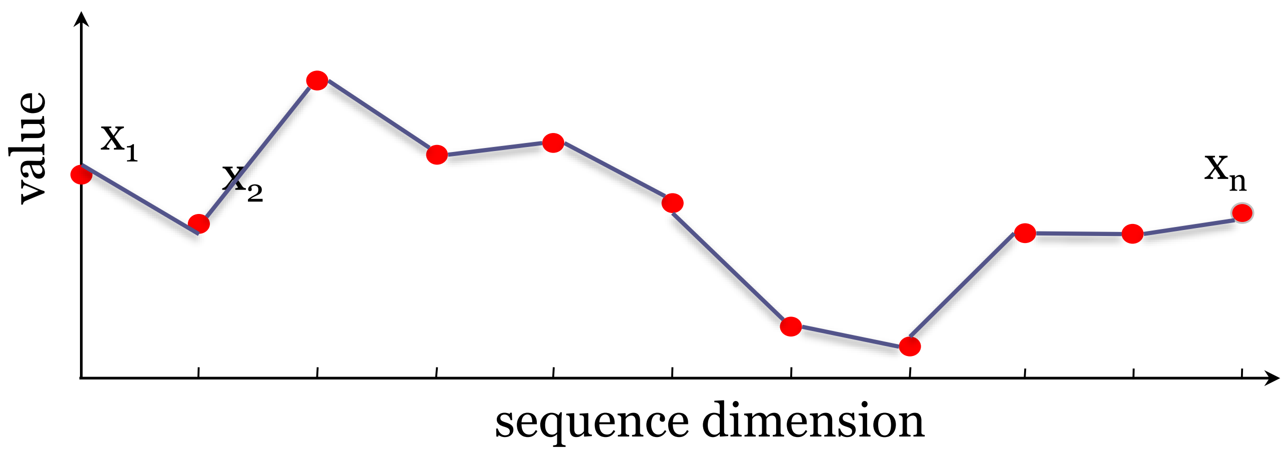


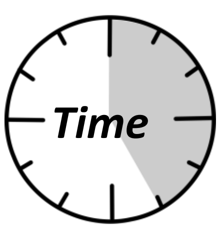
- data collected at unprecedented rates
- they enable data-driven scientific discovery
- lots of these data are sequences
  - takes **days-weeks** to analyze big sequence collections

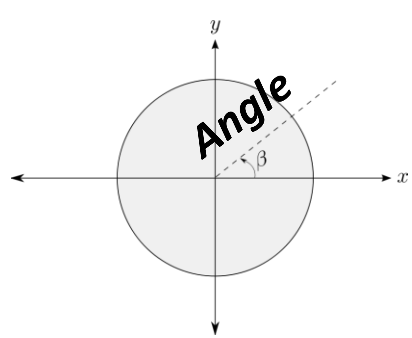
goal: analyze big sequences in **minutes/seconds**

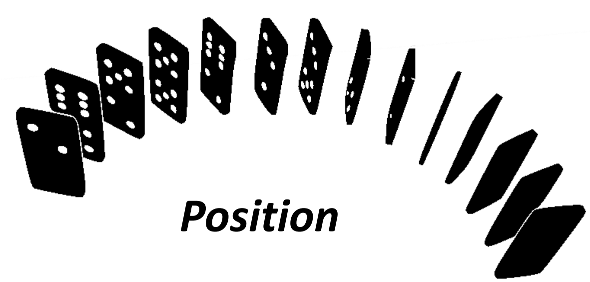
Data series

- Sequence of points ordered along some dimension



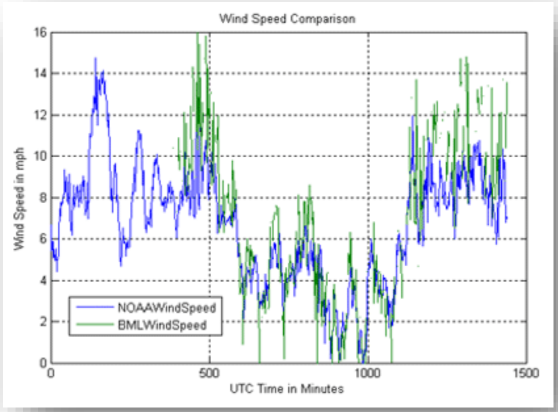






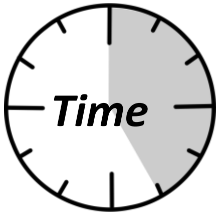
Scientific Monitoring

- meteorology, oceanography, astronomy, finance, sociology, ...

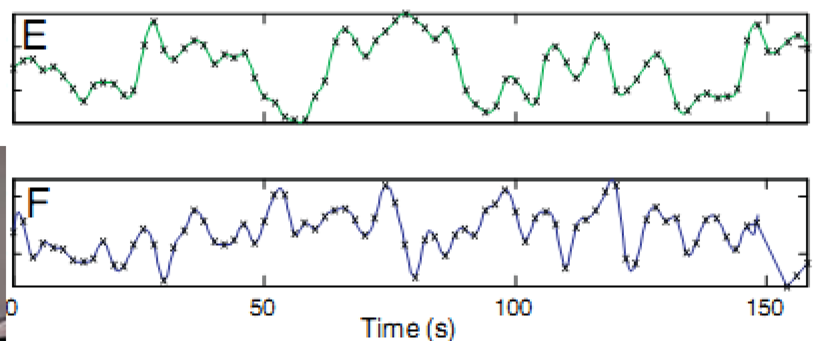


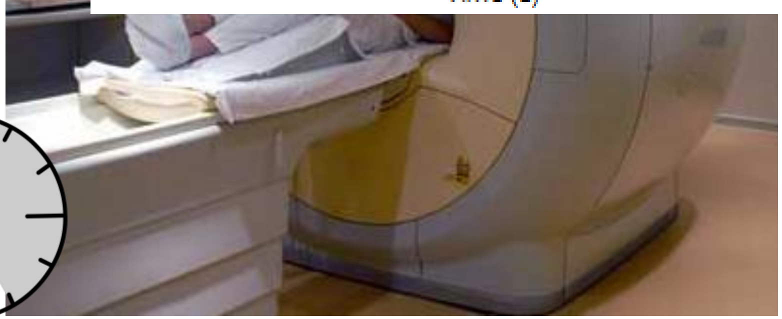
Wind speed
From ocean observing node project
http://bml.ucdavis.edu/boon/wind.html

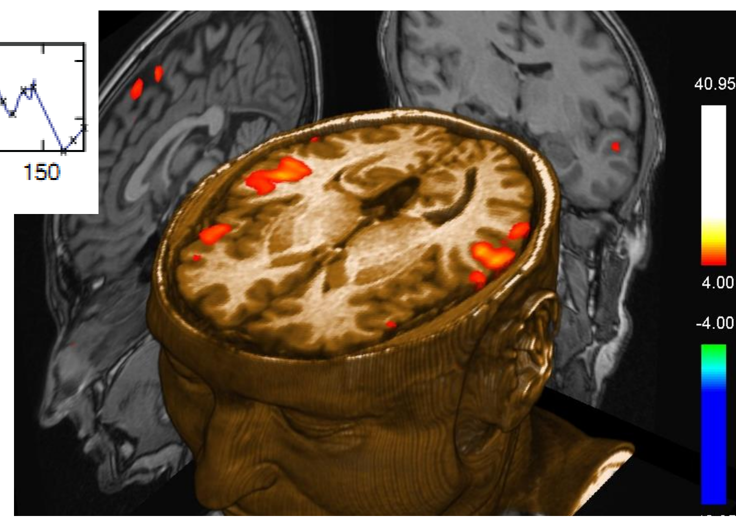
Historical stock quotes
http://money.cnn.com/2012/04/23/markets/walmart_stock/index.htm

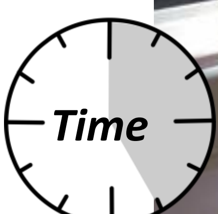


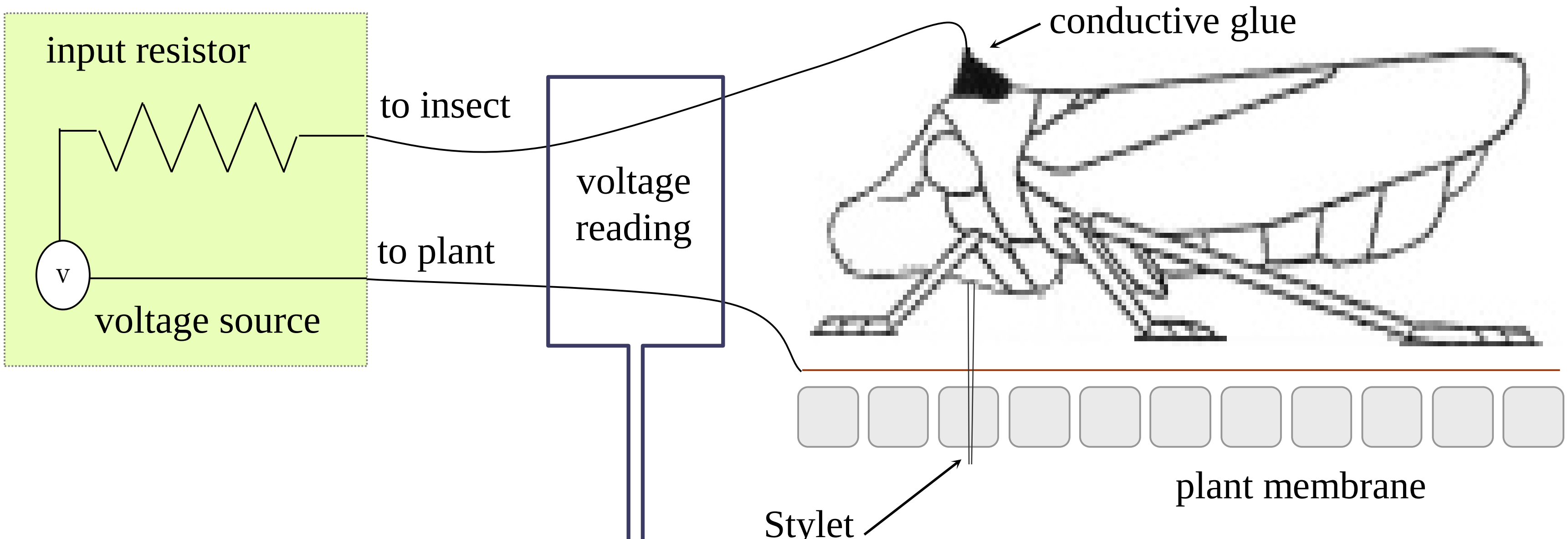
- functional Resonance Magnetic Imaging (fMRI) data
  - primary experimental tool of neuroscientists
  - reveal how different parts of brain respond to stimuli

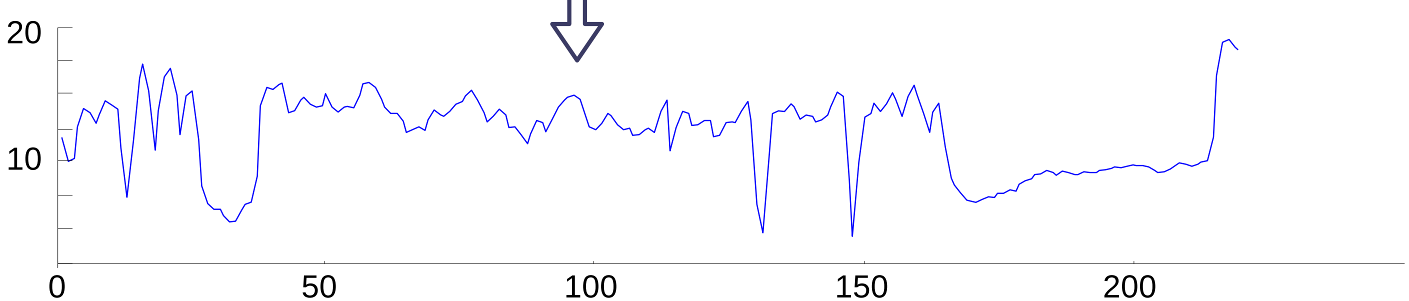









input resistor
to insect
v
to plant
voltage source
voltage reading
conductive glue
plant membrane
Stylet


20
10
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100
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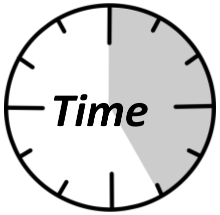
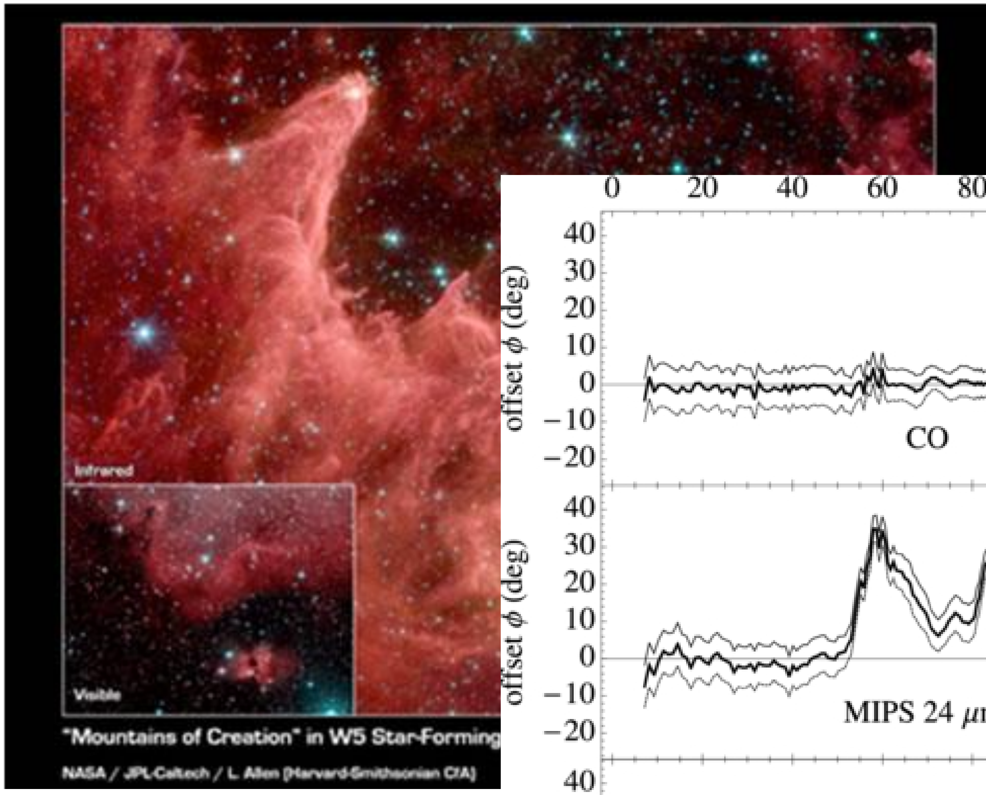
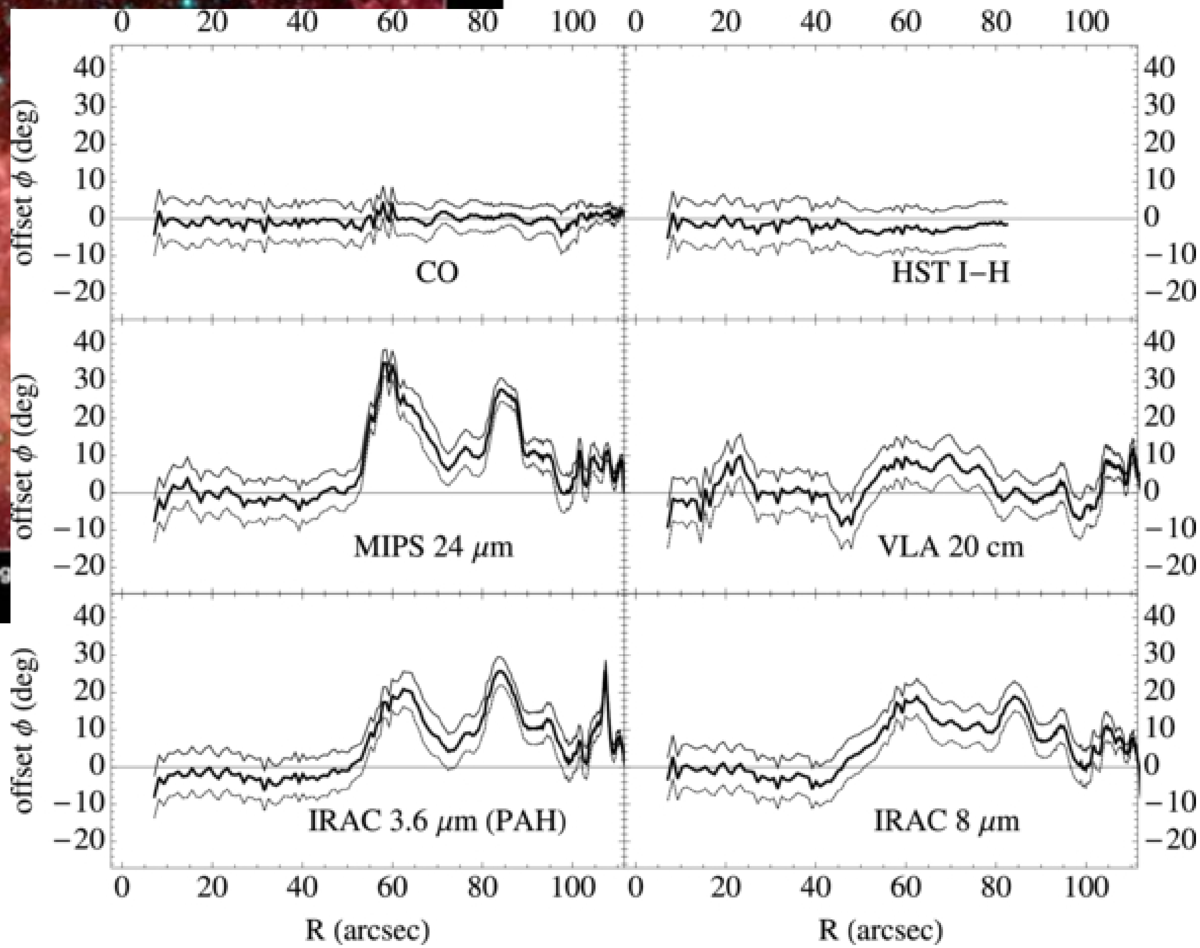
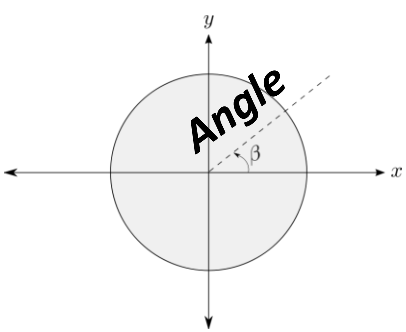
200


Time







Schinnerer et al.

GTCAATGGCCAGGATATTAGAACAGTACTCTGTGAACCCTATTTATGGTGGCACCCCTTAGACTAA
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CTCCTCCACAG GCCAGAGGATC
TGTAAAAGAGA ACAAGCAAAA
AAGAGCACTCA GGCCACCAAG
CCAGTTGTCAAT GAGTGTCTTCT
ATTTCTTCCAGC CCTTTACAATT
GTTATTTATGTC CATACTGTCTT
GGCCAAGCATC TGCACGTGGT
TATTTATTAGTC AAGAGCAGAAT
CAATGAGCCGC AGATGAGCATT
GAAGAGGATGC CAGGTTGTTGC
CATGTTTGTTTT TTAGAACAGTA
CTCTGTGAACC AGAGGTTGACA
GGAAAGCCAGG TTTCTAAGGCA
CATGATGGATC TAATCCGATTC
TTGGCAGAAGA ATAAACAAATA

ATTGAATAATCC AGGCAGAACCG
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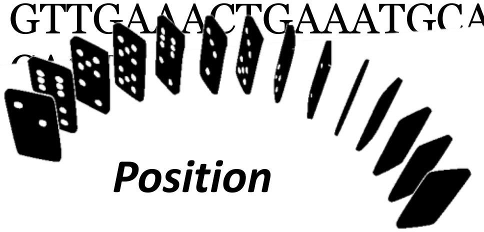


Position

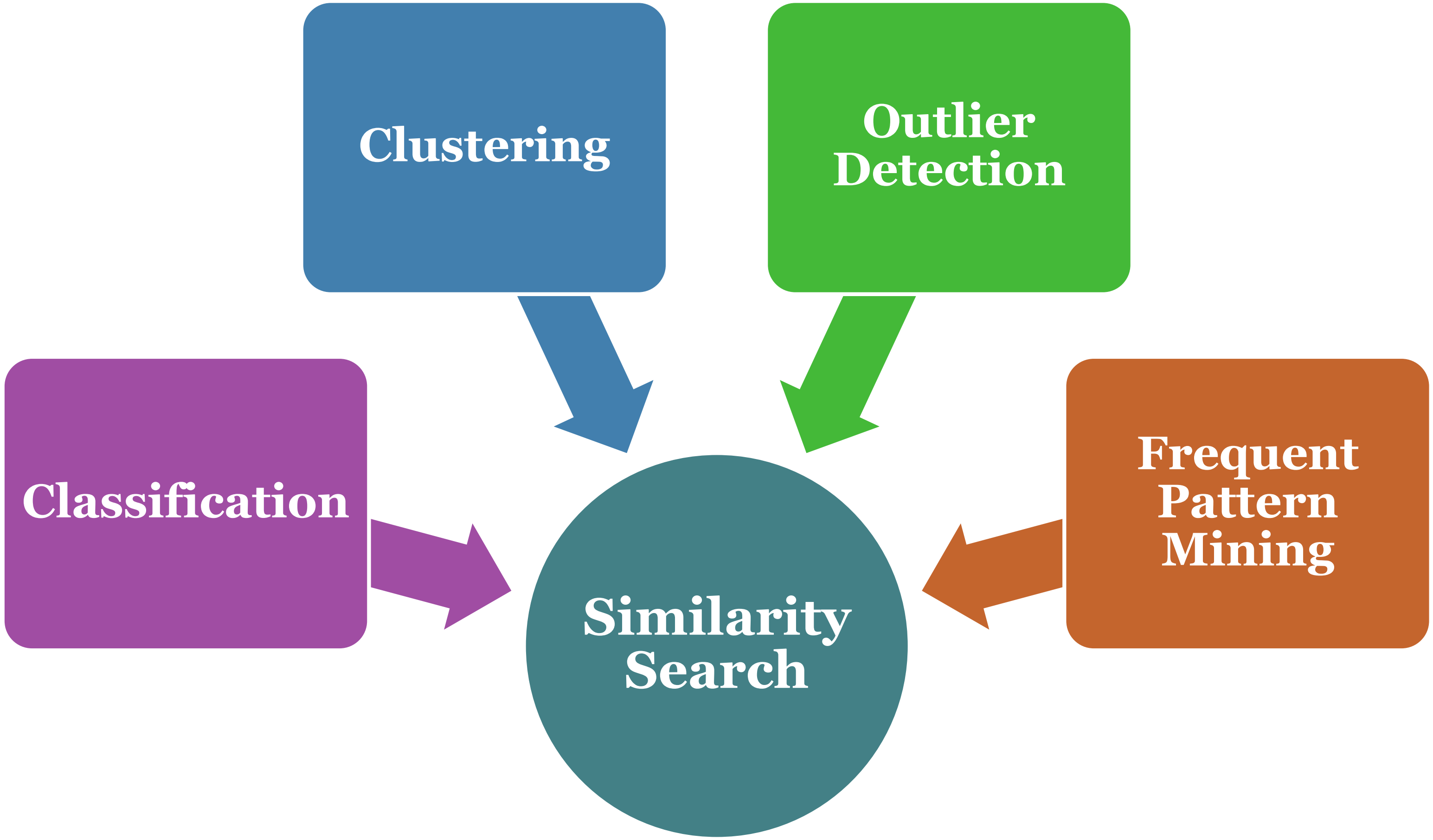
What do we want to do with them? - simple query answering

- select values in time interval
- select values in some range
- select some data series
- combinations of those

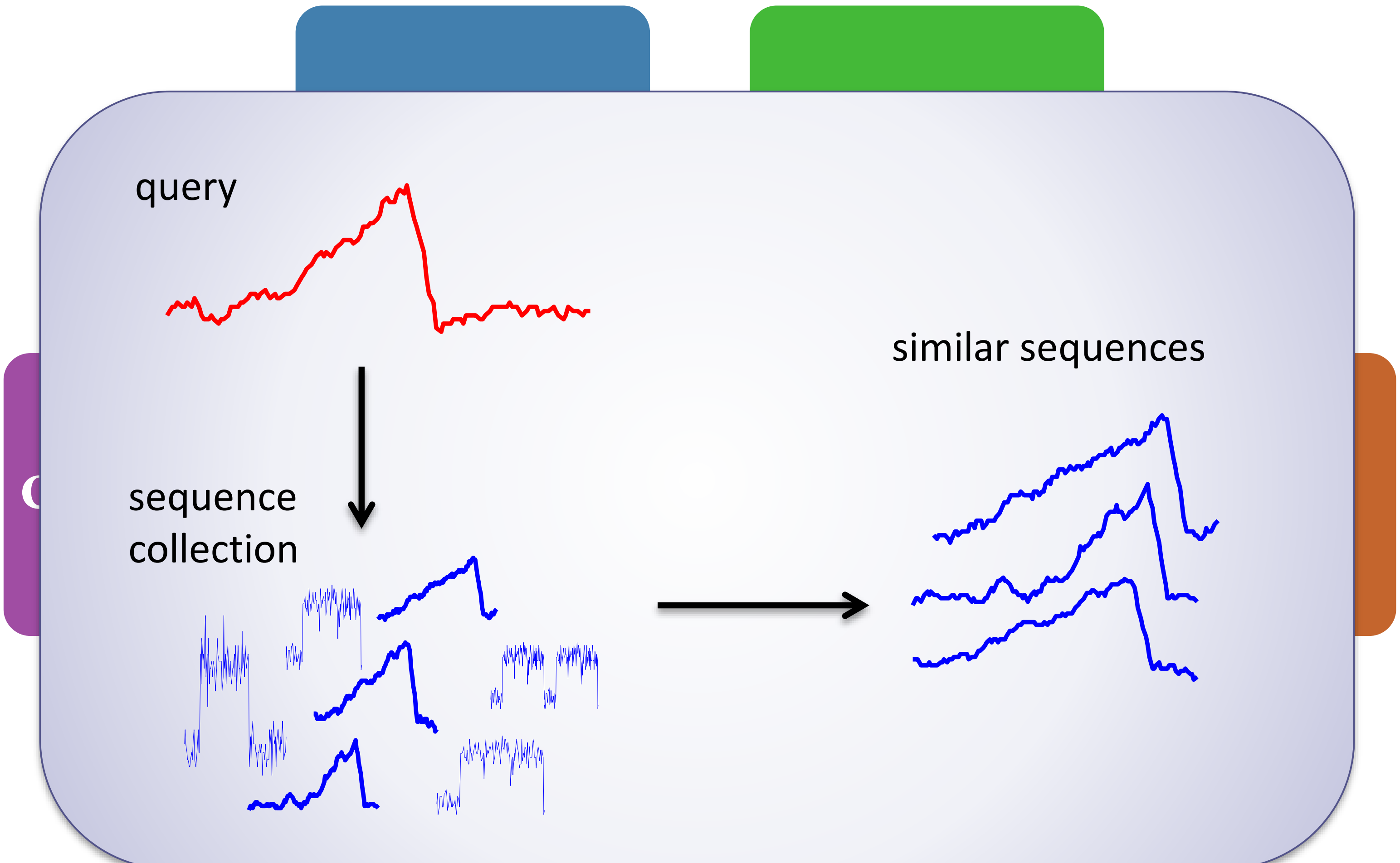
What do we want to do with them? - simple query answering

- a solved(?) problem
  - your favorite DBMS
  - …
  - InfluxData
  - kx
  - Riak TS
  - OpenTSDB
  - TimescaleDB
  - KairosDB
  - Druid
  - …

What do we want to do with them? - complex analytics



What do we want to do with them? - complex analytics



What do we want to do with them? - complex analytics

Euclidean

$$D(X,Y) \equiv \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Dynamic Time Warping (DTW)

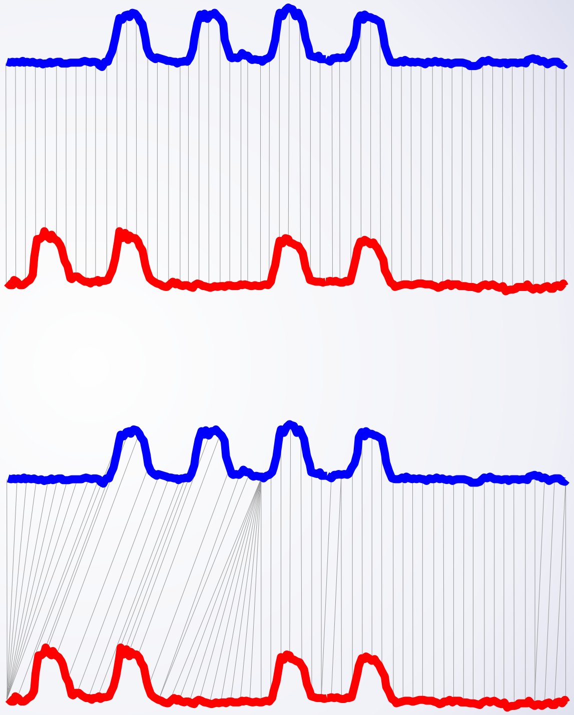
$$D_{dtw}(X,Y) = f(n,m)$$

$$f(i,j) = \|x_i - y_j\| + \min\begin{cases} f(i, j-1) \\ f(i-1, j) \\ f(i-1, j-1) \end{cases}$$

What do we want to do with them? - complex analytics

Euclidean

Dynamic Time Warping (DTW)



What do we want to do with them? - complex analytics

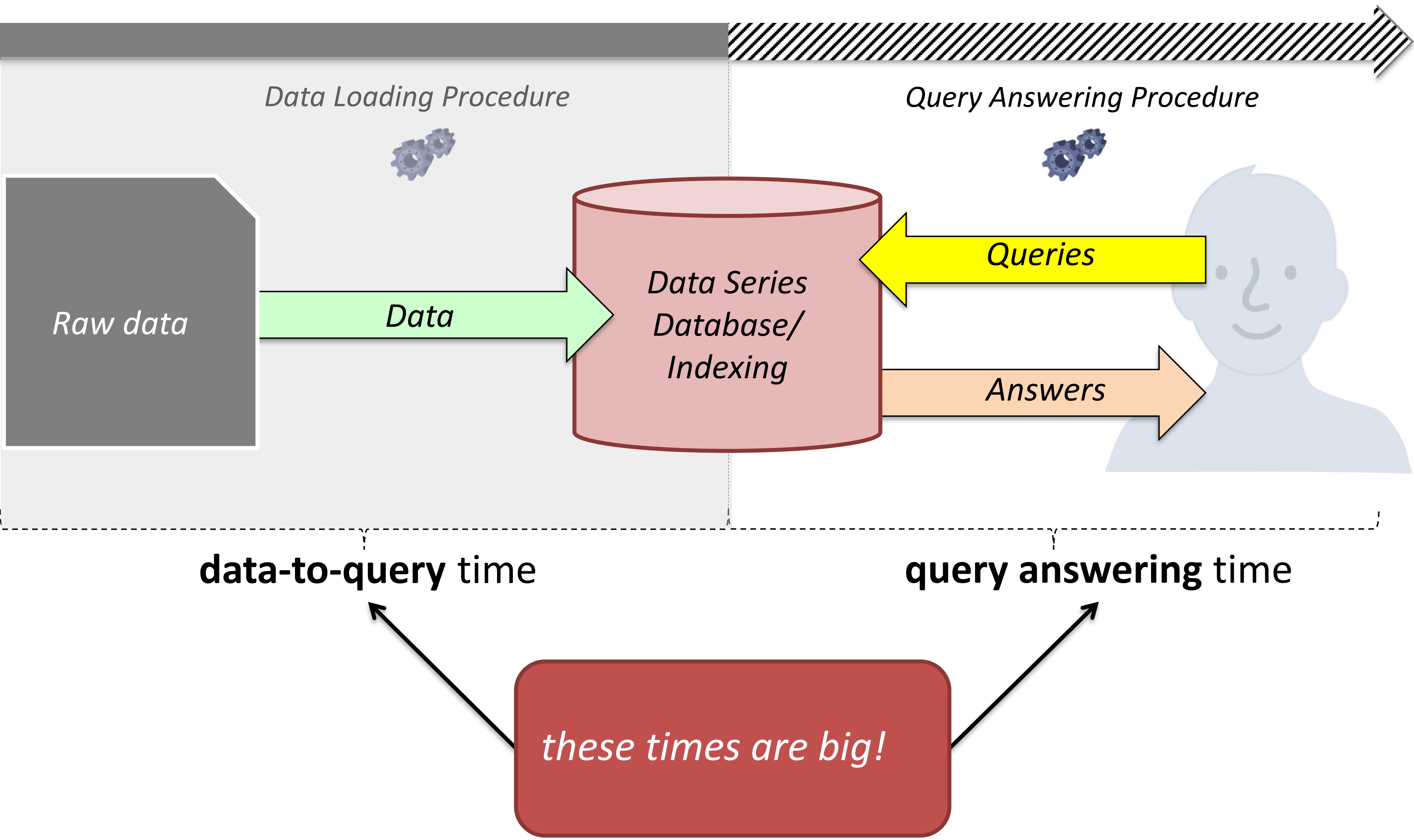
Clustering

Outlier Detection

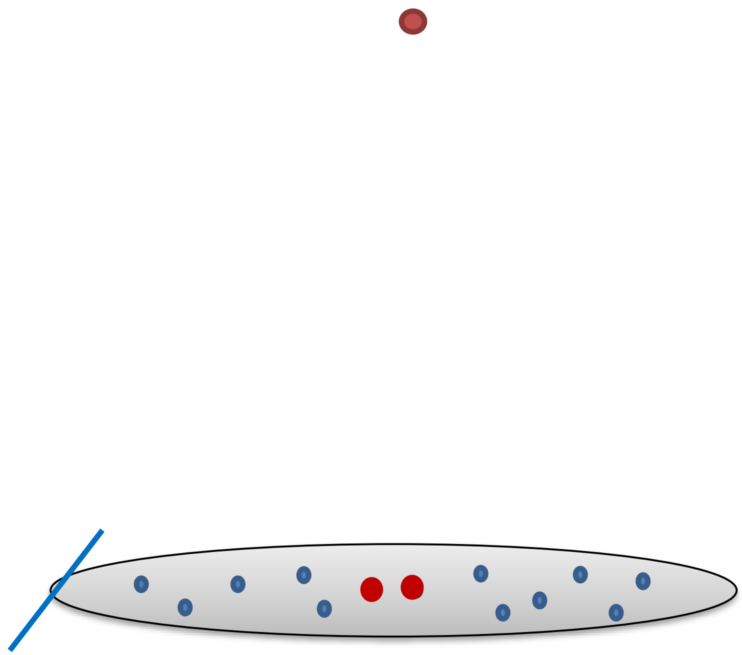
HARD, because of very high dimensionality:
each data series has 100s-1000s of points!

even HARDER, because of very large size:
millions to billions of data series (multi-TBs)!

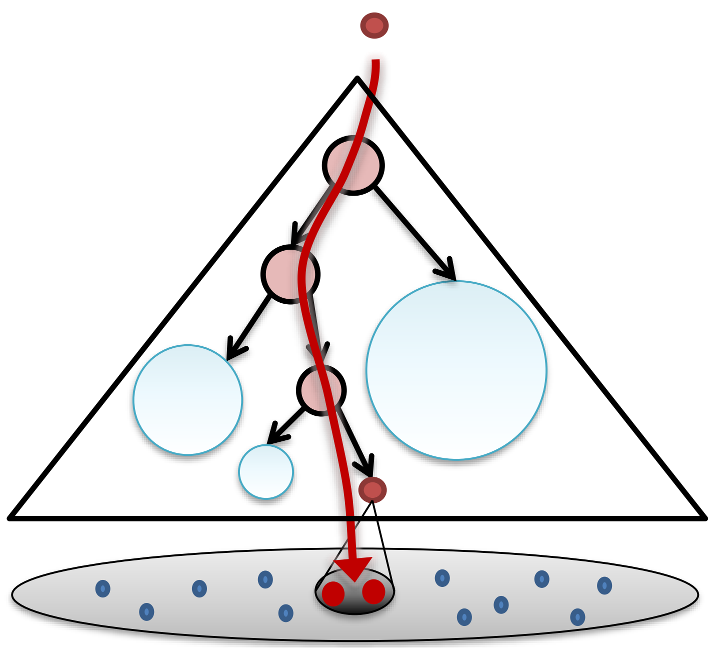
Query answering process



Similarity Search via
Serial Scan



Similarity Search via
Indexing



Traditional Approaches

answer **nearest neighbor queries** on a **1TB** dataset:

serial scan takes 45 minutes/query

Query Answering

but building the index takes **too long!**

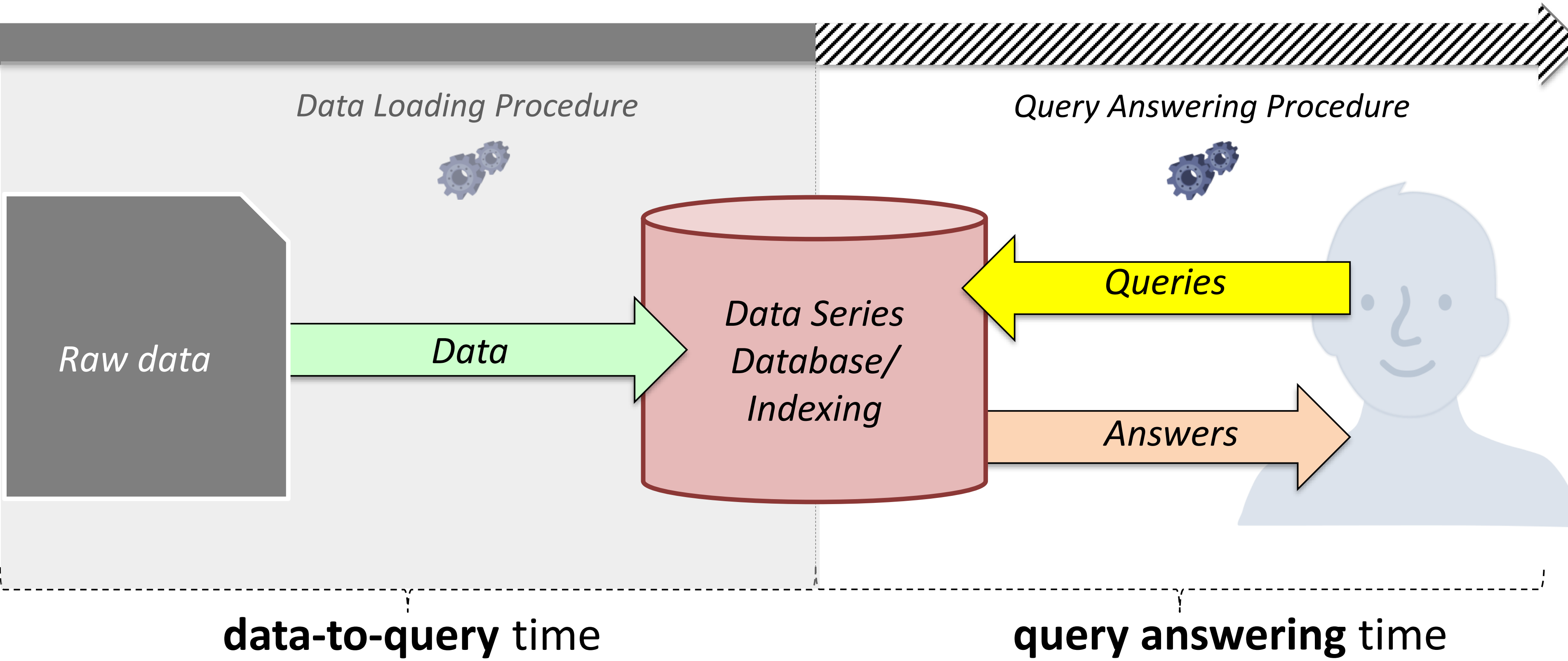
indexing a 1TB dataset takes days

a **data series index** can **reduce** querying time

Query Answering

complex analytics in days…

Query answering process



we have proposed the state-of-the-art solutions for both problems!

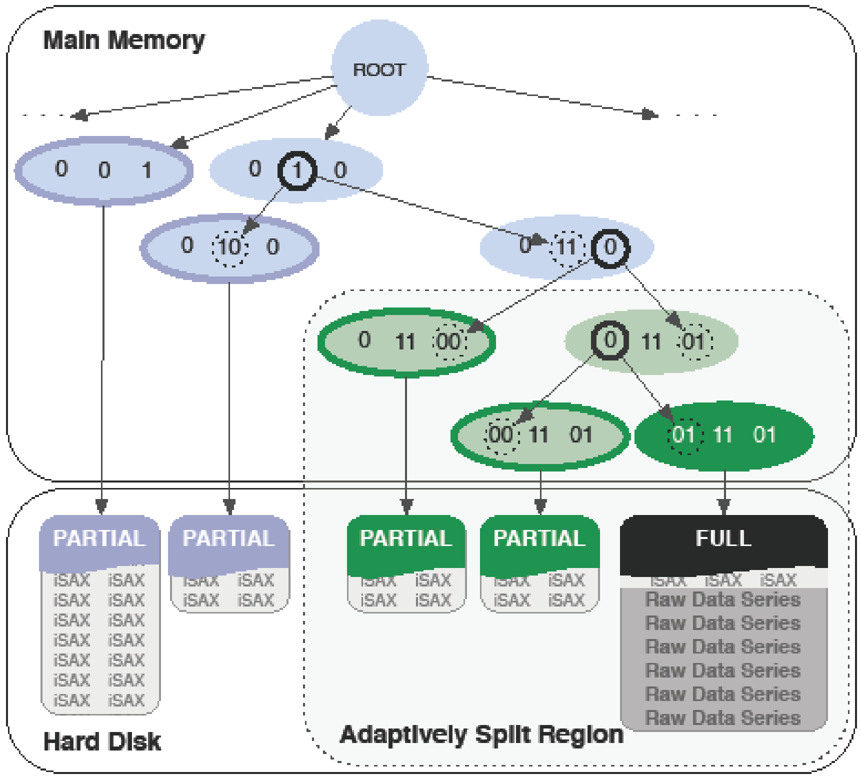
State of the Art Approach: ADS+

Publications

SIGMOD'14

PVLDB'15

VLDBJ'16

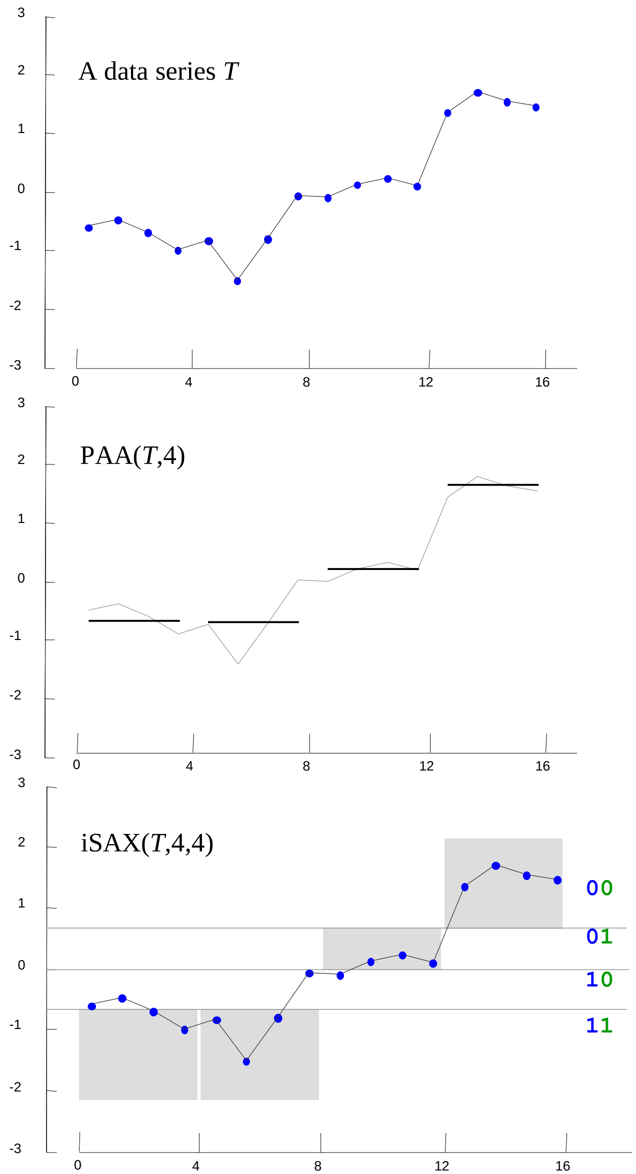


complex analytics in hours!

SAX Representation

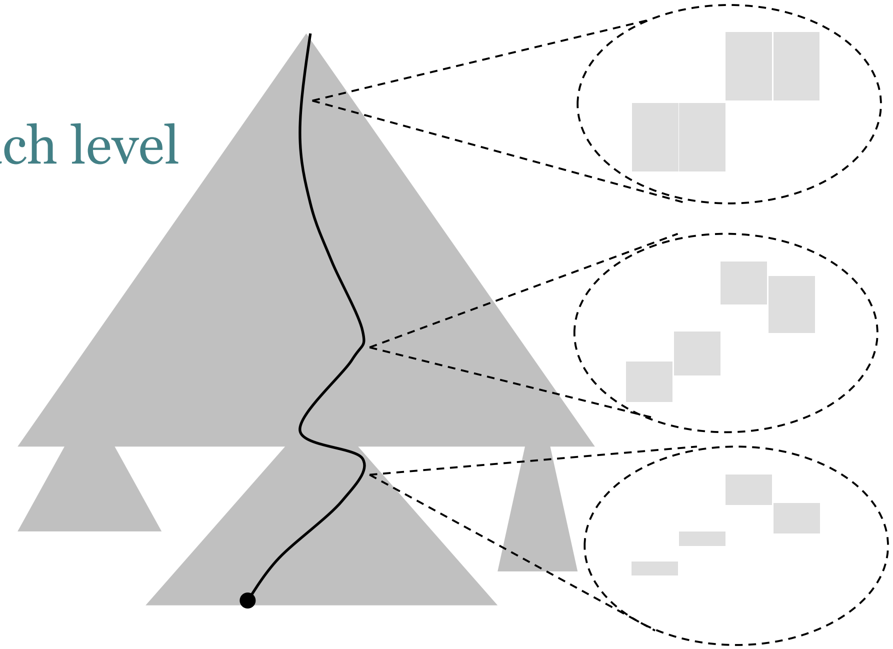
- **S**ymbolic **A**ggregate appro**X**imation (SAX)
  - **(1)** Represent data series T of length $\boldsymbol{n}$ with $\boldsymbol{w}$ segments using Piecewise Aggregate Approximation (PAA)
    - T typically normalized to $\mu = 0$, $\sigma = 1$
    - $\text{PAA}(T,w) = \bar{T} = \bar{t}_1, \ldots, \bar{t}_w$

      where $\bar{t}_i = \frac{w}{n} \sum_{j=\frac{n}{w}(i-1)+1}^{\frac{n}{w}i} T_j$
  - **(2)** Discretize into a vector of symbols
    - Breakpoints map to small alphabet $\boldsymbol{a}$ of symbols



*i*SAX Index

- non-balanced tree-based index with non-overlapping regions, and controlled fan-out rate
  - base cardinality ***b*** (optional), segments ***w***, threshold ***th***
  - hierarchically subdivides SAX space until num. entries ≤ ***th***
- Approximate Search
  - Match *i*SAX representation at each level
- Exact Search
  - Leverage approximate search
  - Prune search space
    - Lower bounding distance



Drawback of iSAX2+

- cannot start answering queries until *entire* index is built!

Adaptive Data Series Index: ADS+

- novel paradigm for building a data series index
  - do not build entire index and then answer queries
  - start answering queries by building the part of the index needed by those queries

- still guarantee correct answers

Publications

SIGMOD'14

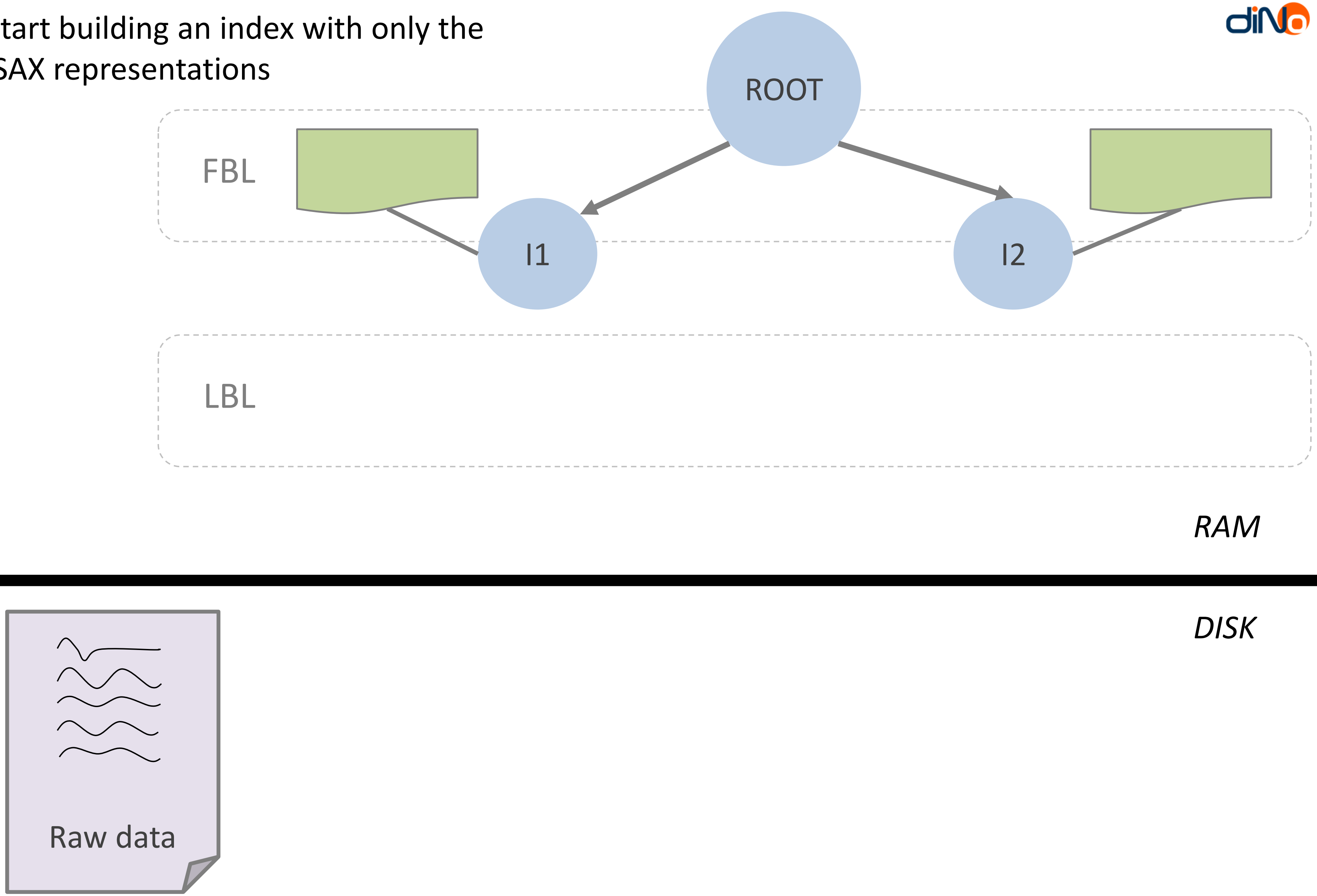
PVLDB'15

VLDBJ'16

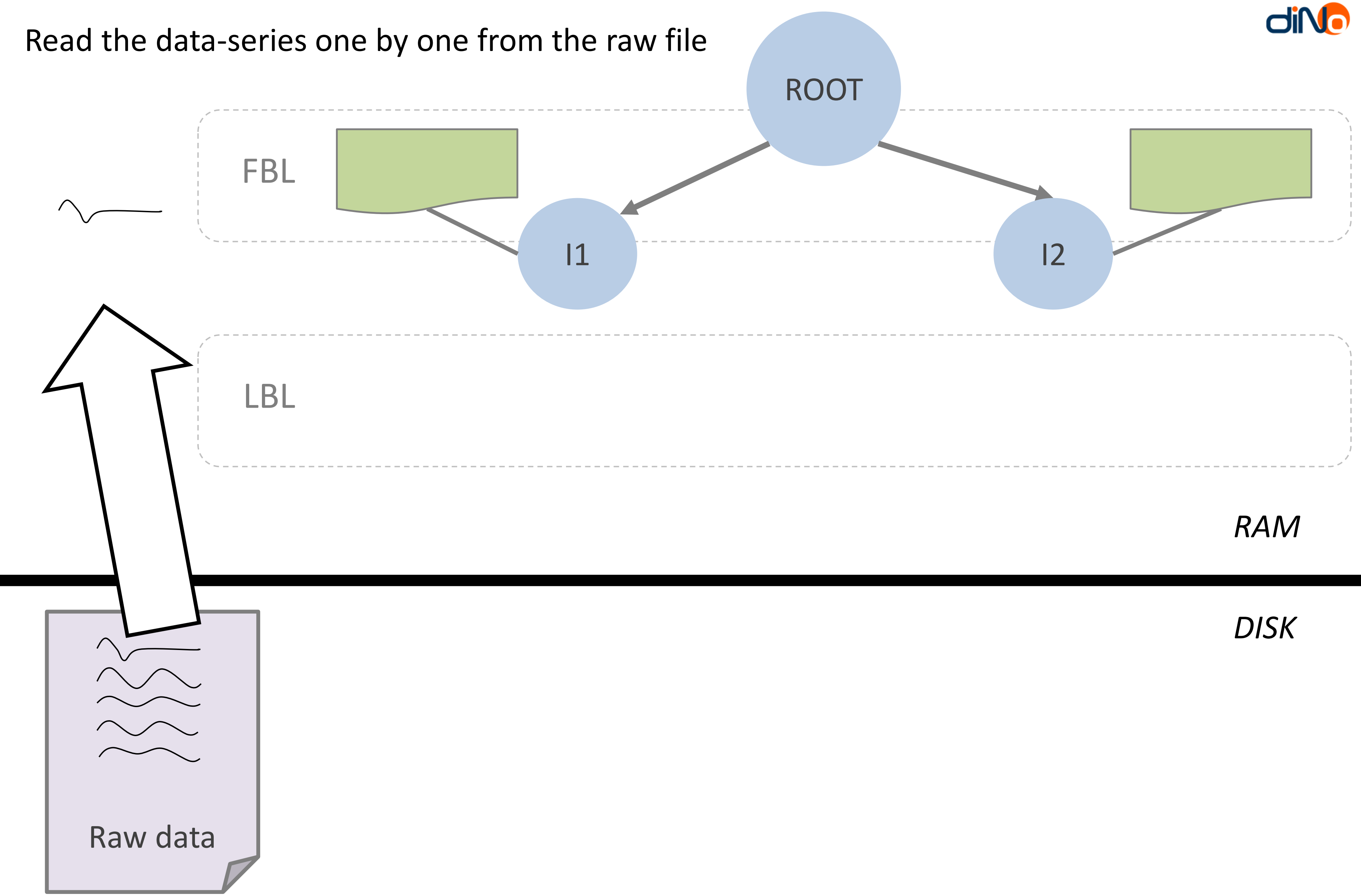
Adaptive Data Series Index: ADS+

- intuition for proposed solution
  - build the iSAX index using the iSAX representations
    - just like iSAX2+
  - but start with a large leaf size
    - minimize initial cost
  - postpone leaf materialization to query time
    - only materialize (at query time) leaves needed by queries
  - parts that are queried more are refined more
    - use smaller leaf sizes (reduced leaf materialization and query answering costs)

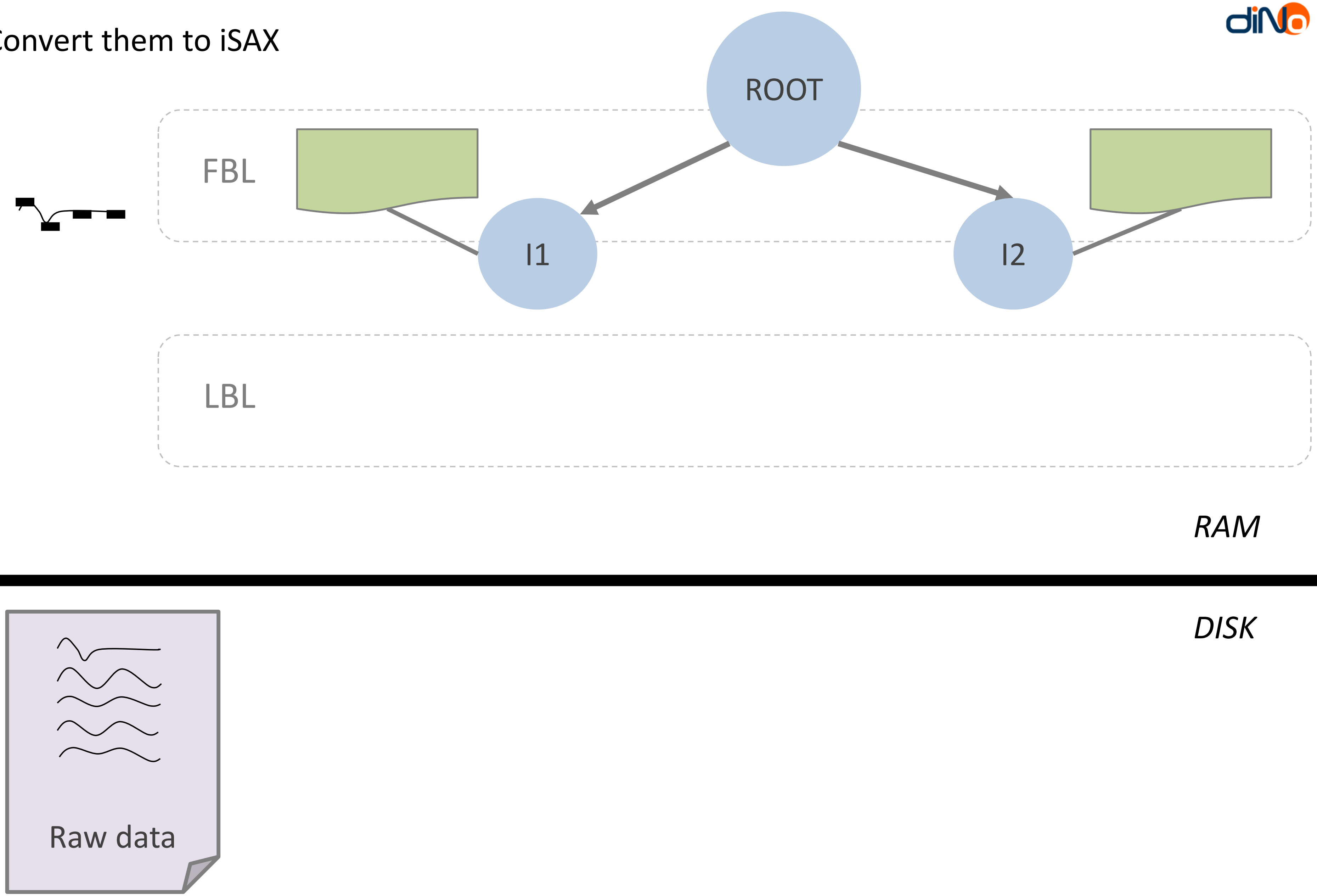
Start building an index with only the iSAX representations



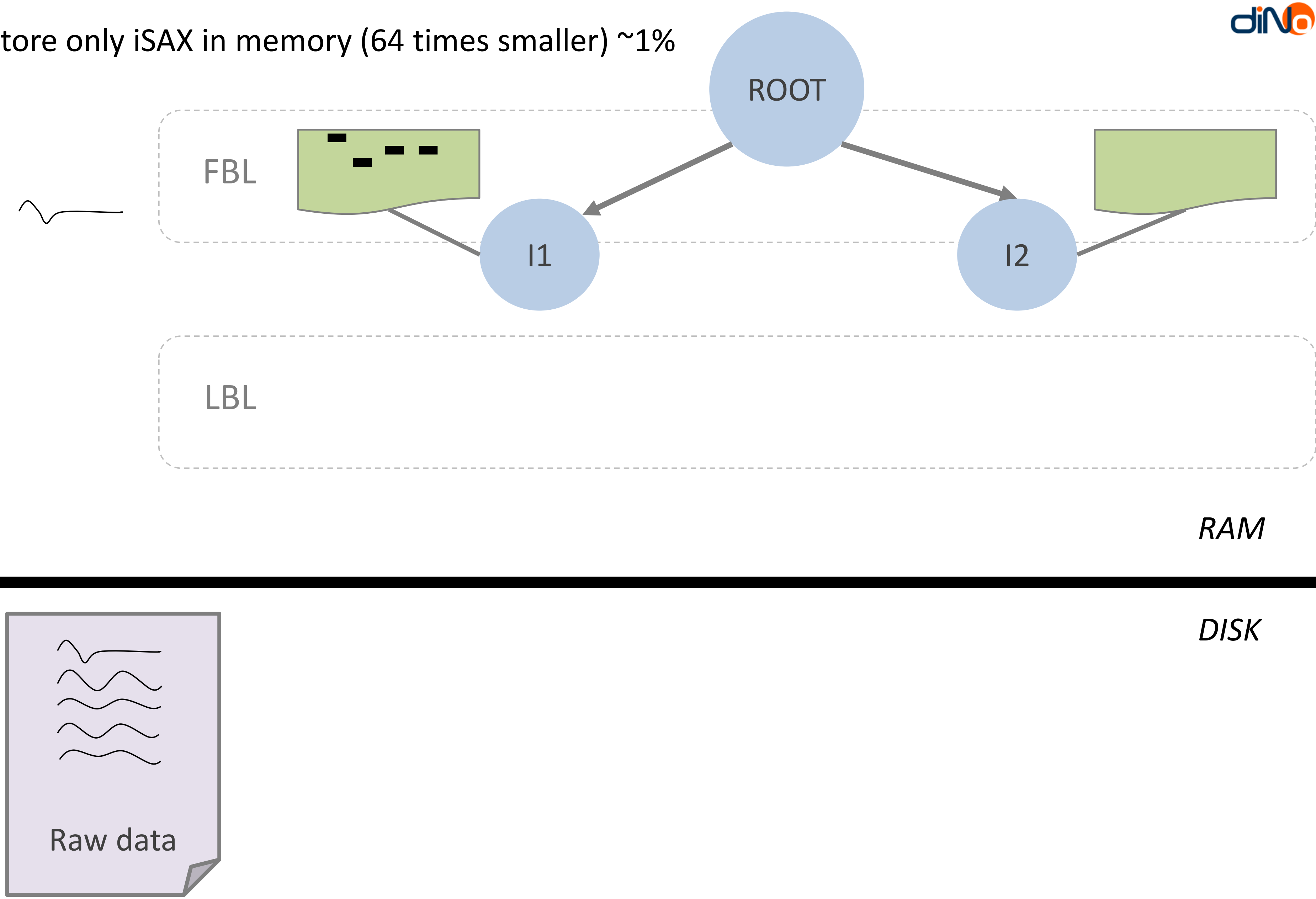
Read the data-series one by one from the raw file



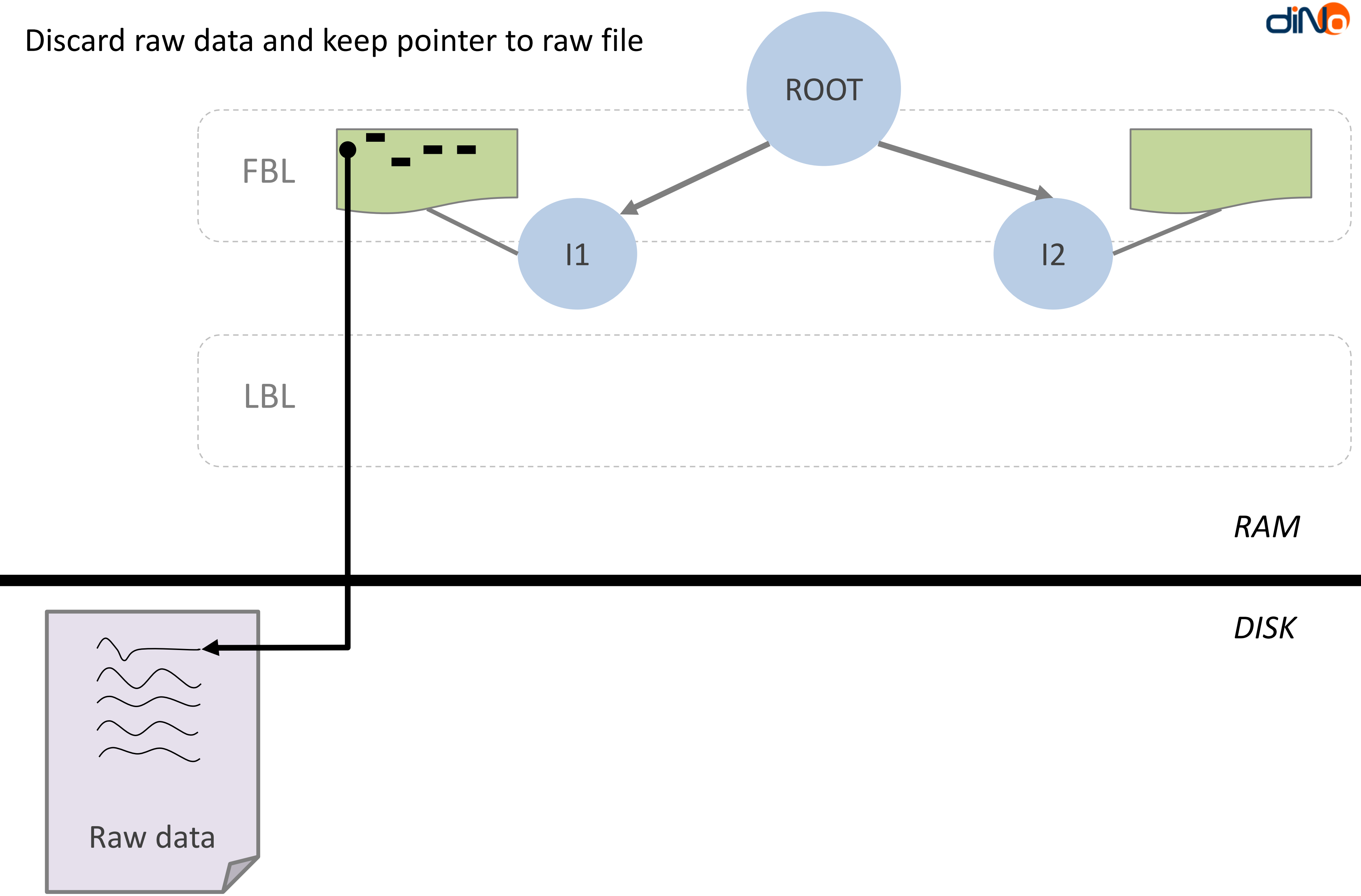
Convert them to iSAX



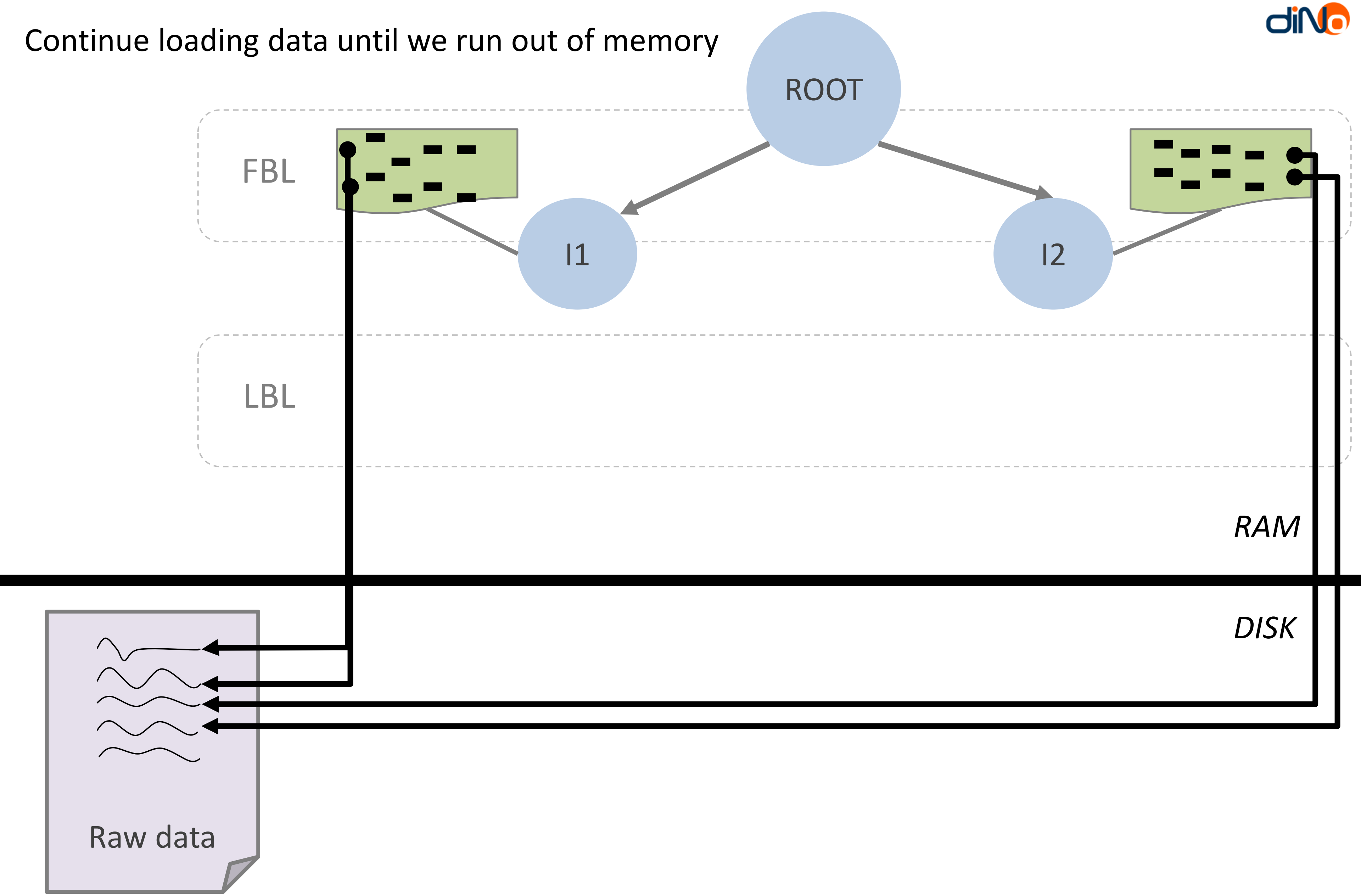
Store only iSAX in memory (64 times smaller) ~1%



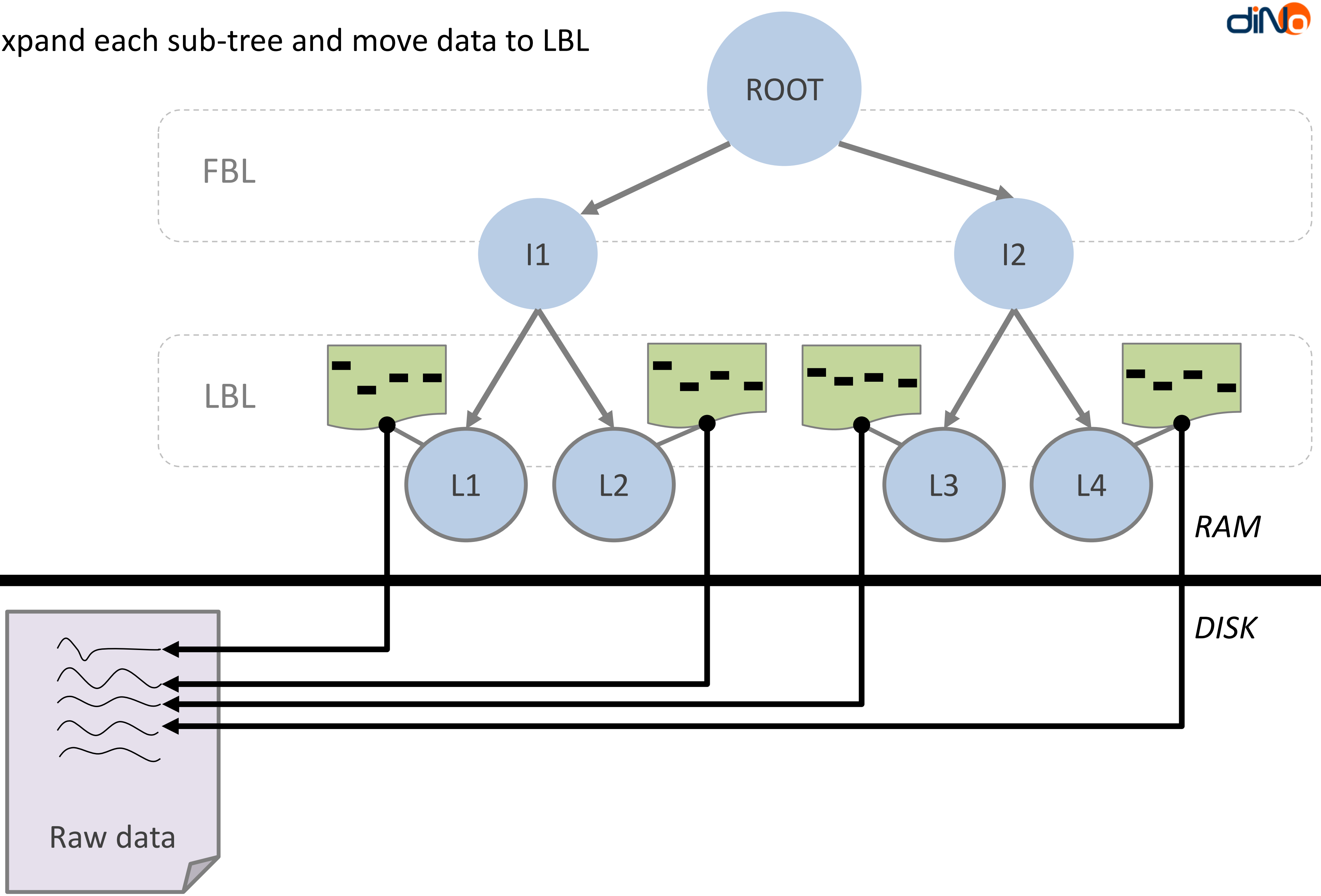
Discard raw data and keep pointer to raw file



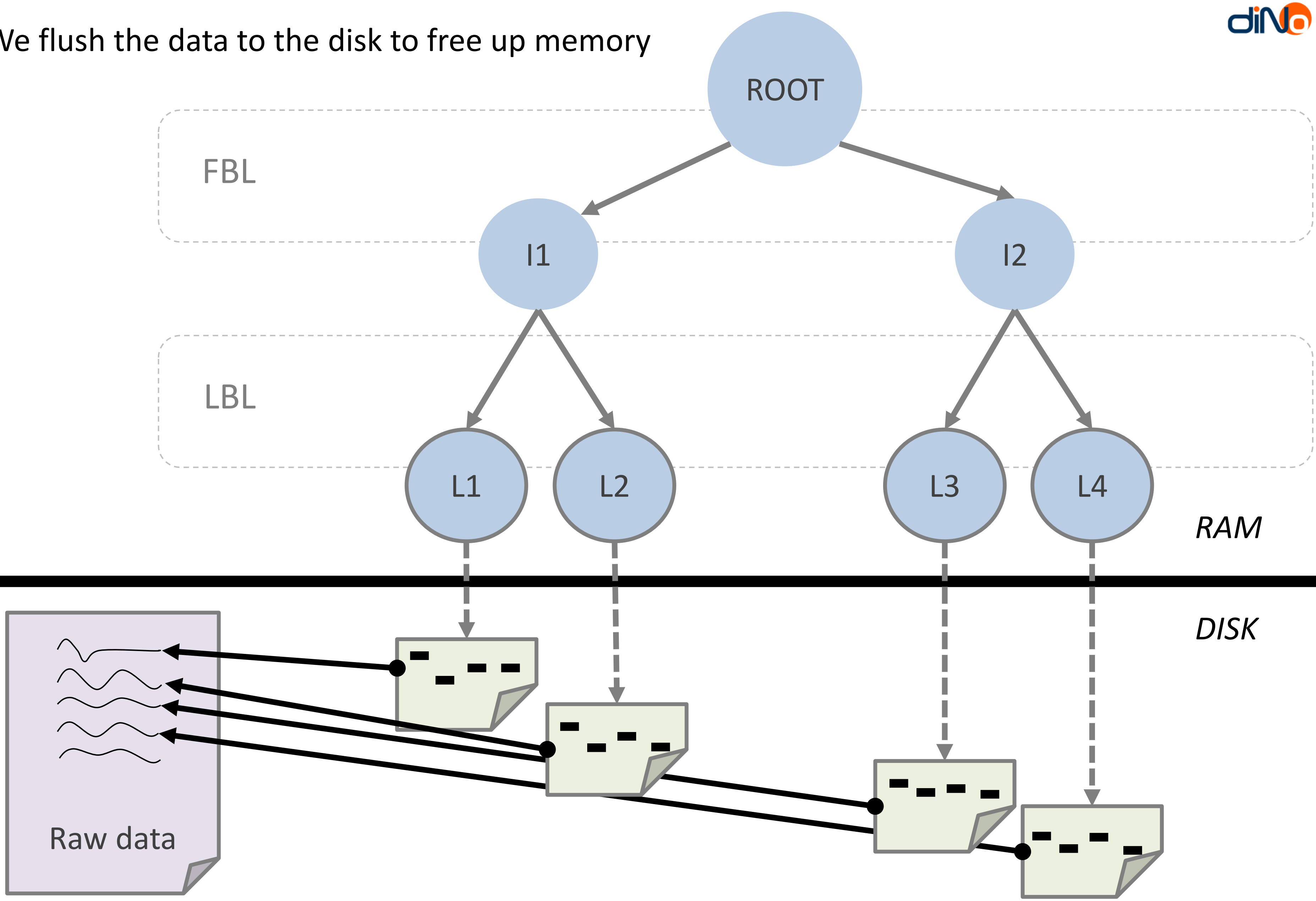
Continue loading data until we run out of memory

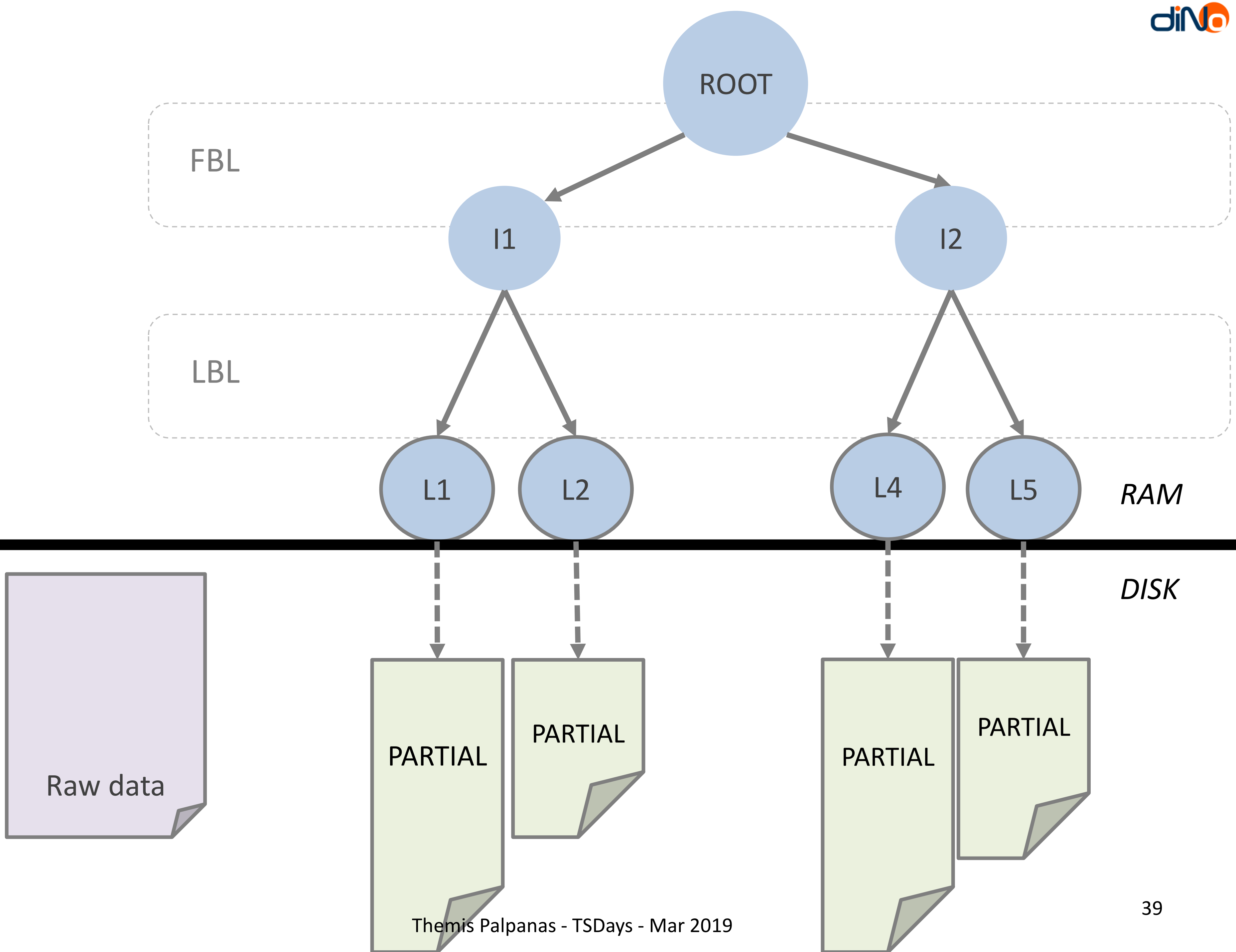


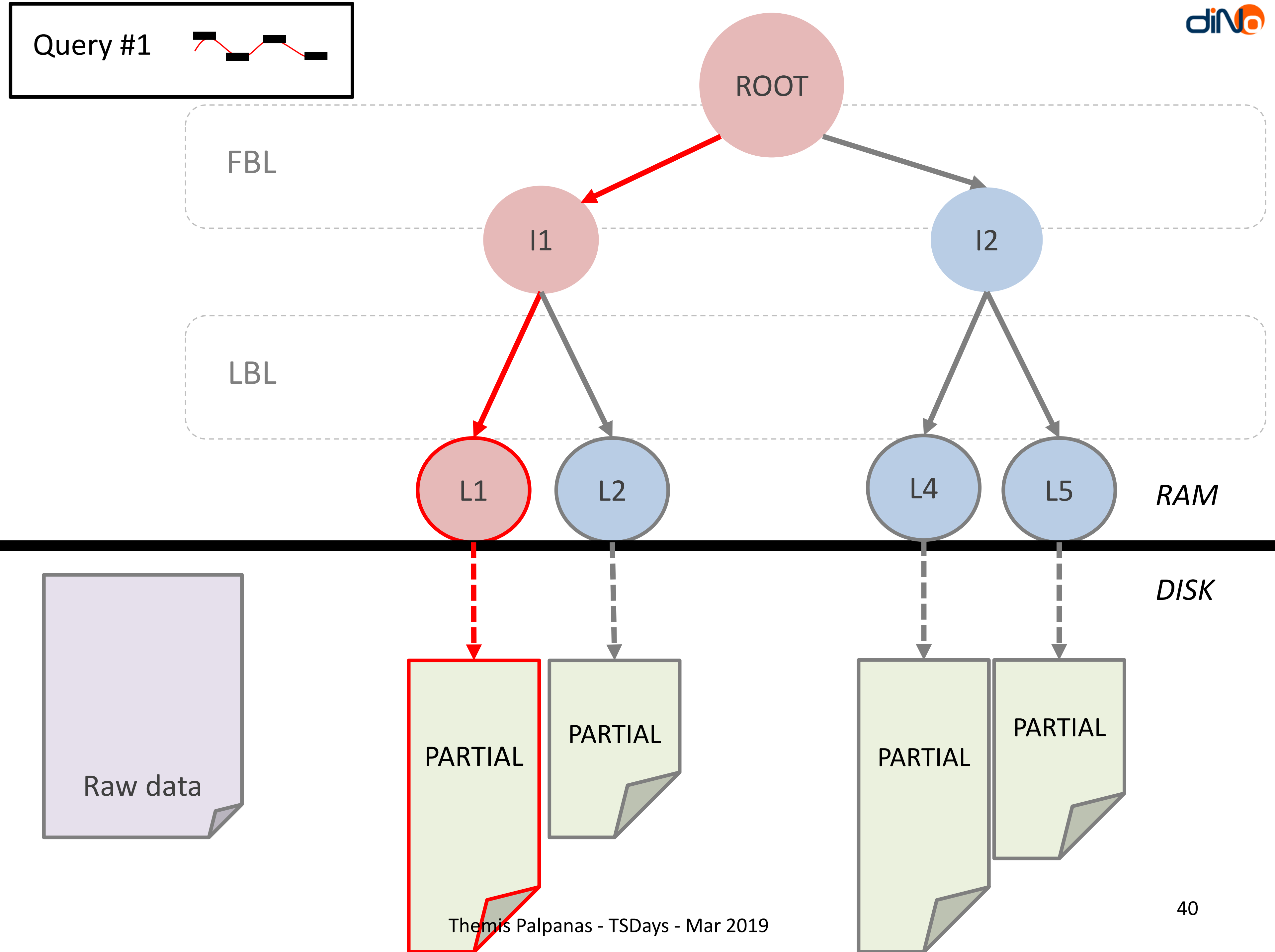
Expand each sub-tree and move data to LBL

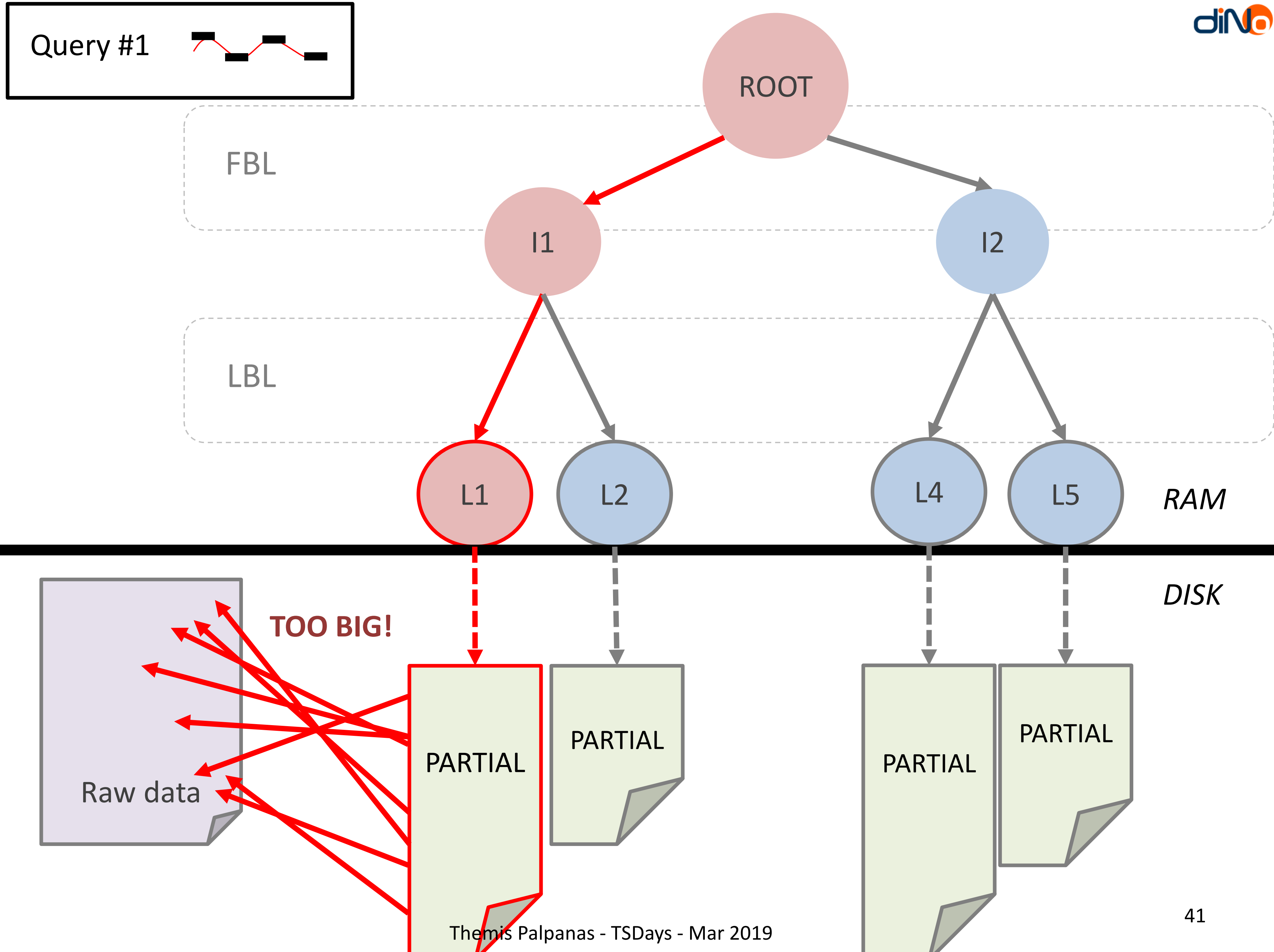


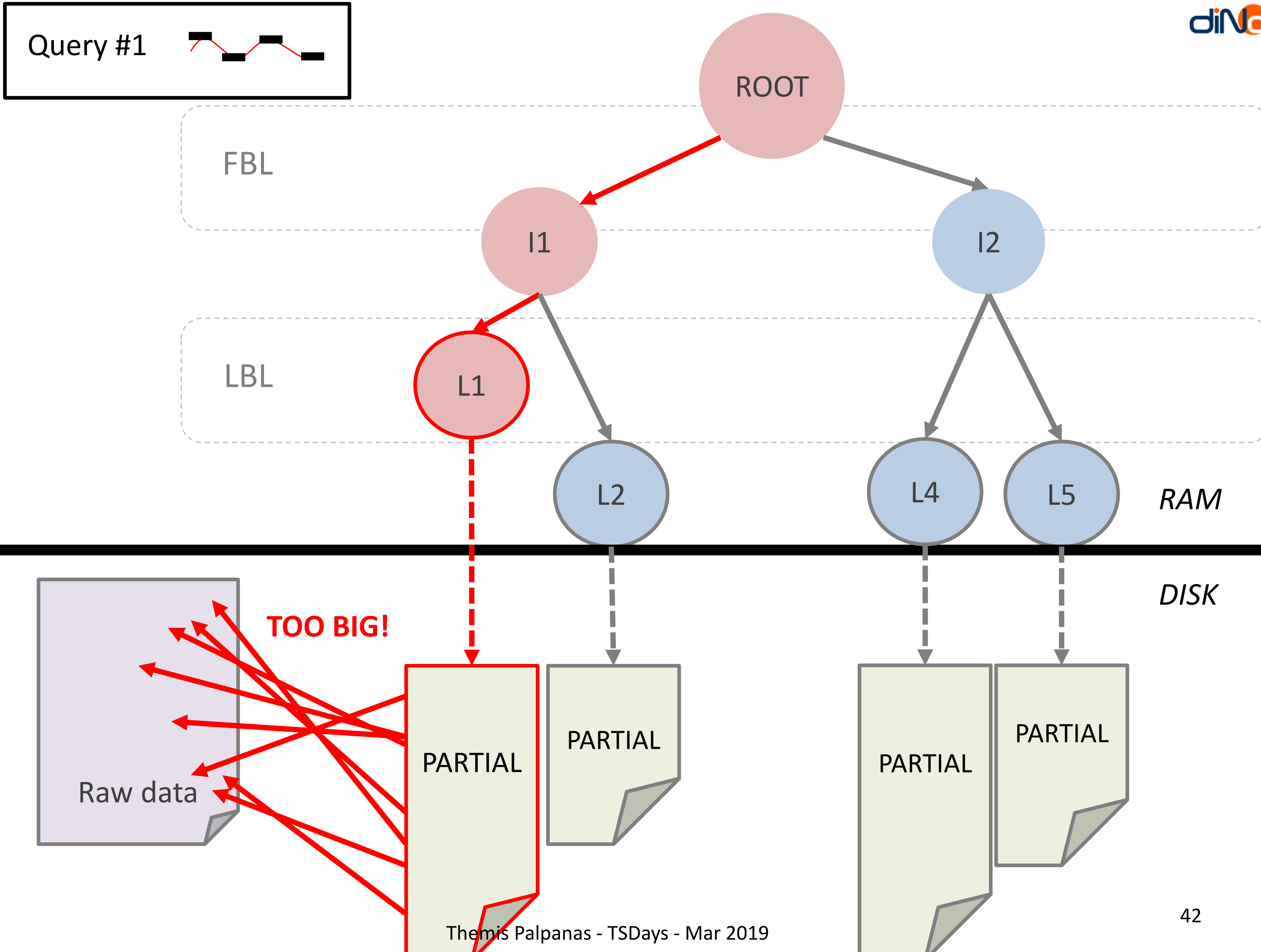
We flush the data to the disk to free up memory




ROOT
FBL
I1
I2
LBL
L1
L2
L4
L5
RAM
DISK
Raw data
PARTIAL
PARTIAL
PARTIAL
PARTIAL


Query #1
ROOT
FBL
I1
I2
LBL
L1
L2
L4
L5
RAM
DISK
Raw data
PARTIAL
PARTIAL
PARTIAL
PARTIAL

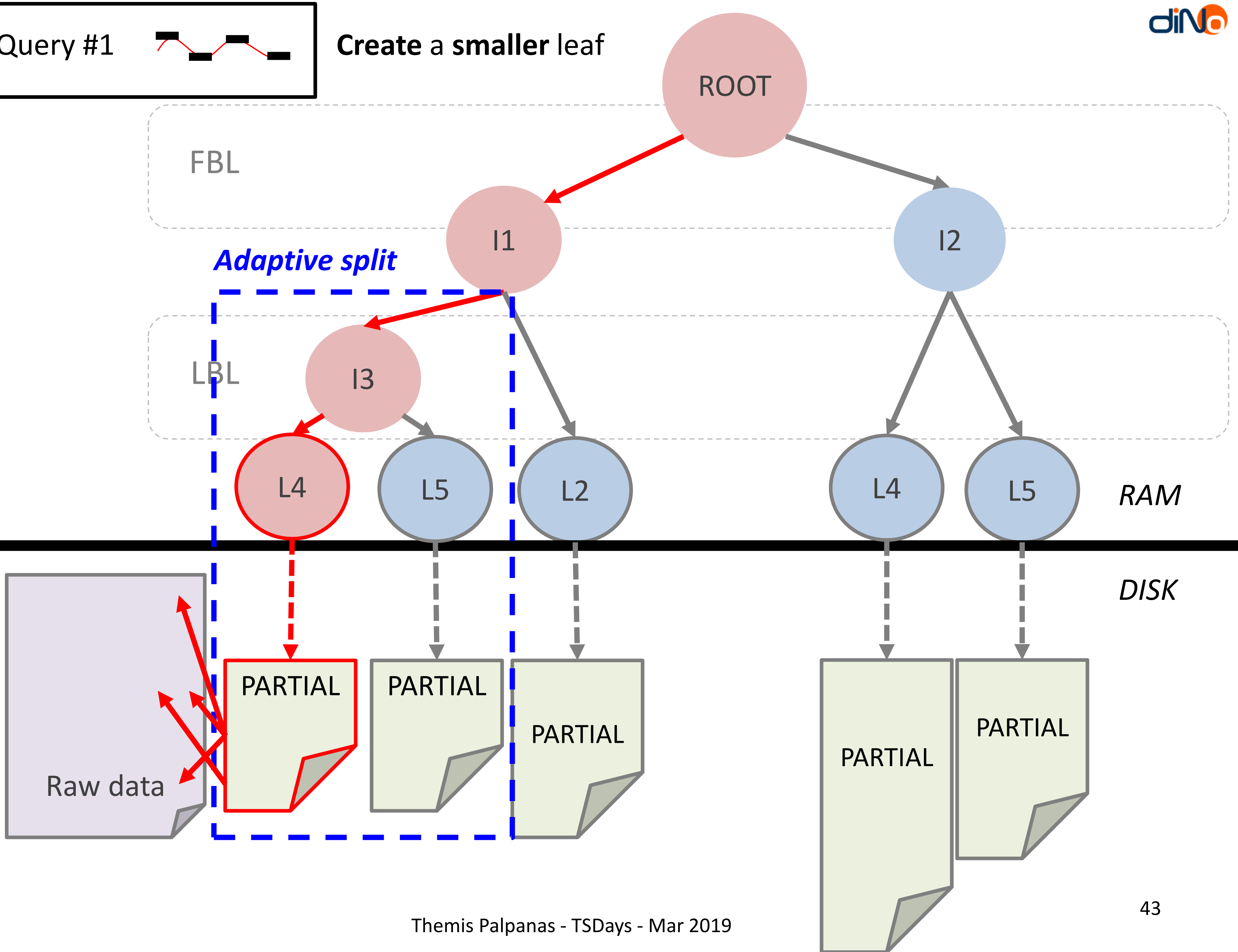

Query #1
ROOT
FBL
I1
I2
LBL
L1
L2
L4
L5
RAM
DISK
TOO BIG!
Raw data
PARTIAL
PARTIAL
PARTIAL
PARTIAL



Query #1
ROOT
FBL
I1
I2
LBL
L1
L2
L4
L5
RAM
DISK
TOO BIG!
Raw data
PARTIAL
PARTIAL
PARTIAL
PARTIAL

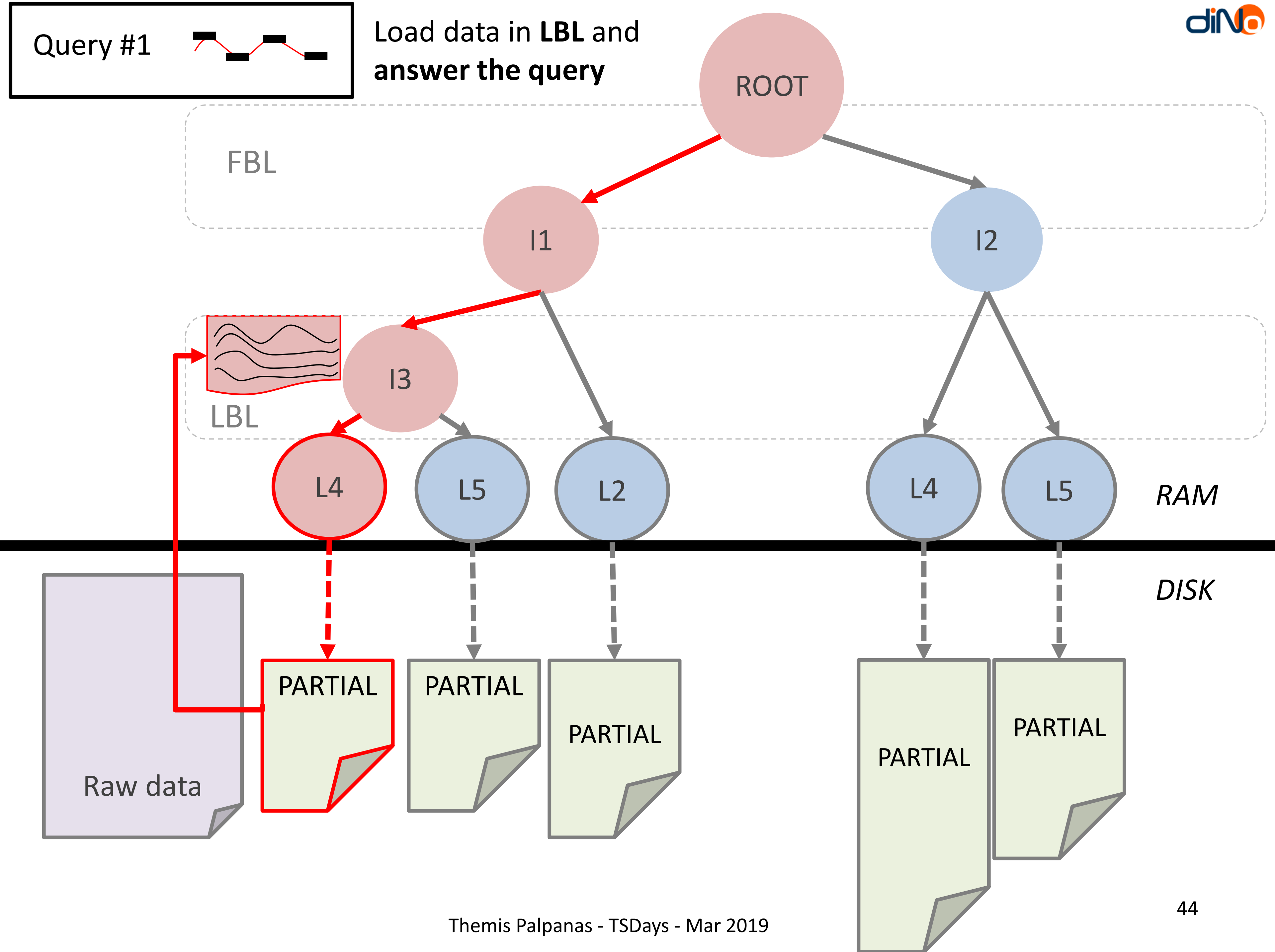
Query #1

Create a **smaller** leaf

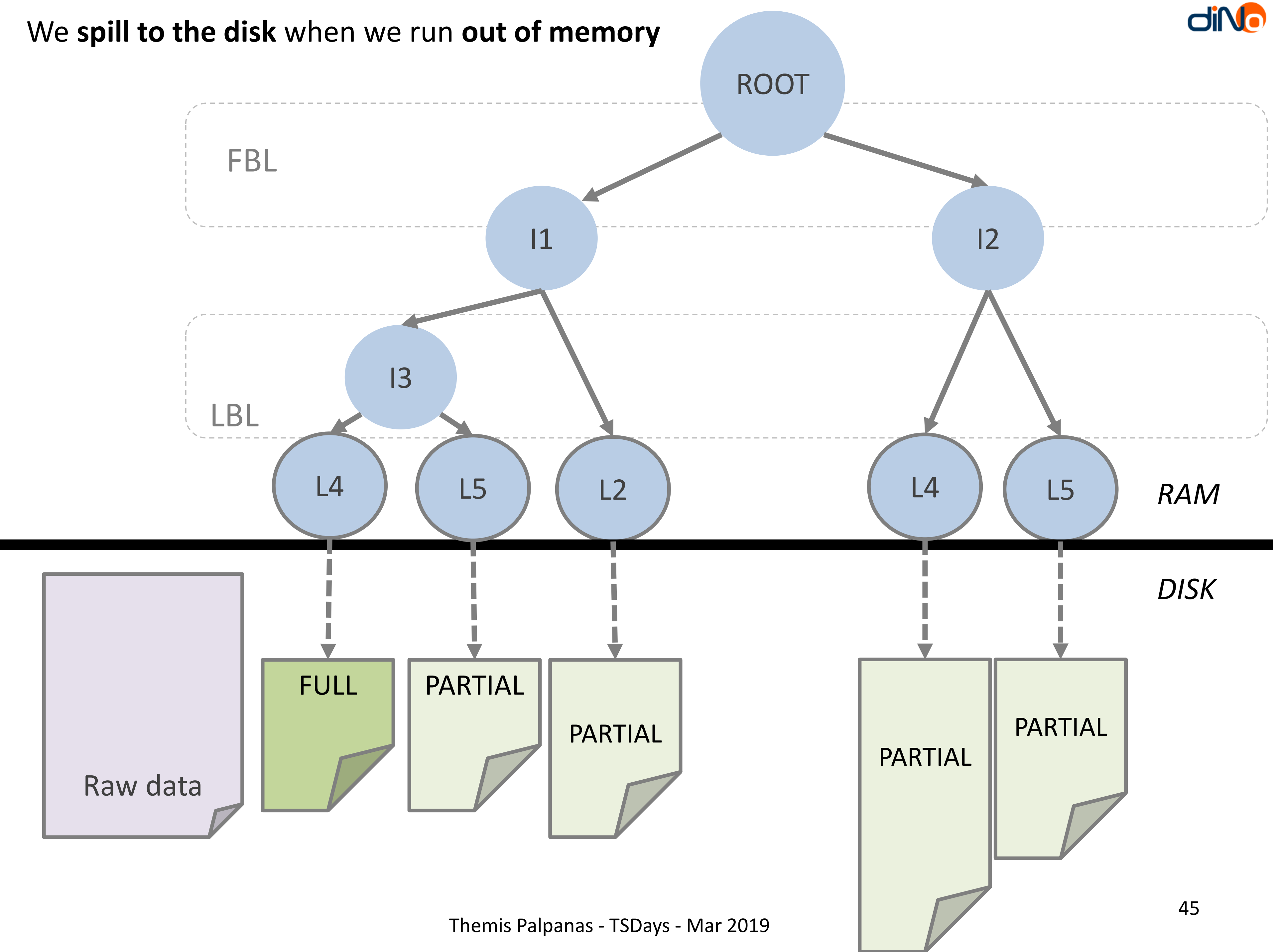


Query #1

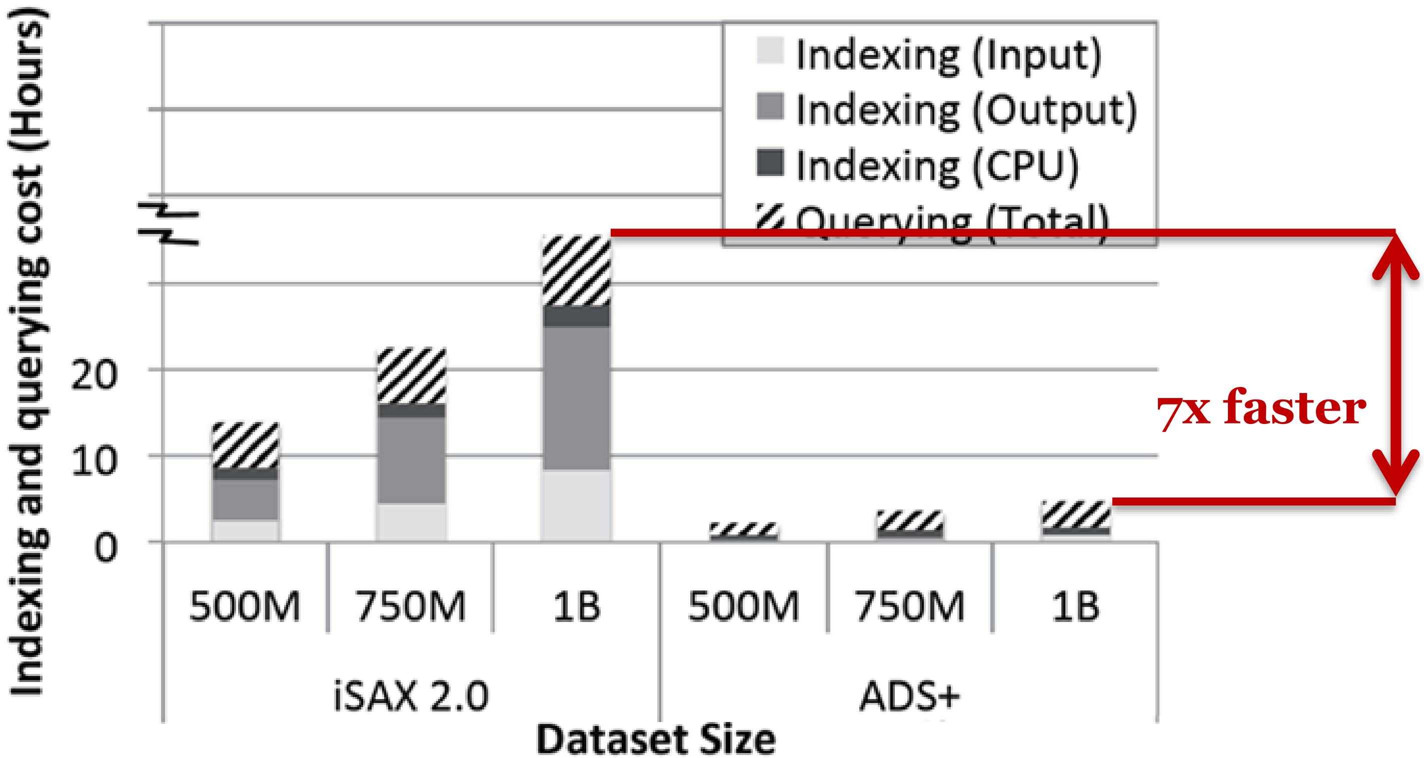
Load data in **LBL** and **answer the query**



We **spill to the disk** when we run **out of memory**



Experimental Evaluation



- iSAX 2.0 needs more than 35 hours to answer 100K approximate queries
- ADS+ answers 100K approximate queries in less than 5 hours

Publications

PVLDB'18

SIGMOD'19

Extensions…

- Coconut: current solution for limited memory devices and streaming time series
  - bottom-up, succinct index construction based on sortable summarizations
  - outperforms state-of-the-art in terms of index space, index construction time, and query answering time

Publications

PVLDB‘18

SIGMOD’19

ICDE’18

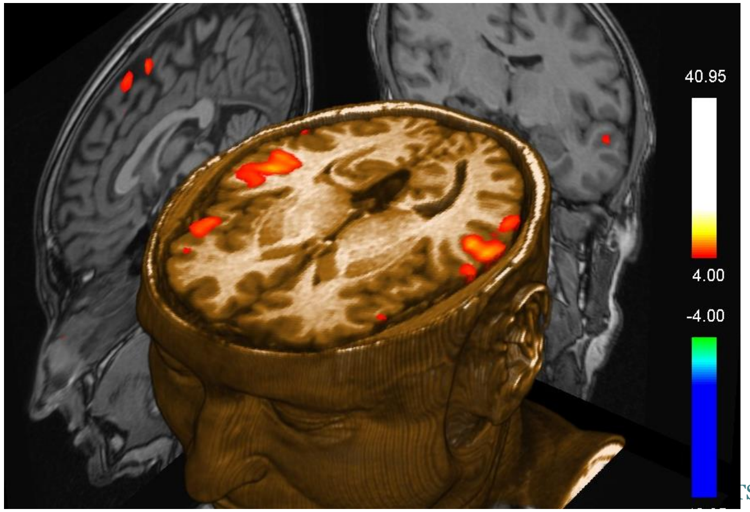
PVLDB‘19

Extensions…

- Coconut: current solution for limited memory devices and streaming time series
  - bottom-up, succinct index construction based on sortable summarizations
  - outperforms state-of-the-art in terms of index space, index construction time, and query answering time
- ULISSE: current solution for variable-length queries
  - single supports of queries of variable lengths
  - orders of magnitude faster than competing approaches

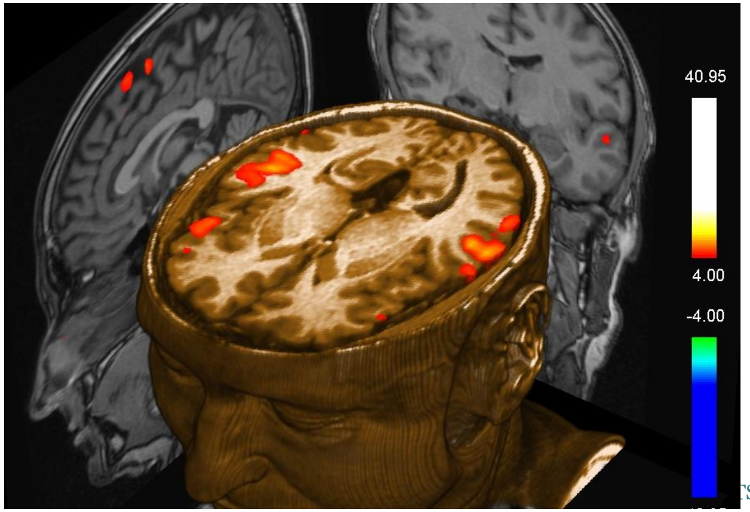
Massive Data Series Collections

- functional Resonance Magnetic Imaging (fMRI) data
  - primary experimental tool of neuroscientists
  - reveal how different parts of brain respond to stimuli
  - single experiment (1 subject, 1 test) produces
    - 60,000 data series of length 3,000: 12 GB



Massive Data Series Collections

- ADHD-200 Global Competition
  - classification task: detect Attention Deficit Hyperactivity Disorder
    - 776 subjects: 9 TB
      - equivalent to: 4.5 billion non-overlapping data series of size 256
      - equivalent to: 1100 billion overlapping data series of size 256



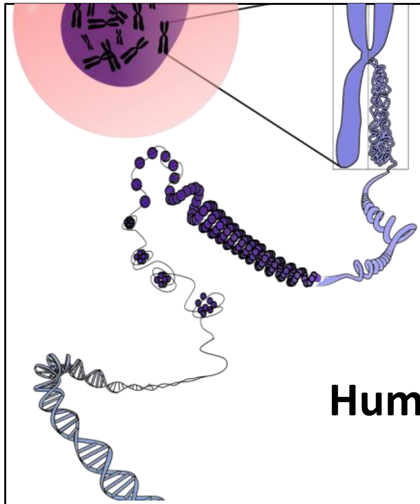
Massive Data Series Collections

NASA's Solar Observatory

1.5 TB per day

Large Synoptic Survey Telescope (2019)

~30 TB per night



Human Genome project

130 TB

passenger aircrafts

20 TB per hour

data center and services monitoring

2B data series

4M points/sec

Publications

ICDE'18

HPCS'17

SIGREC'15

The Road Ahead

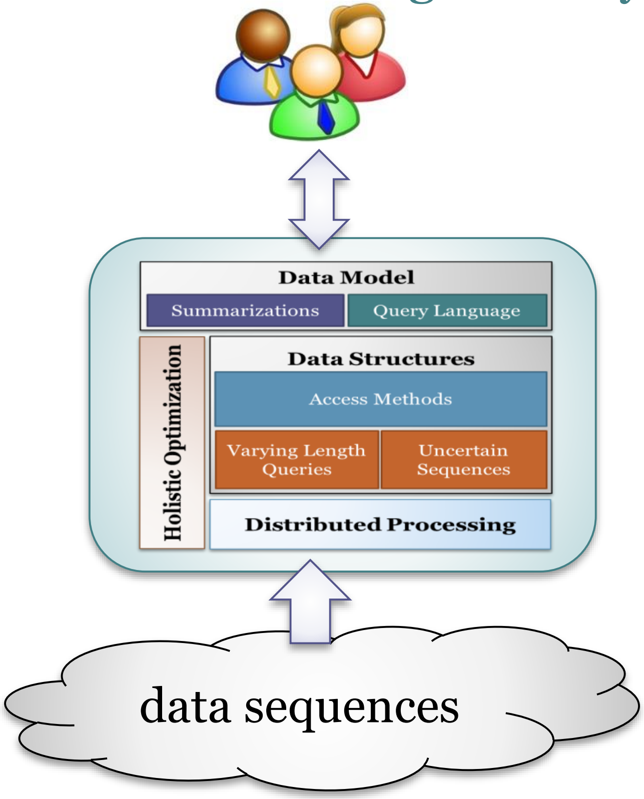
"enable practitioners and non-expert users to easily and efficiently manage and analyze massive data series collections"

Publications

- ICDE'18
- HPCS'17
- SIGREC'15

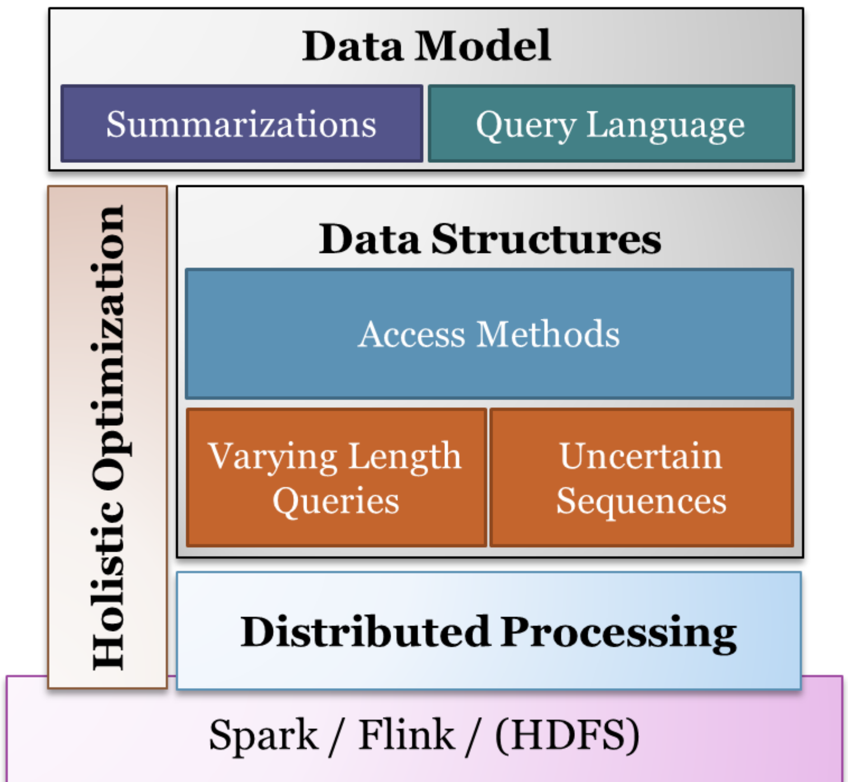
The Road Ahead

- Big Sequence Management System
  - general purpose data series management system



The Road Ahead

- Big Sequence Management System



Publications

- ICDE'18
- HPCS'17
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The Road Ahead

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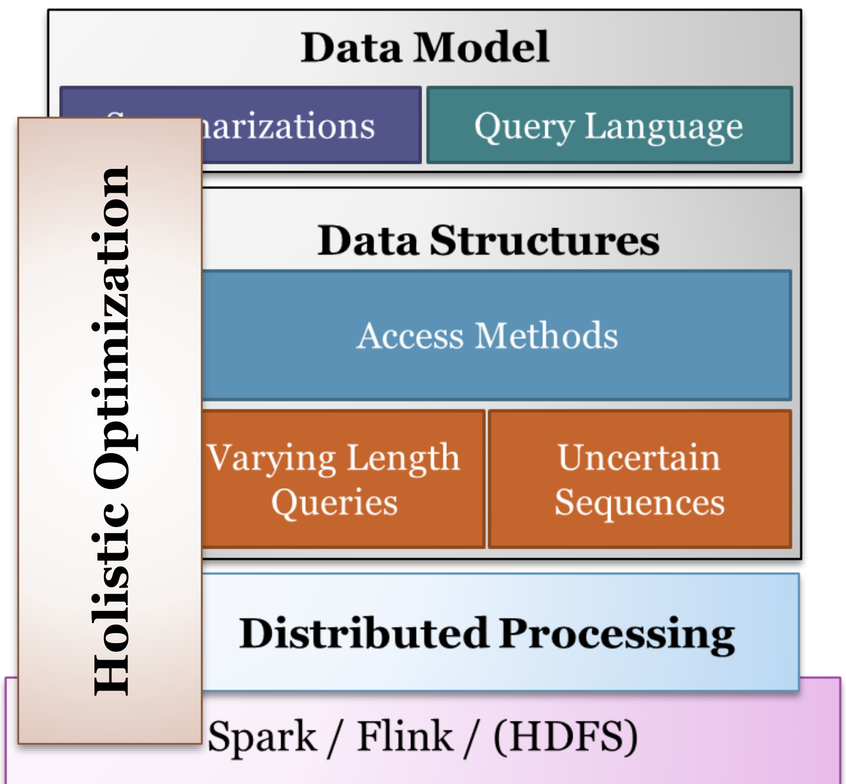


Parallelization/Distribution?

- discussion so far assumed serial execution in a single core
  - focus on efficient resource utilization
  - squeeze the most out of a single core
  - produce scalable solutions at lowest possible cost
    - also suitable for analysts with no access to/expertise for clusters

Publications

HPCS'17

Need for Parallelization/Distribution

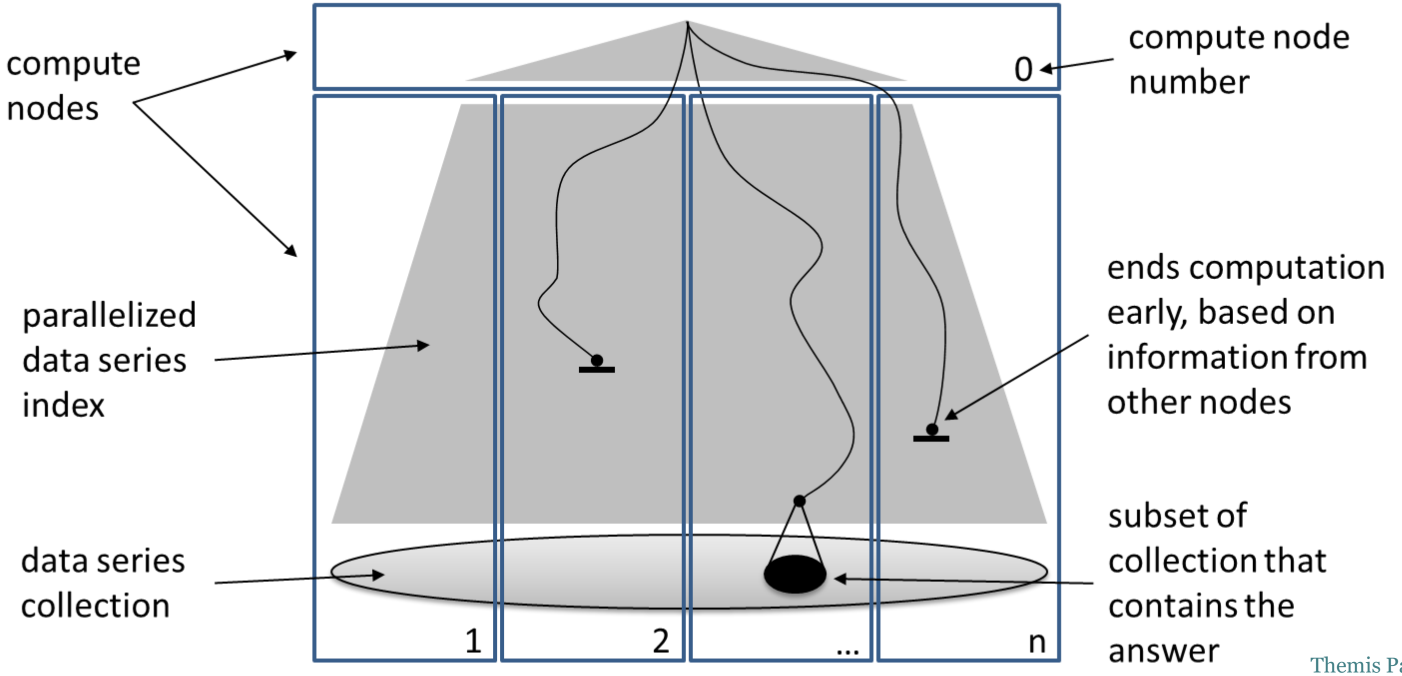
- take advantage of modern hardware!
  - Single Instruction Multiple Data (SIMD)
    - natural for data series operations
  - multi-tier CPU caches
    - design data structures aligned to cache lines
  - multi-core and multi-socket architectures
    - use parallelism inside each computation server
  - Graphics Processing Units (GPUs)
    - propose massively parallel techniques for GPUs
  - new storage solutions: SSDs, NVRAM
    - develop algorithms that take these new characteristics/tradeoffs into account
  - compute clusters
    - distribute operation over many machines

Publications

HPCS'17

Need for Parallelization/Distribution

- further scale-up and scale-out possible!
  - techniques inherently parallelizable
    - across cores, across machines



Publications

HPCS'17

Need for Parallelization/Distribution

- further scale-up and scale-out possible!
  - techniques inherently parallelizable
    - across cores, across machines
- more involved solutions required when optimizing for energy
  - reducing execution time is relatively easy
  - minimizing total work (energy) is more challenging

Need for Parallelization/Distribution

Publications

ICDM'17

TKDE'18

- DPiSAX: current solution for distributed processing (Spark)
  - balances work of different worker nodes
  - performs 2 orders of magnitude faster than centralized solution

Need for Parallelization/Distribution

Publications

- ICDM'17
- TKDE'18
- BigData'18

- DPiSAX: current solution for distributed processing (Spark)
  - balances work of different worker nodes
  - performs 2 orders of magnitude faster than centralized solution
- ParIS: current solution for modern hardware
  - completely masks out the CPU cost
  - answers exact queries in the order of ms
    - 3 orders of magnitude faster then single-core solutions

Interactive Analytics?

- data series analytics is computationally expensive
  - very high inherent complexity
- may not always be possible to remove delays
  - but could try to hide them!

Need for Interactive Analytics

Publications

BigVis'19

- interaction with users offers new opportunities
  - progressive answers
    - produce intermediate results
      - iteratively converge to final, correct solution
    - provide bounds on the errors (of the intermediate results) along the way
  - imprecise queries
    - enable user to specify varying accuracy requirements for different parts of the same query

Need for Interactive Analytics

Publications

BigVis'19

VIS'18

- interaction with users offers new opportunities
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    - produce intermediate results
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    - provide bounds on the errors (of the intermediate results) along the way
  - imprecise queries
    - enable user to specify varying accuracy requirements for different parts of the same query

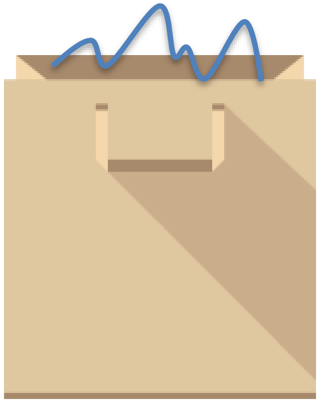
- several exciting research problems in intersection of visualization and data management
  - *frontend*: HCI/visualizations for querying/results display
  - *backend*: efficiently supporting these operations

Benchmarking Data Series Indexes?

Previous Studies

evaluate **performance** of **indexing methods** using **random queries**

- chosen from the data (with/without noise)



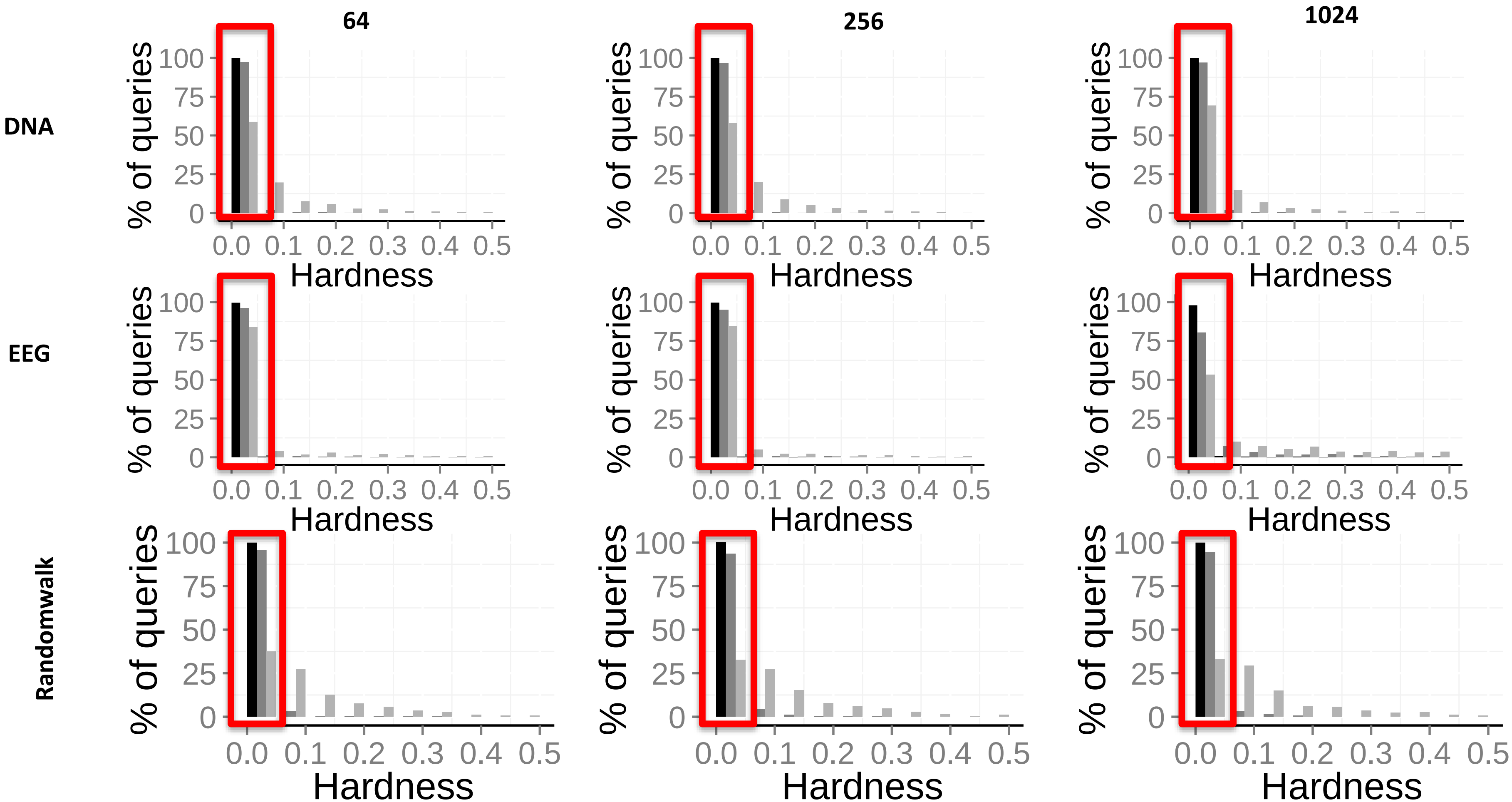
Publications

KDD ‘15

TKDE ‘18

Previous Workloads

Most previous workloads are ***skewed*** to ***easy*** queries



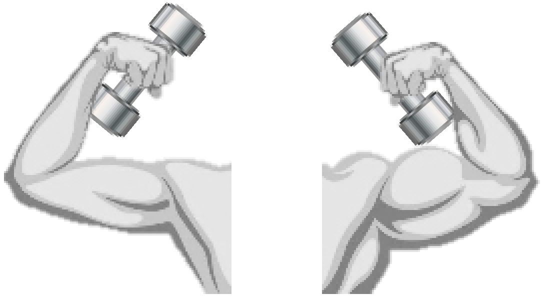
Publications

KDD '15

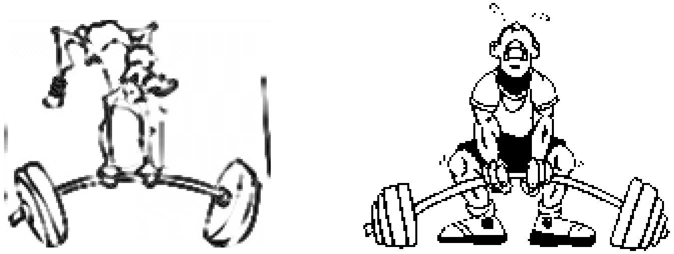
TKDE '18

Benchmark Workloads

If all queries are **easy**
all indexes look **good**



If all queries are **hard**
all indexes look **bad**



need **methods** for **generating** queries of **varying hardness**

Conclusions

- data series is a very common data type
  - across several different domains and applications
- complex data series analytics are challenging
  - have very high complexity
  - efficiency comes from data series management/indexing techniques
- current approaches used in practice are ad-hoc
  - waste of time and effort
  - suboptimal solutions
- need for Sequence Management System
  - optimize operations based on data/hardware characteristics
  - transparent to user

Conclusions

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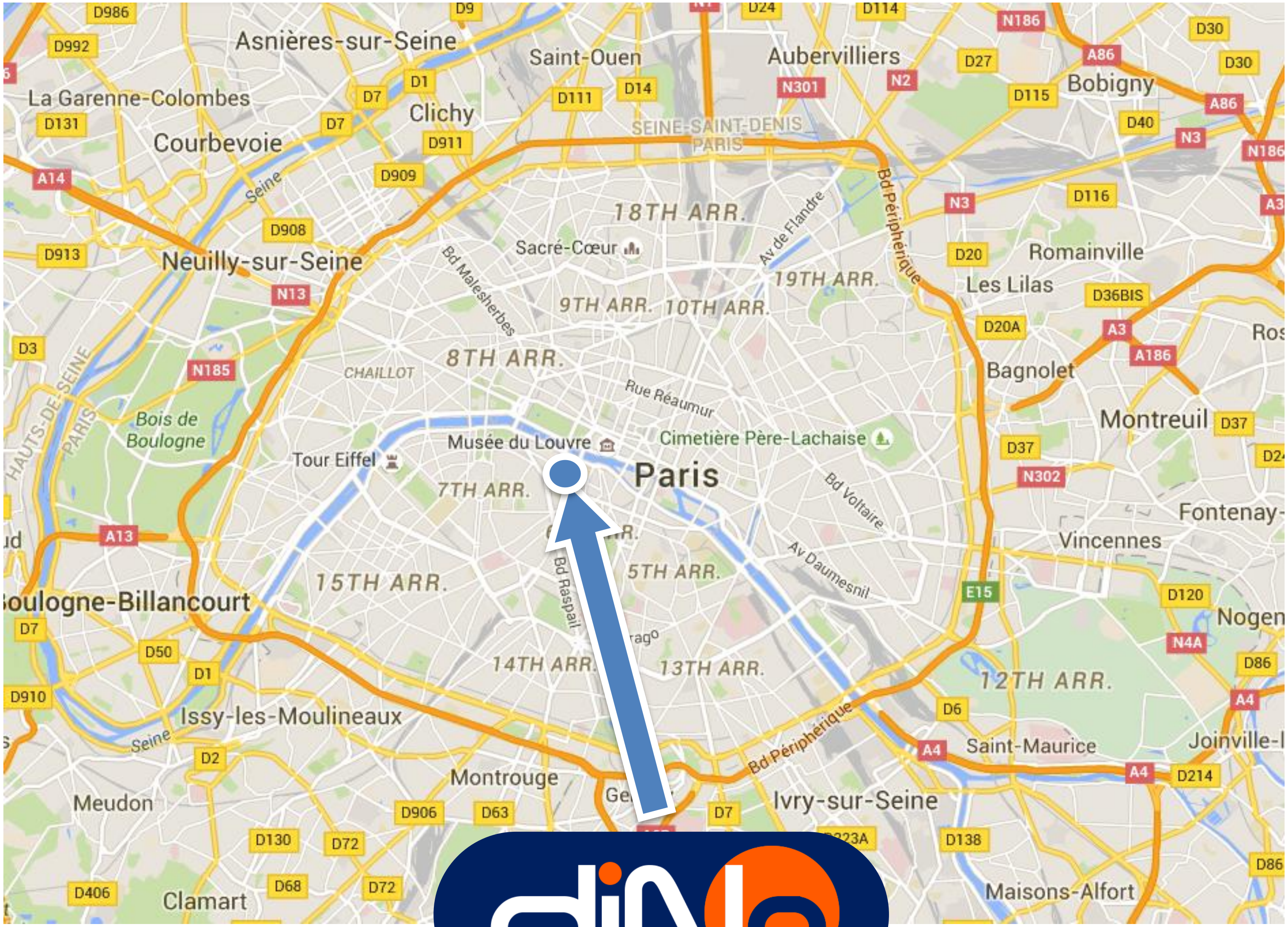
- need for Sequence Management System
  - optimize operations based on data/hardware characteristics
  - transparent to user
- several exciting research opportunities

collaborations!

Data-Intensive and Knowledge-Oriented systems



thank you!

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