MULTIMEDIA AND WEB DATABASES - CSE515

Multimedia Data Management, Retrieval, and Analytics

K. Selçuk Candan

Name: K. Selçuk Candan

- Professor of computer science and engineering at (CIDSE) ASU
- ACM Distinguished Scientist
- Director, ASU Center for Assured and Scalable Data Engineering (CASCADE)
- Senior Sustainability Scientist- Global Institute of Sustainability
- Faculty member Information Assurance Center
- Director, Enterprise, Media, and Information Technologies Labs (EmitLab)
  - ~10 PhD/MS students (both in US, Italy)
- publications
  - 170+ conference and journal articles + book chapters
  - 9 patents
  - 1 text book

What do I do??

- Executive Committee member, ACM Special Interest Group on Management of Data (SIGMOD)
- Associate editor, IEEE Transactions on Multimedia
- Associate editor, ACM Transactions on Database Systems
- Associate Editor, IEEE Transactions on Knowledge and Data Engineering
- Associate Editor, IEEE Transactions on Cloud Computing
- Associate editor, the Very Large Data Bases journal (2005-2012)
- Associate editor, Journal of Multimedia
- General Chair, IEEE International Conference on Cloud Engineering (IC2E) 2015.
- Workshops Chair, International Conference on Extending Database Technology (EDBT) 2014
- Organizing Committee Member, ACM SIG Multimedia Conference 2013
- Panels Chair, Very Large Databases (VLDB) Conference 2012
- Publicity Chair, ACM SIG Multimedia Conference 2012
- General Chair, ACM SIGMOD Conference 2012
- General Chair, ACM SIG Multimedia Conference 2011
- Program Group leader, ACM SIG Management of Data (SIGMOD) Conference 2010
- PC Chair, the ACM International Conference on Image and Video Retrieval (CIVR) 2010

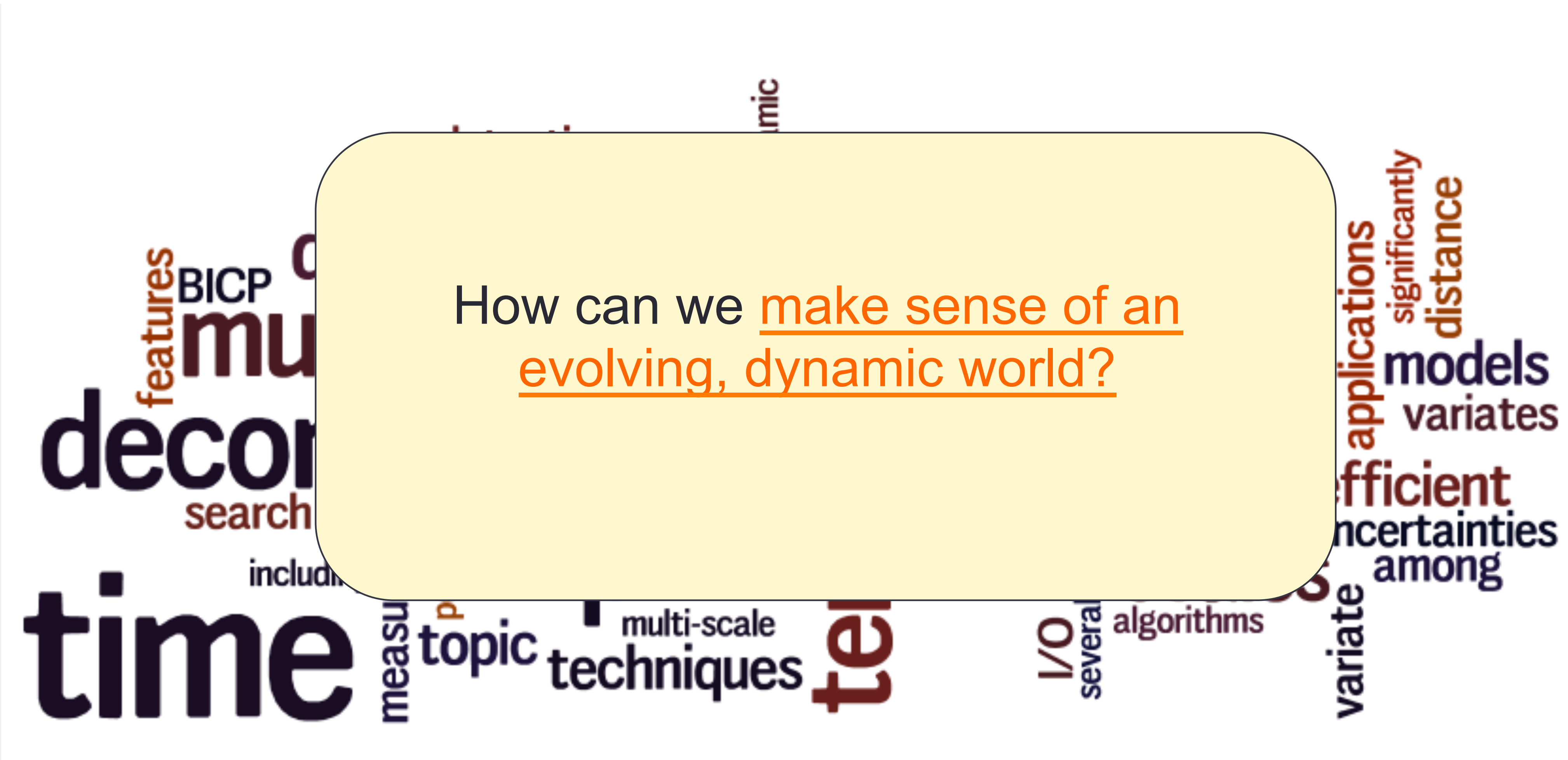
Research Overview…

- **Recent Relevant Grants/Projects:**
  - [NSF] National Science Digital Library (NSDL) Middleware for Network- and Context-aware Recommendations
  - [KRA] A Framework for Real-time Context Monitoring in Sensor-rich Personal Mobile Environments
  - [NSF] AURA: D ss Space, Time, and Human I
  - [with SHES Simulations
  - [with SHES reak in West-Africa and hrough Large Scale Simu
  - [NSF] Ranl calable Multimedia
  - [with JCI, N tware
  - [JCI] Multi-S
  - [NSF] An Infrastructure to Support Complex Financial Patterns (CFP) based Real-Time Services Delivery and Visual Analytics
  - [NSF] One Size Does Not Fit All: Empowering the User with User-Driven Integration
  - [RAI]: A media and social-driven ontology-based TV knowledge management system

- How can we provide
  - the relevant data/information
  - to the right person/application
  - fast

  to support effective decision making

So what about my team's (recent) work?



How can we make sense of an evolving, dynamic world?

We are living in a dynamic, data-rich world…

energy

rehabilitation

finance

security

smart-offices

smart-rooms

production

life-sciences

defense

sports

robotics

elderly-care

retail

child-care

supply-chain

entertainment

personal-data management

transportation

education

space exploration

pet-care

health-care

arts

business/enterprise

advertisement

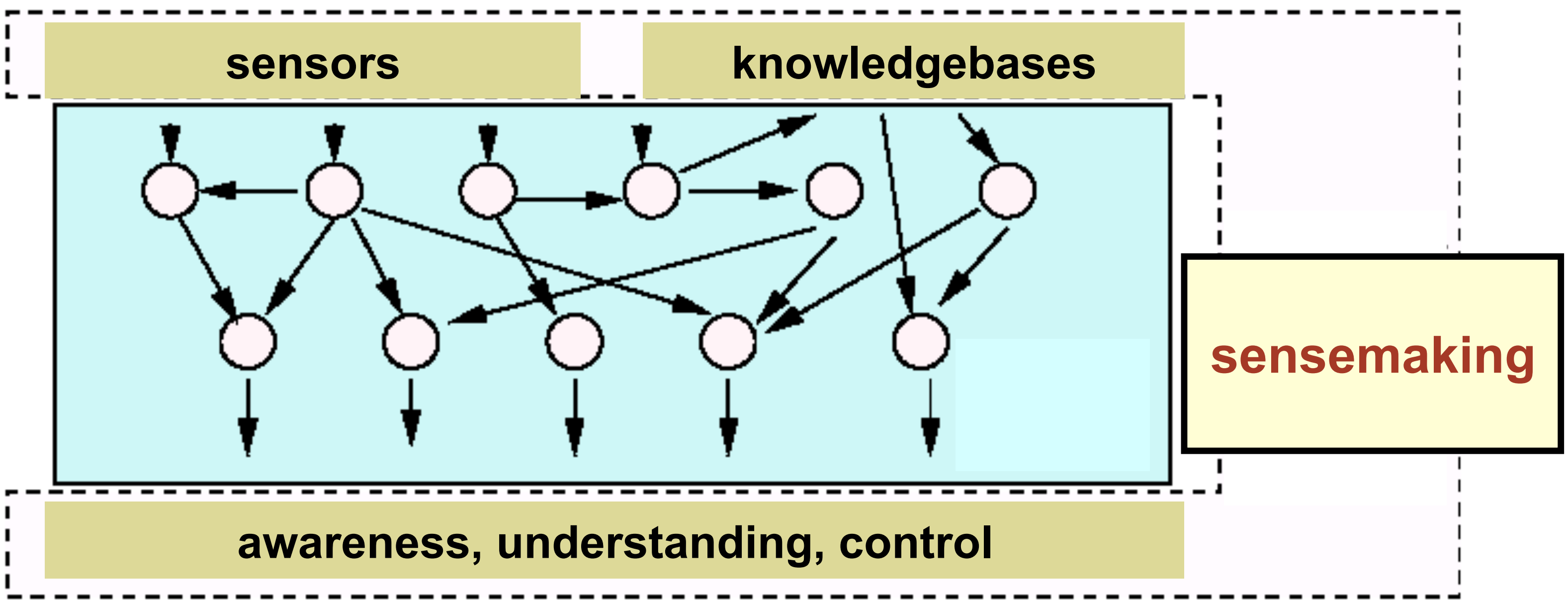
sciences

“Sense”making…what does it mean?

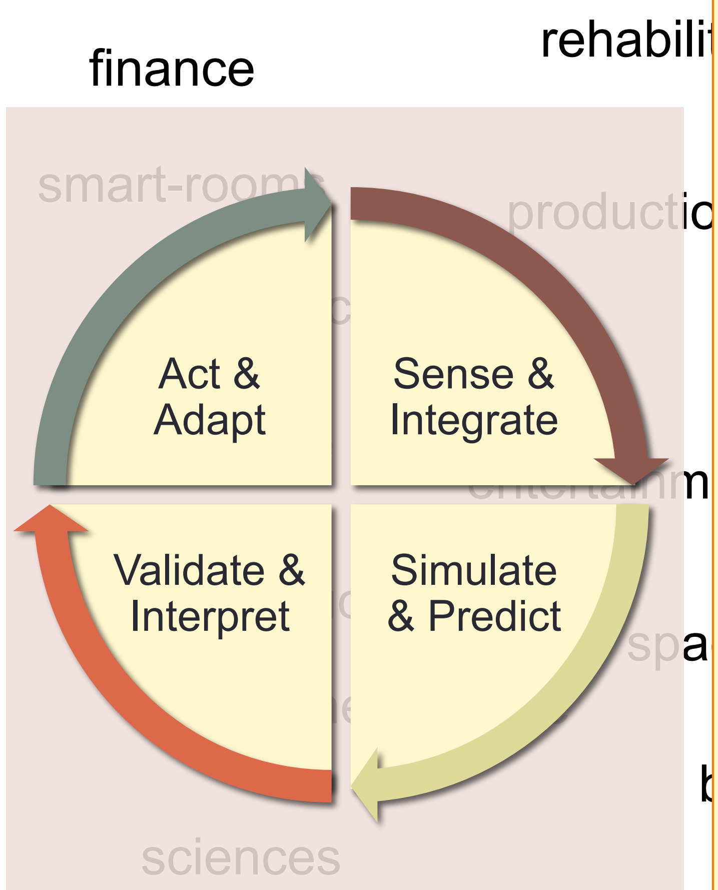
- Etymology:
  - 1st sense: from latin “sentire” or “to perceive”
    - any of the faculties, as sight, hearing, smell, taste, or touch, by which humans and animals perceive stimuli originating from outside or inside the body
  - 2nd sense: “to attain awareness or understanding of…”
    - “awareness” implies vigilance in observing or alertness in drawing inferences from what one experiences
    - “understanding” is the power to make experience intelligible by applying *concepts and categories*

..did you notice something?

- …there is a gap between the first meaning (feel, measurement) and the second (awareness, understanding)
- ..and that gap (or the data infrastructure needed to bridge that gap) has been motivating a big chunk of my research



Sensemaking in a dynamic world…



(a) **Sense & Integrate:**
take as inputs, and integrate, data, and models of the application space and continuously sensed real-time observational data,

(b) **Simulate & Predict:**
support data-driven simulation and predictive analysis over integrated data sets and models,

(c) **Validate & Interpret:**
enable validation of observations, models, and simulation/prediction results and intuitive data and result representation to provide trustworthy and accurate decision making, and

(d) **Act & Adapt:**
provide continuous adaptation of models and predictions based on the validated predictions and observations.

Starting discussions….

- What is media?
  - A means to communicate "information" in the most compact form
- Popular media
  - unstructured text, structured text (SGML/XML)
  - images (GIF, TIFF,JPG),
  - video (MJPG, MPEG),
  - audio,
  - 3D media (VRML/X3D)

What is media?

- What is multimedia?????

- What is hypermedia????

What is media?

- Hypermedia brings together multiple media objects and allows users to interact with the collection to select relevant information.

Media challenges in a dynamic world

finance rehabilitation energy security smart-offices

SIS

(S)parsity
(I)mprecision
(S)ubjectivity

3Vs

(V)olume
(V)elocity
(V)ariety

HMLE

(H)igh-dimensional
(M)ulti-modal
Inter-(L)inked
(E)volving

Da allenges in a dynamic world

HUMAN

energy

rehabilitation

security

training

smart-offices

sm

uction

life sciences

ISQ

3Vs

HMLE

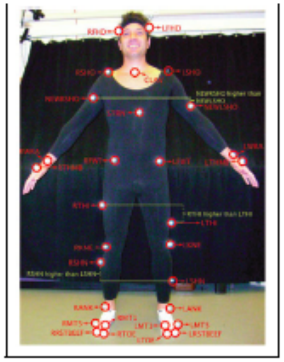
for many applications,

the final consumer is (H)uman

n

(E)volving

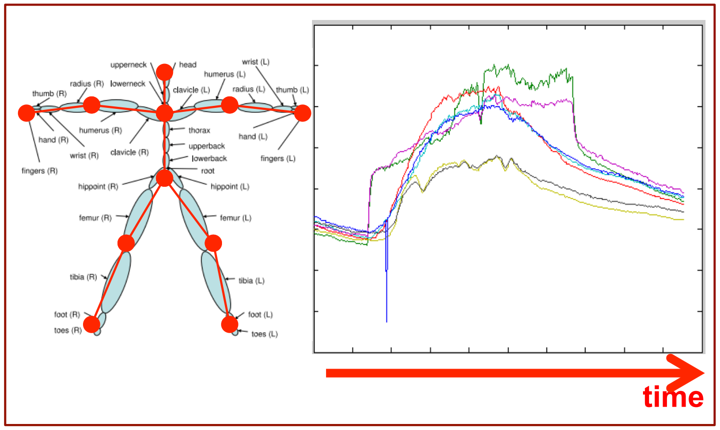
dver

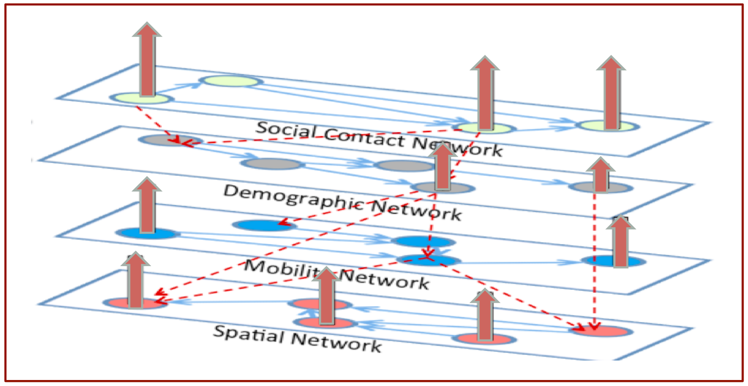


http://mocap.cs.cmu.edu/

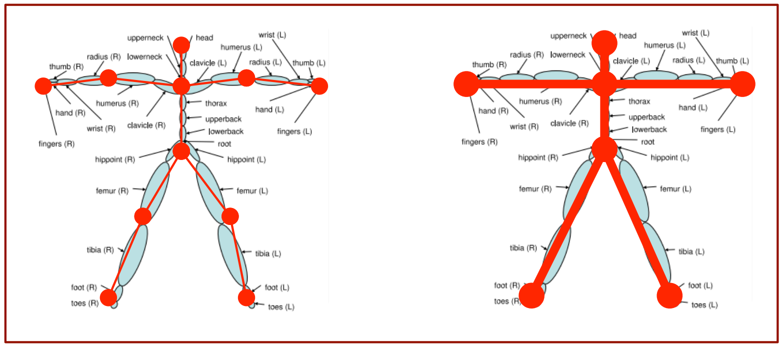
Common data characteristics…

- The key characteristics of the multimedia data sets include the following:
  - multi-dimensional
  - multi-modal
    - temporal,
    - spatial,
    - hierarchical,
    - graphical
  - multi-layer
  - multi-resolution
  - imprecise / ambiguous / subjective



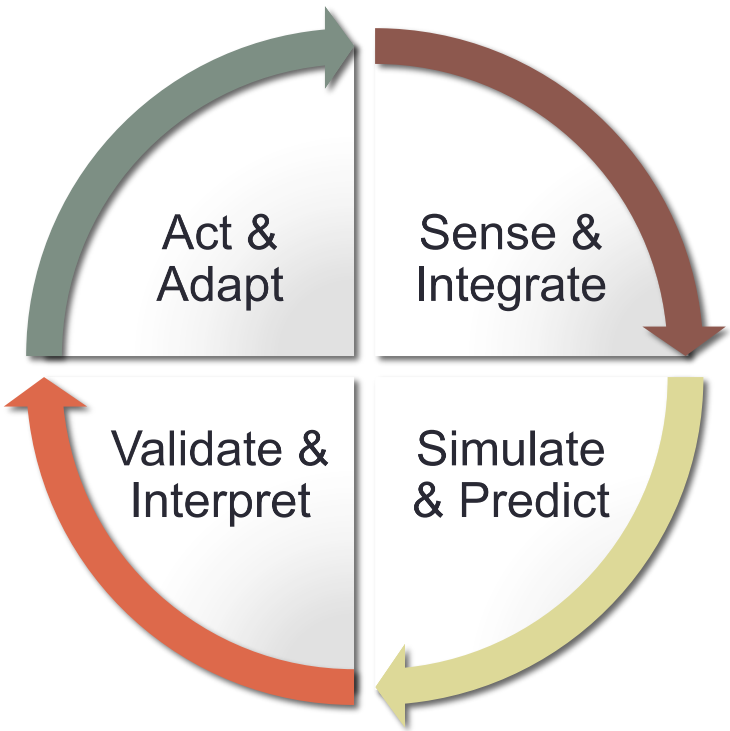


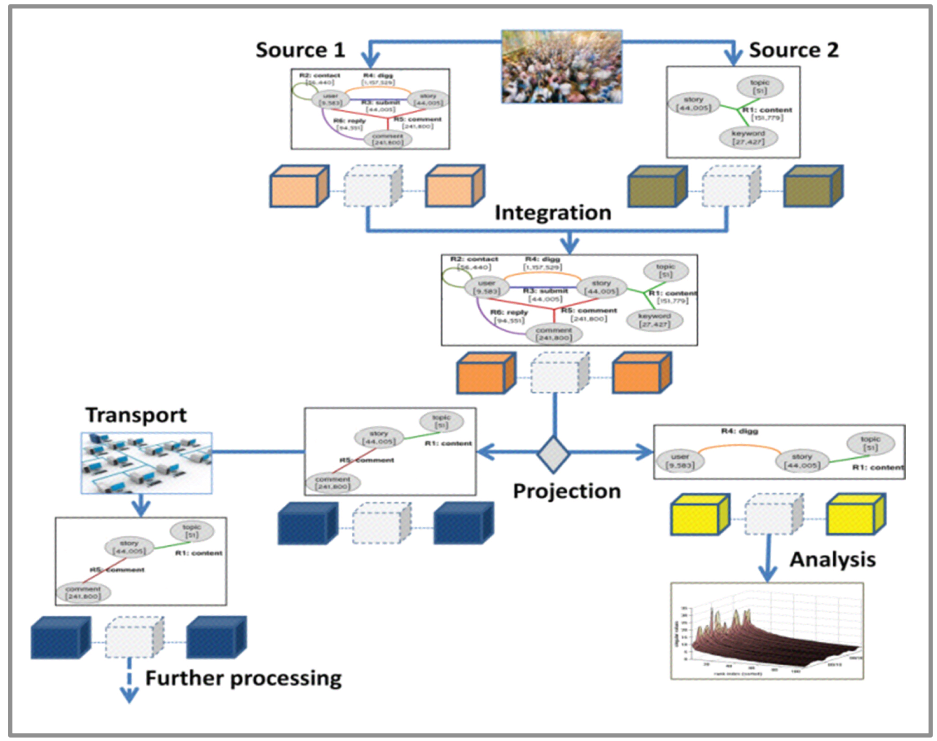
http://gesture.chalearn.org/2013-multi-modal-challenge/data-2013-challenge



….the important question is “How to support the complete data life-cycle??”

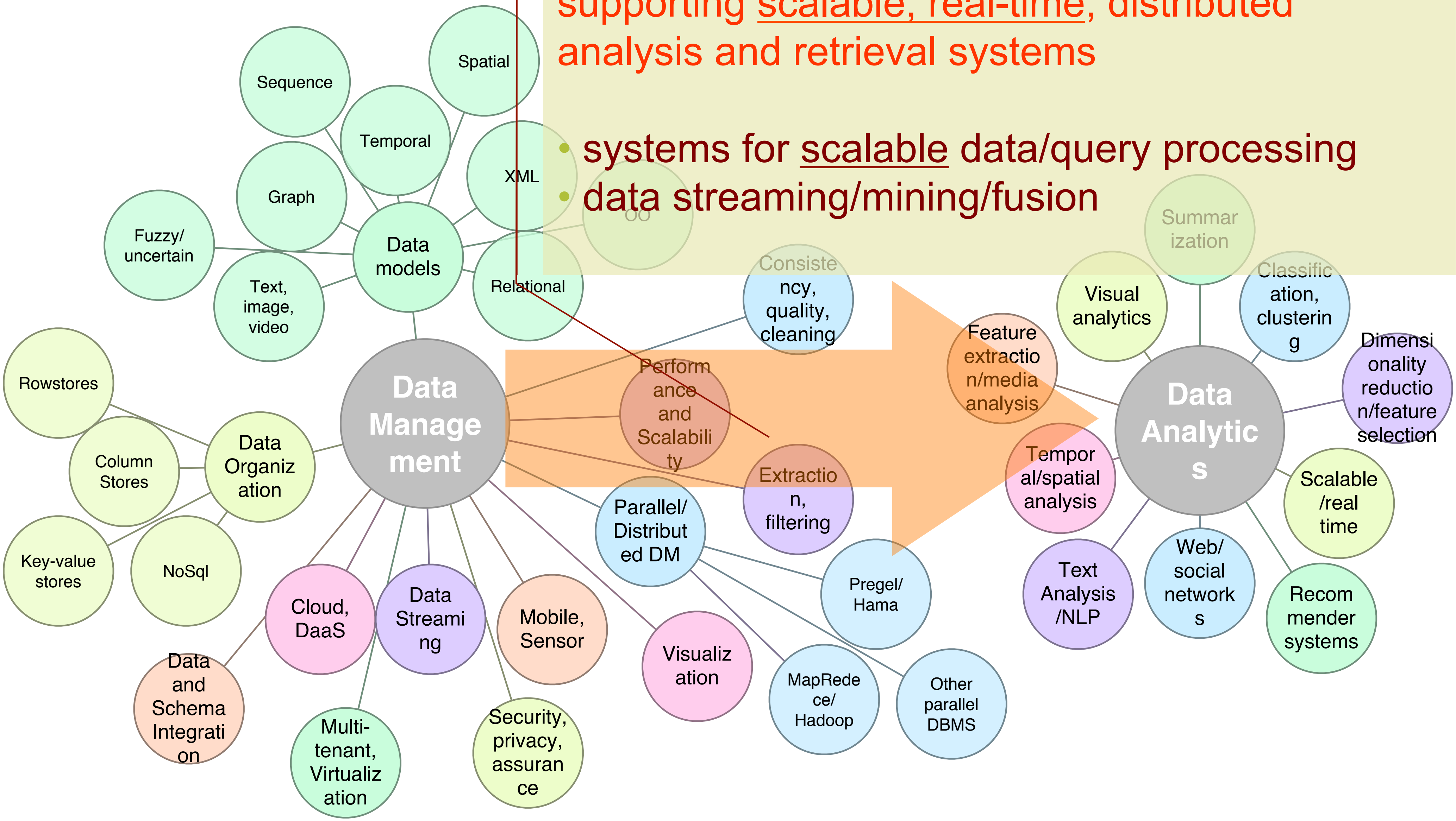
....the data life cycle includes phases of capture, integration, (semantic) manipulation, and analysis





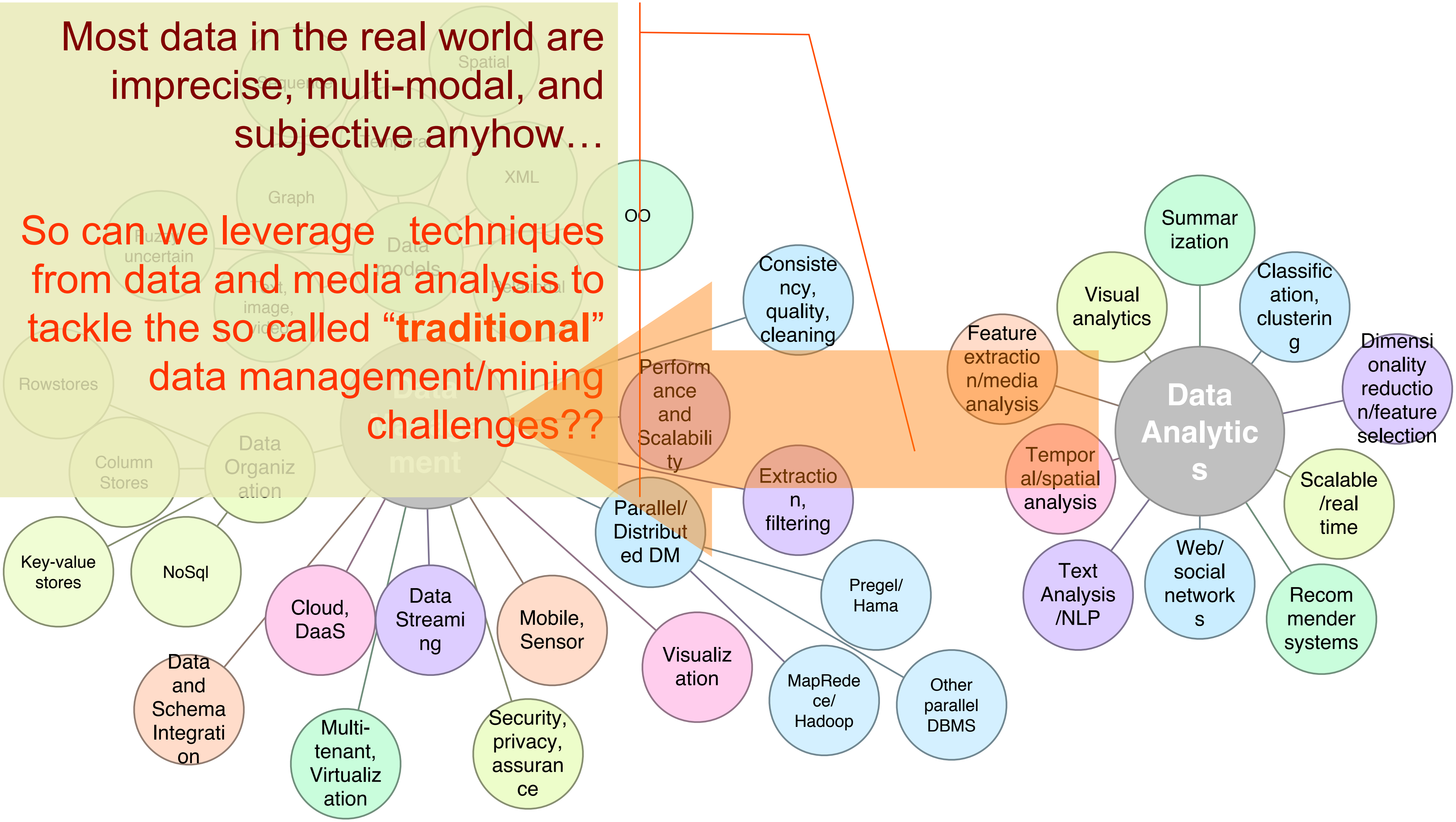
Data management/mining techniques for supporting scalable, real-time, distributed analysis and retrieval systems

- systems for scalable data/query processing
- data streaming/mining/fusion



Most data in the real world are imprecise, multi-modal, and subjective anyhow…

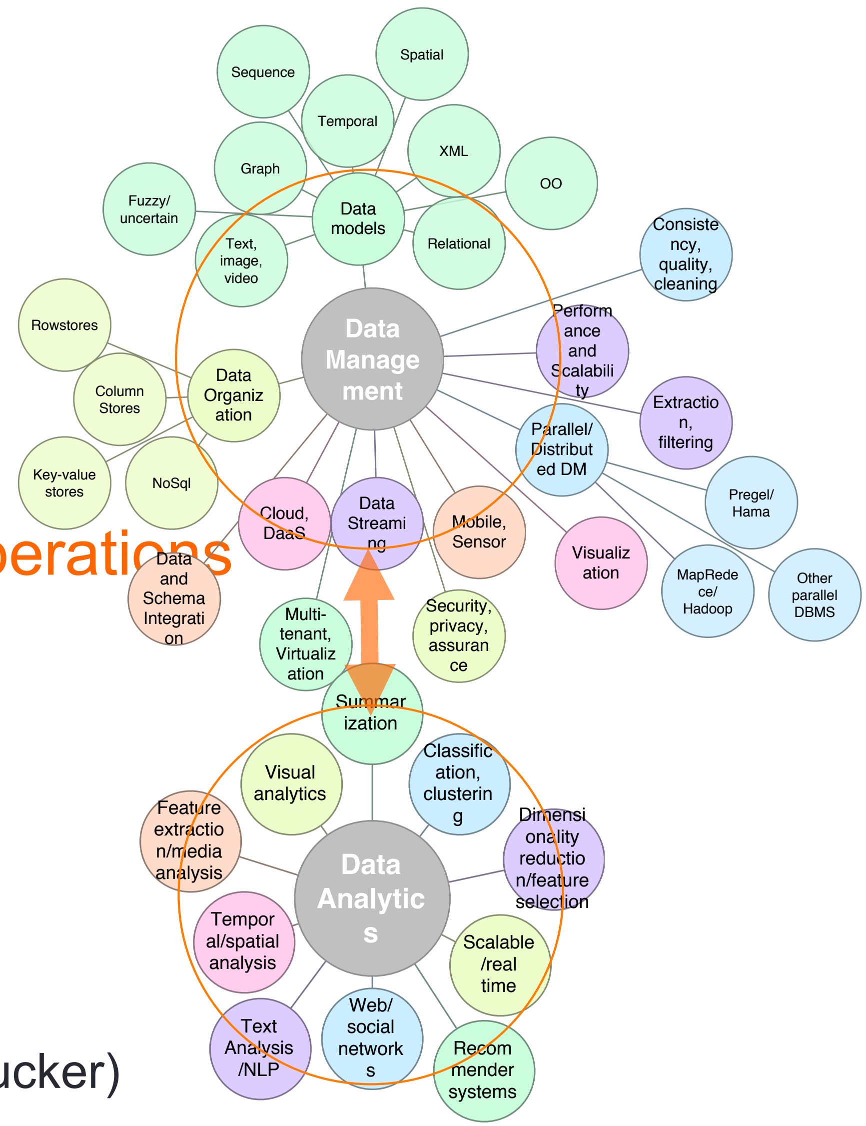
So can we leverage techniques from data and media analysis to tackle the so called “**traditional**” data management/mining challenges??



Therefore, data systems need to support both…

- …data/media manipulation operations
  - filtering: projection, selection,
  - integration: join, nearest neighbor joins
  - set operations: union and intersection

- …data/media retrieval and analysis operations
  - feature extraction,
  - similarity search
    - top-k, range, skyline, nearest-neighbor
  - clustering, partitioning
  - aggregation, summarization
  - classification
  - latent analysis
    - e.g., for tensor data - decomposition (CP, Tucker)



“Big Data” Industry Roundtable at ASU

- Co-organized with IBM
- On-site or off-site participation
  - Aerojet,
  - Avnet,
  - Boeing,
  - Facebook
  - Google
  - IBM TJ Watson (Exascale System Software),
  - IBM Smart Analytics
  - IO Data Centers,
  - Johnson Controls,
  - LinkedIn,
  - Lockhed Martin,
  - Mayo Clinic,
  - NEC Labs,
  - Oracle,
  - Salt River Project,
  - SAP

2nd Event…

EARLY WARNING™

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RiskSense®

SAE INTERNATIONAL

PI CUBE

CYBERSPONSE
ENABLED SECURITY

hp

SCIENCE foundation ARIZONA
Innovation at Work

ORION HEALTH

Johnson Controls

IBM

OFR
OFFICE OF FINANCIAL RESEARCH

Honeywell

intel

DTCC

sas

NSF

MAYO CLINIC

NEC

NEC LABORATORIES AMERICA, INC.
Relentless passion for innovation

STATE STREET

Microsoft Research

YAHOO!

NIST
National Institute of Standards and Technology

Adobe

FEDERAL RESERVE BANK of KANSAS CITY

AMERICAN EXPRESS

yaap

Greater Phoenix
ECONOMIC COUNCIL

Positive Energy

Key knowledge gaps..

- Six most critical knowledge competency groups (in terms of the value gap – i.e., the difference between current and desired states of the knowledge area)
  1. temporal and spatial analyses,
  2. summarization, cleaning, visualization, anomaly detection,
  3. real-time processing for streaming data,
     - media analytics
  4. representations and fusion for unstructured/structured data, semantic Web,
     - make unstructured data queriable, prioritize and rank data, correlate and identify the gaps in the data
  5. graph-based models, social networks,
     - entity analytics, (social and other) network analytics
  6. performance and scalability, distributed architectures.

"Hunting for the Value Gaps in Data Management, Services, and Analytics"
ACM SIGMOD blog; http://wp.sigmod.org/

Key challenges and applications..

- Key challenges:
  - Scalable batch processing techniques for “data at rest”,
  - real-time processing of temporally and spatially distributed observations for “data in motion”
  - tools that can support
    - federated and scalable data storage, analysis, and modeling
    - make unstructured data queriable, prioritize and rank data, correlate and identify the gaps in the data
    - entity analytics, (social and other) network analytics, and media analytics
    - take into account for known models, but also adapt to new emerging patterns
- Key applications,
  - human behavior modeling at individual and population scales.
  - credit card authentication, fraud detection systems,
  - financial services, retail,
  - monitoring and security
  - mobile/location-aware services, and
  - healthcare.

CIDSE MS/MCS Concentration in "Big Data Systems"

- 15 credits of coursework in data engineering and data analytics
- Required
  - Database Management System (DBMS) Implementation
  - Distributed and Parallel Data Systems
  - Data Mining
- Elective (2 out of 5)
  - Virtualization and Cloud Computing
  - Semantic Web Mining
  - Data Visualization
  - Multimedia and Web Databases
  - Statistical Machine Learning

CASCADE team

Name	*Title*	*Area(s) of Specialization as they relate to proposed concentration*
K. Selcuk Candan	Professor	Scalable data management and media analysis
Hasan Davulcu	Assoc. Professor	Databases and data extraction
Gail Joon Ahn	Professor	Security and privacy in distributed data systems
Huan Liu	Professor	Data mining and analysis
Ross Maciejewski	Assistant Professor	Data visualization
Baoxin Li	Professor	Statistical machine learning, media analysis
Rao Kambhampati	Professor	Data integration, data cleaning
Chitta Baral	Professor	Knowledge representation, NLP
Dijuang Huang	Associate Professor	Data clouds
Hanghang Tong	Assistant Professor	Graph structured data
Mohamed Sarwat	Assistant Professor	Data management systems
Jingrui He	Assistant Professor	Data analysis and sparse learning
Paolo Shakarian	Assistant Professor	Data and network analysis
Rong Pan	Assoc. Professor	Data analytics
Jing Li	Assoc. Professor	Data analytics
Ron Askin	Professor	Data-driven decision models
Teresa Wu	Professor	Decision support, health informatics
Ming Zhao	Associate Professor	Scalable data processing
Adam Doupe	Assistant Professor	Data security
Yezhou Yang	Assistant Professor	Multimedia, vision

Recap: Common data characteristics…

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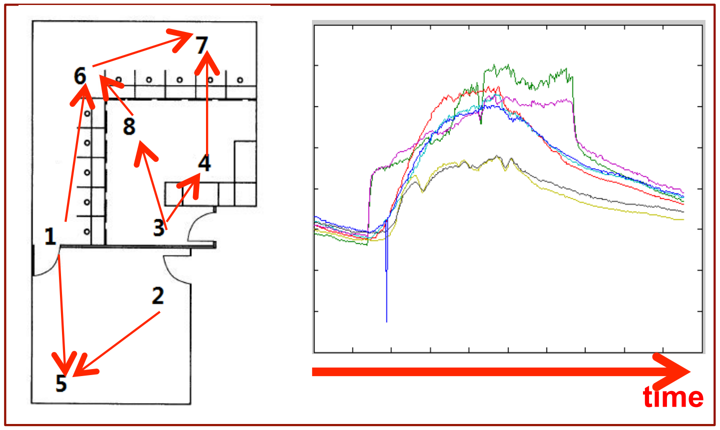

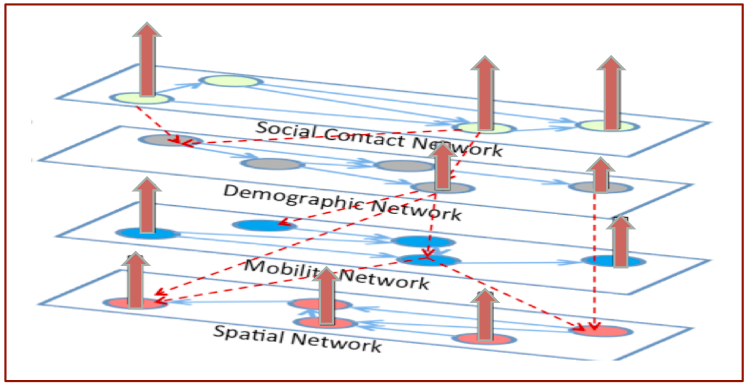

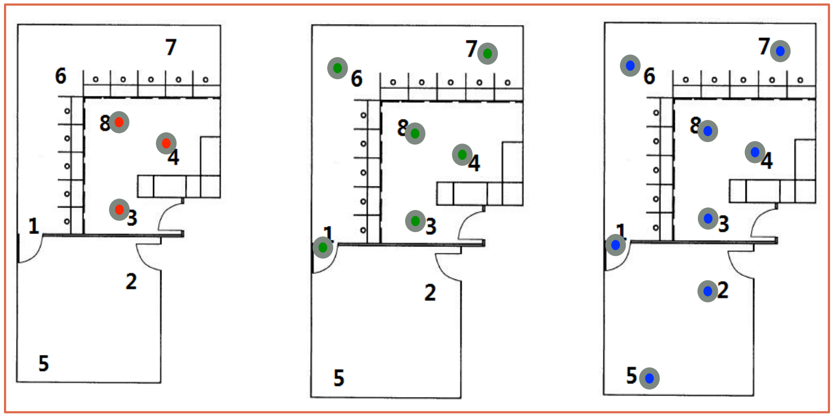

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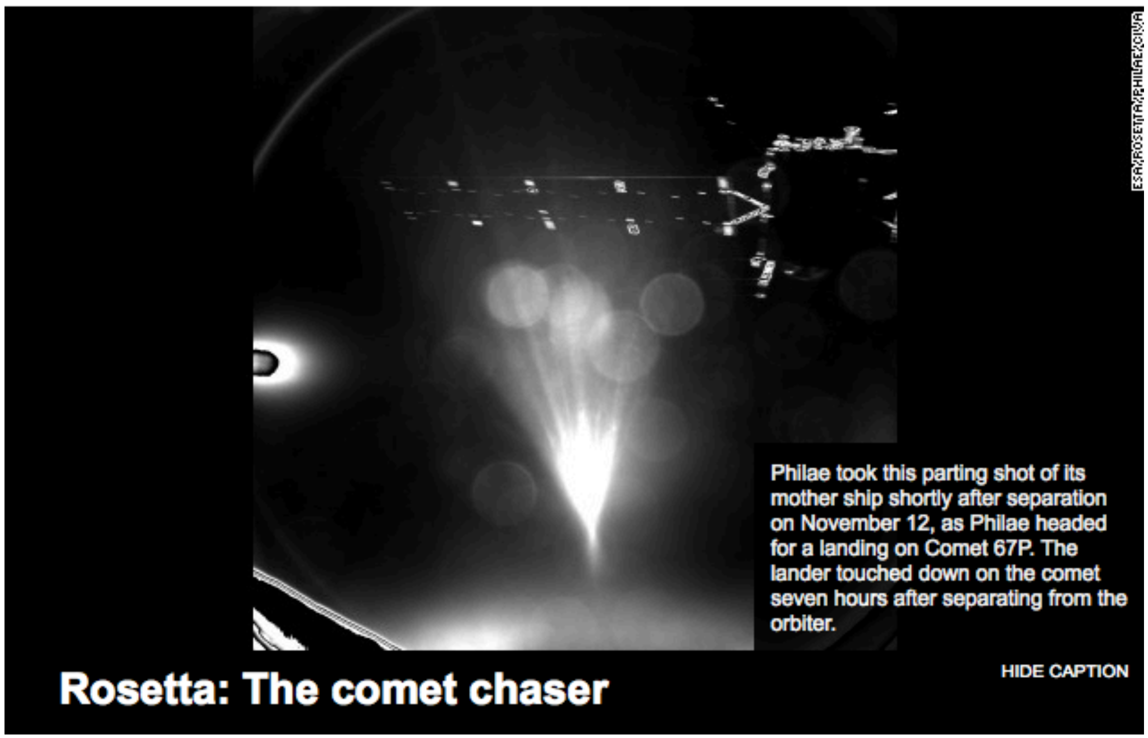
Inherent imprecision in media retrieval

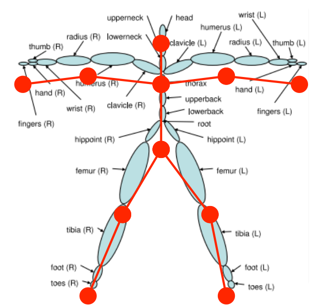
- imperfections in data capture



Inherent imprecision in media retrieval

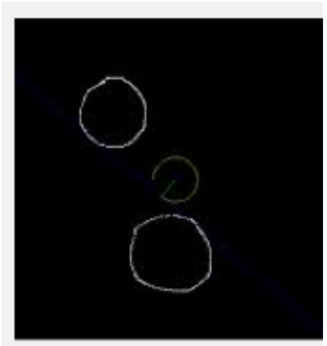
- imperfections in data capture

- imperfections in the feature extraction process



Inherent imprecision in media retrieval

- imperfections in data capture
- imperfections in the feature extraction process
- similarity/correlation in media features
    - circle vs. ellipse



Inherent imprecision in media retrieval

- imperfections in data capture
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  - circle vs. ellipse
- imperfections in the query formulation
  - Query-By-Example (what does a given example really mean?)

Queries

- Metadata queries

- Example queries
  - Exact
  - Partial match

- Semantic/Object queries
  - visual similarity
  - semantic similarity
  - spatial similarity

Metadata queries

- Find me all images created by “John Smith”

Example queries

- Find all images which look like "im_ex.gif"
  - Find me top-5 images which look like "im_ex.gif"
- Find all images which look like "sketch.bmp"
- Find all images which contain a part which look like ….

Sematic/Object queries?

- Find all images of sunny days
  - advertisement
- Find all images which contain a car
- Find all images which contain a car and a man who looks like”mugshot.bmp”
  - surveillance
- Find all image pairs which contain similar objects
  - data mining

What kind of queries?

- Find all objects contained in images of sunny days

- Find all images which contain two objects
  - first object looks like "im.gif"
  - second object is a car
  - first obj. to the right of second obj.

  and return the semantics of these two objects.

Example

select image P, *object* object1, *object* object2

where P *contains* object1

and P *contains* object2

and object1.semantical_property *s_like* "mountain"

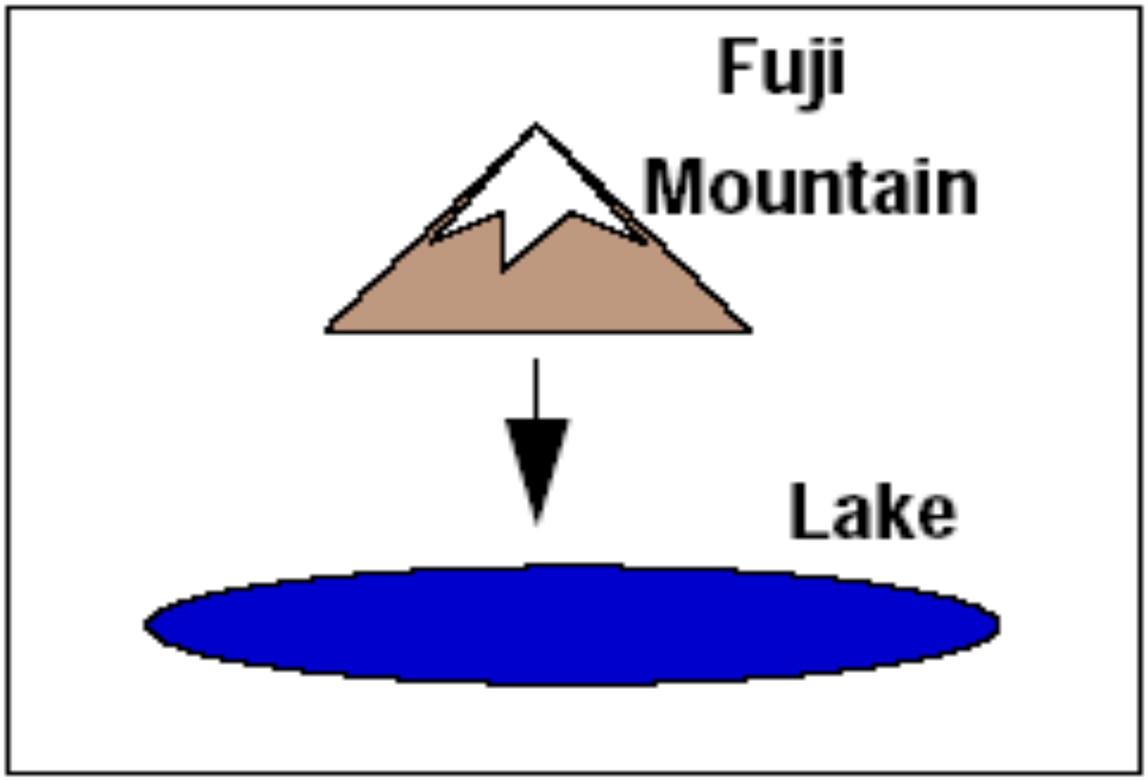
and object1.image_property *image_match* "Fuji_mountain.gif"

and object2.semantical_property *is* "lake"

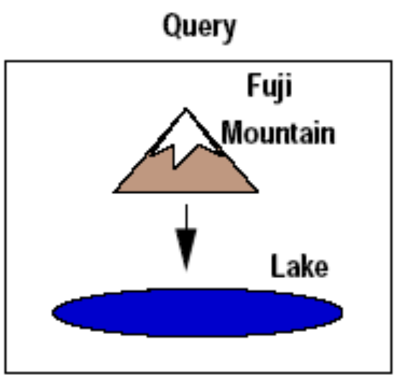
and object2.image_property *image_match* "lake_image_sample.gif"

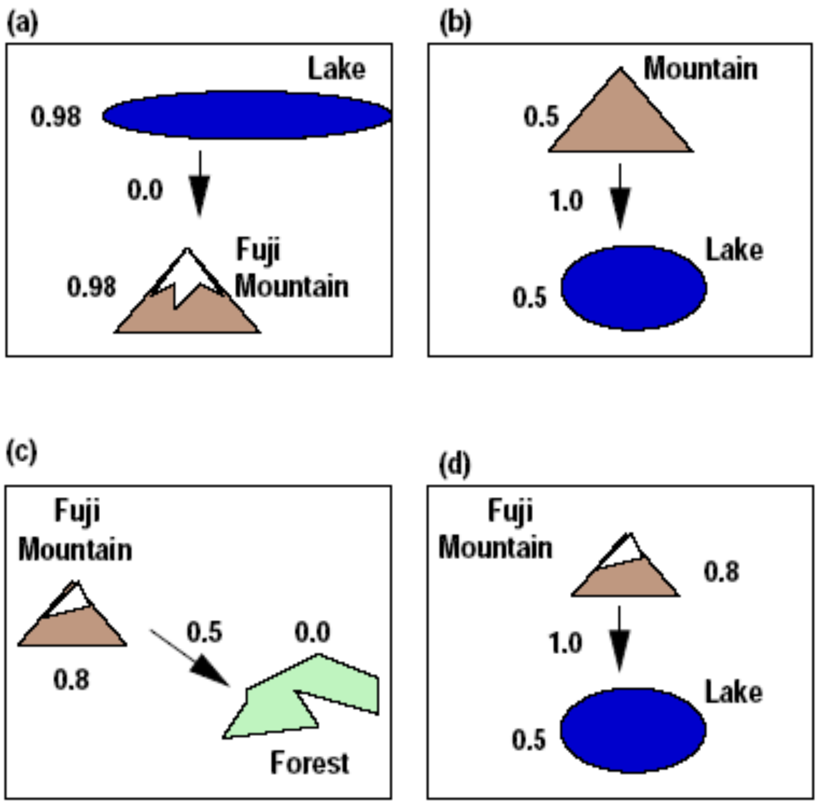
and object1.position *is_above* object2.position

QBE (visual representation)



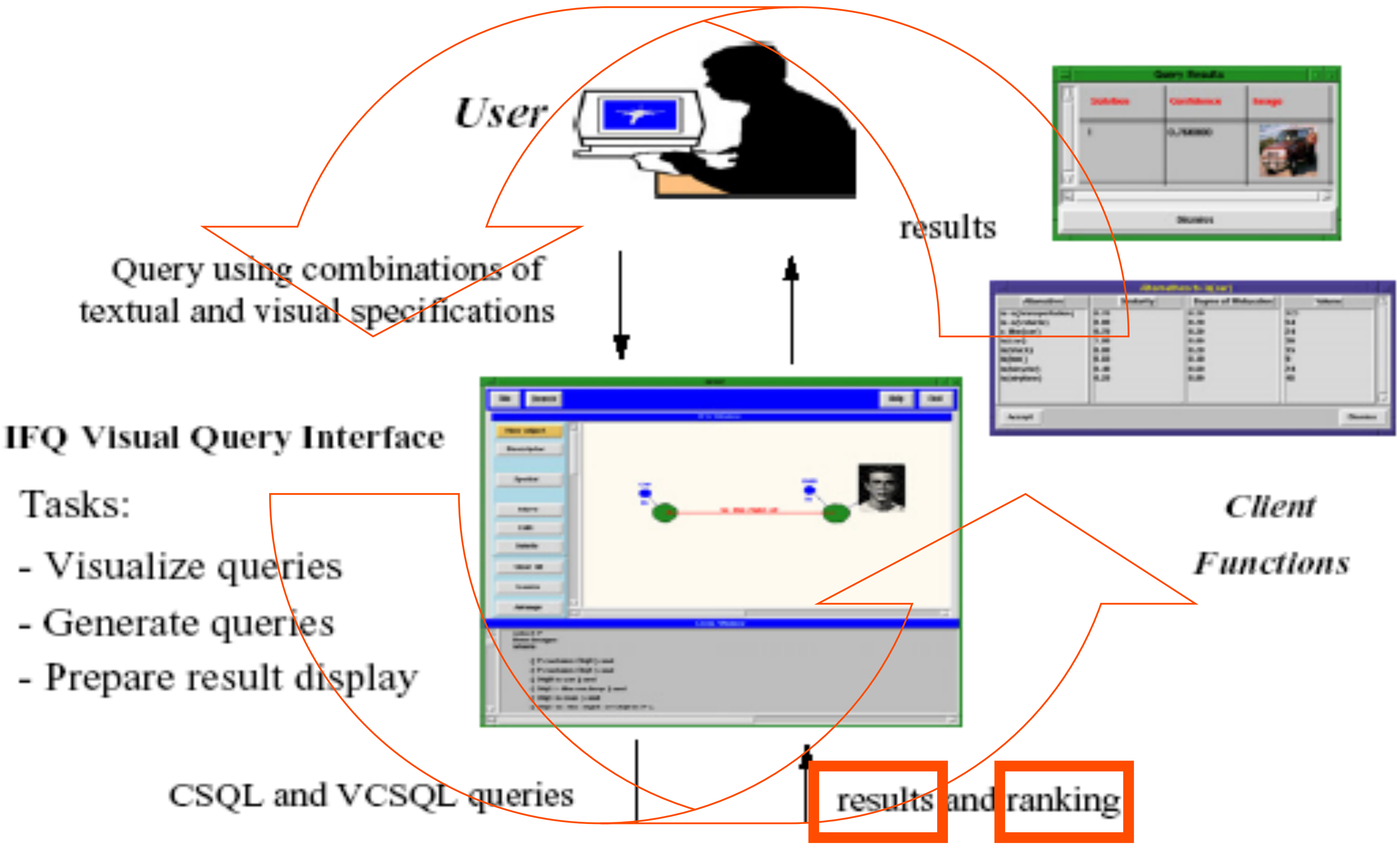
Query…and results…





K. Selcuk Candan

Subjectivity



Inherent imprecision in media retrieval

- imperfections in data capture
- imperfections in the feature extraction process
- similarity/correlation in media features
    - circle vs. ellipse
- imperfections in the query formulation
    - Query-By-Example (what does a given example really mean?)
- imperfections in the available data structures
    - cost/accuracy trade-off

Partial matches

- partial match requirements
  - not all sub-goals need to be satisfied

Progressiveness in media retrieval

- Users are not interested in a single result, but $k>=1$ ranked results.
- We would prefer to generate j^{th} result only we generate $(j-1)^{th}$ result
- Since the solution space is generally very large, we can not touch or enumerate all solutions

(Measurable) Approximate results

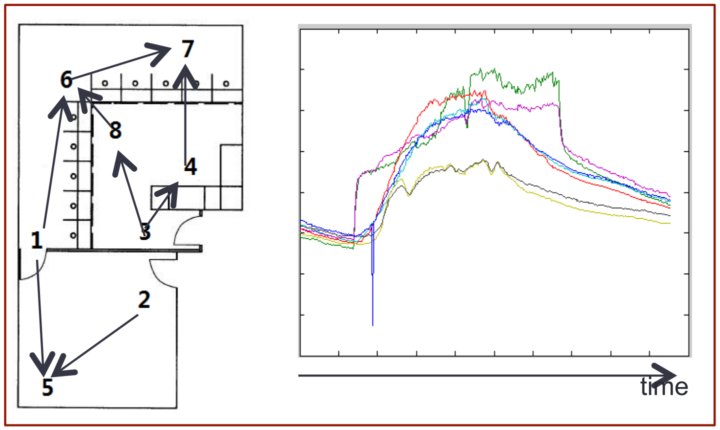
- How do we avoid generating all solutions?
  - Approximate results: use statistics and known properties of the data to provide approximate results.

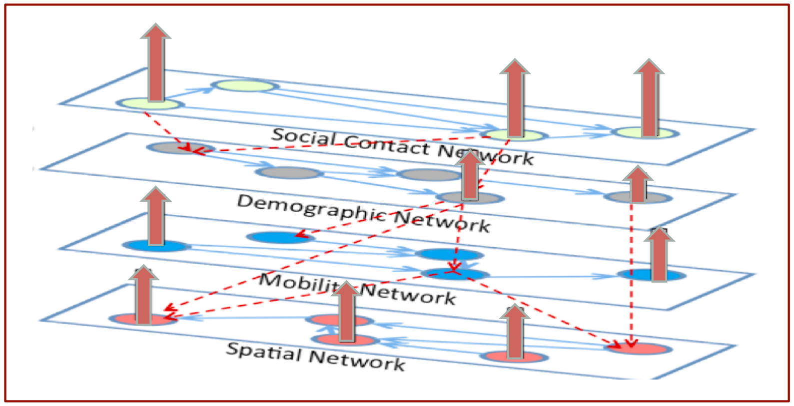
System feedback

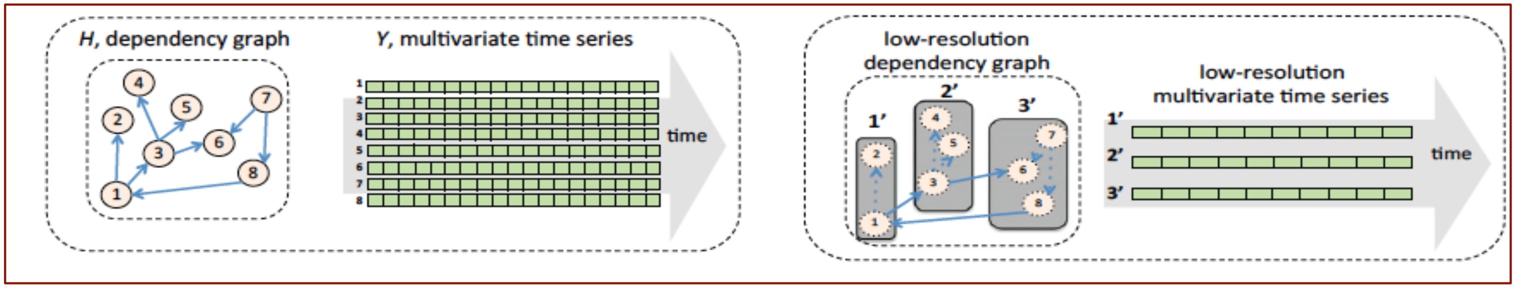
- Guide and inform users
  - harness statistics that will also act as feedback to the users

- Merge querying and browsing
  - visualize query results as “presentations” that users can browse through
  - use user/query profiles to prefetch objects that a user may intend to view in a near future

Q#1: How to Represent and Analyze Multi-variate, Multi-modal, Spatio-temporal Data??







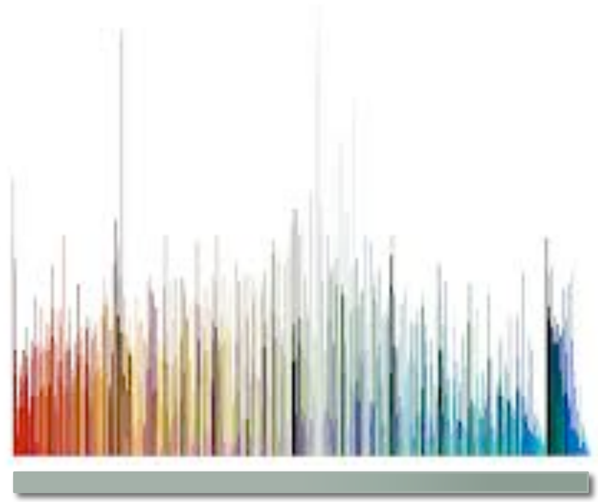
Features (of an image)

- Colors,
  - “sunny day”, “sea”
- Edges
  - “maps”, “aerial surveillance”
- Texture
- Segments
  - shape, location, color
- Objects
  - visual features, semantics
- Metadata, captions, tags

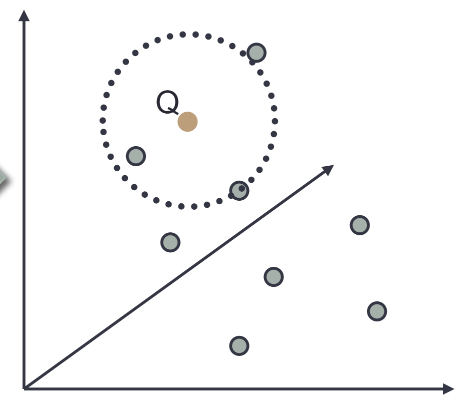
Common Data Representations

- Vector models
  - e.g. text, images

An image



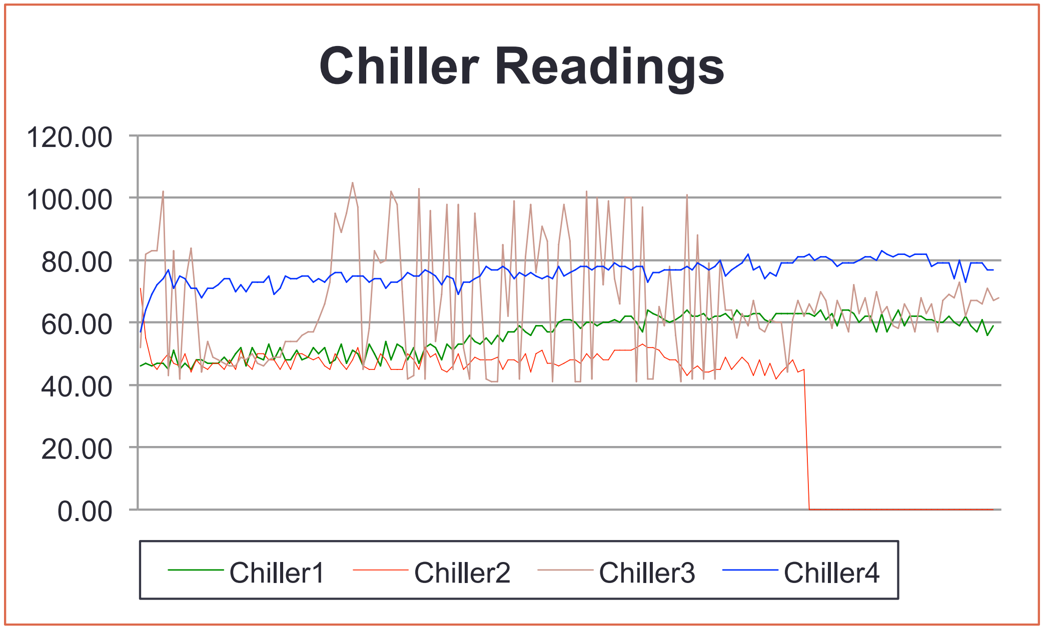
A color histogram (vector)



A set if images
and a query
mapped to a vector space

Common Data Representations

- Vector models
  - e.g. text, images
- Sequence models
  - e.g. video, audio, sensors



Common Data Representations

- Vector models
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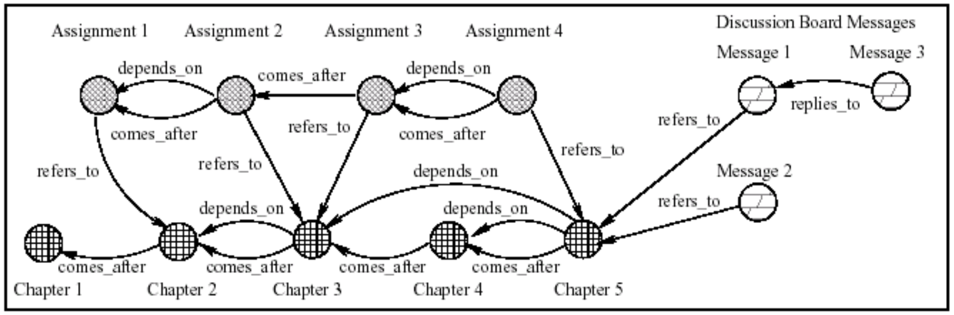
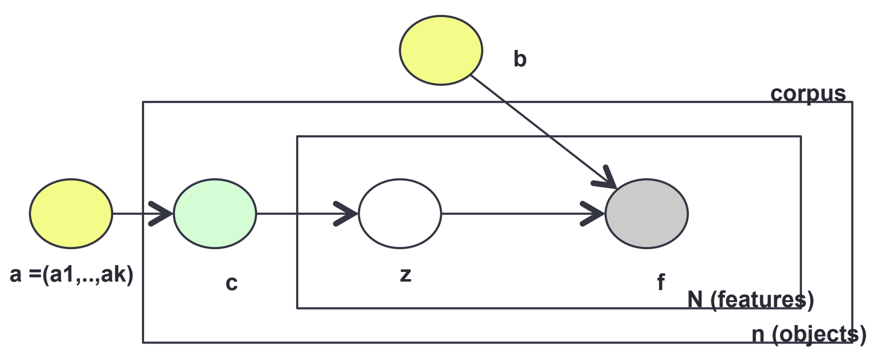
- Sequence models
  - e.g. video, audio, sensors
- Trees/Graph models
  - e.g. social networks, knowledge networks



Common Data Representations

- Vector models
  - e.g. text, images
- Sequence models
  - e.g. video, audio, sensors
- Trees/Graph models
  - e.g. social networks, knowledge networks
- Fuzzy/Probabilistic models
  - e.g. imprecision, subjectivity, generative models

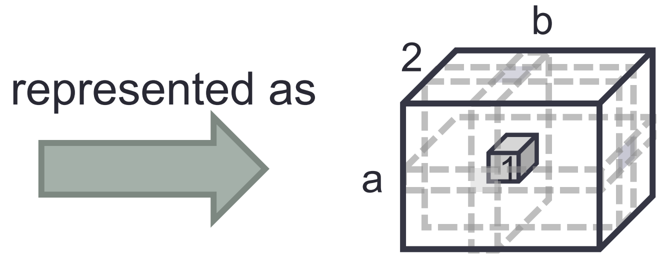


Tensor representation of data

- Most media and sensor data are
  - multi-dimensional and
  - multi-relational

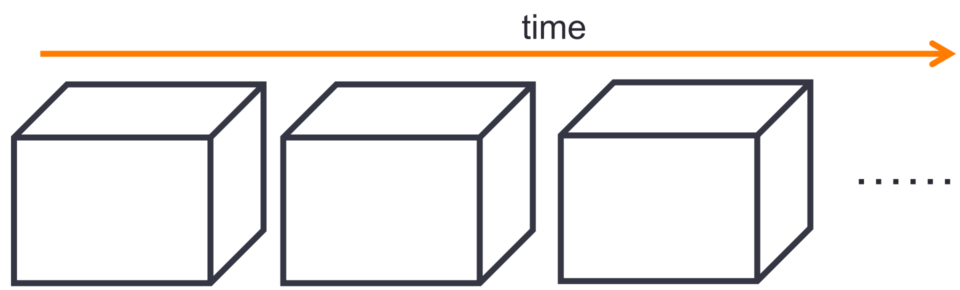
E.g.

A	B	C
:	:	:
a	b	2
:	:	:



- Temporally evolving data…

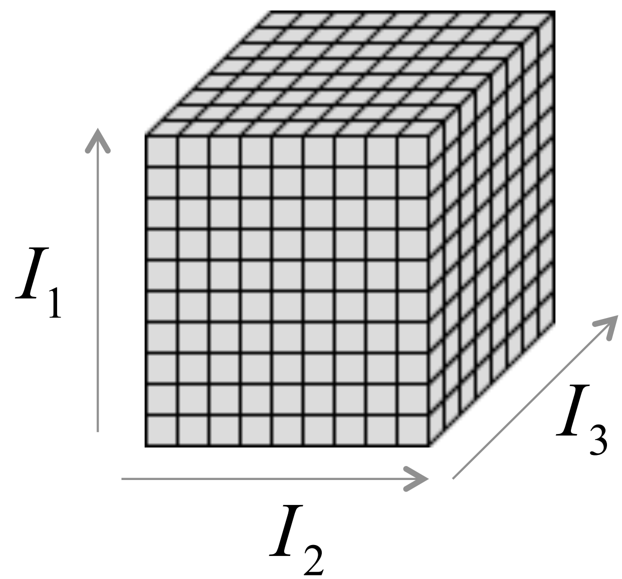
Alternative #1: incrementally growing tensor



Alternative #2: sequence of tensor snapshots

Examples

- Digital Libraries:
  - DocumentID – Keywords – Year
- Scientific networks
  - AuthorID – Keywords – Venue
- Email networks
  - Source – Destination – Time
- Movie recommendation
  - User – Movie – Rating
- Social networks
  - User – User – InteractionType



..and the metadata……

- Different modes of the tensor can have different types of metadata..

..and the metadata……

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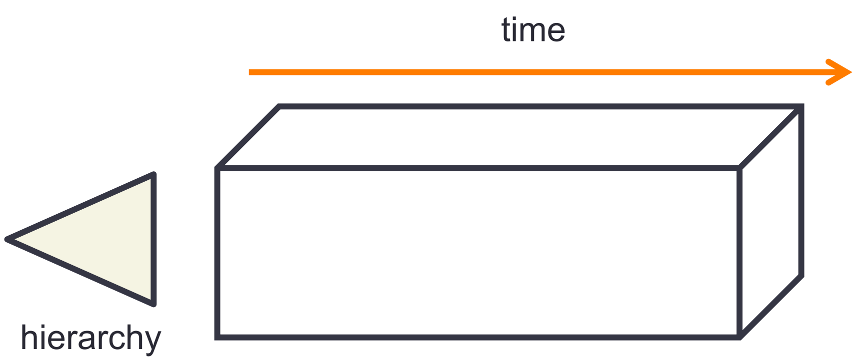
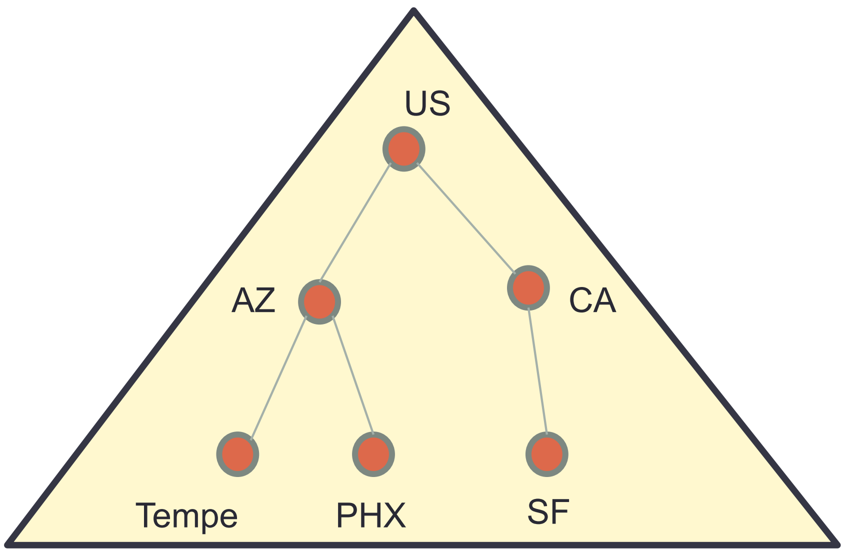
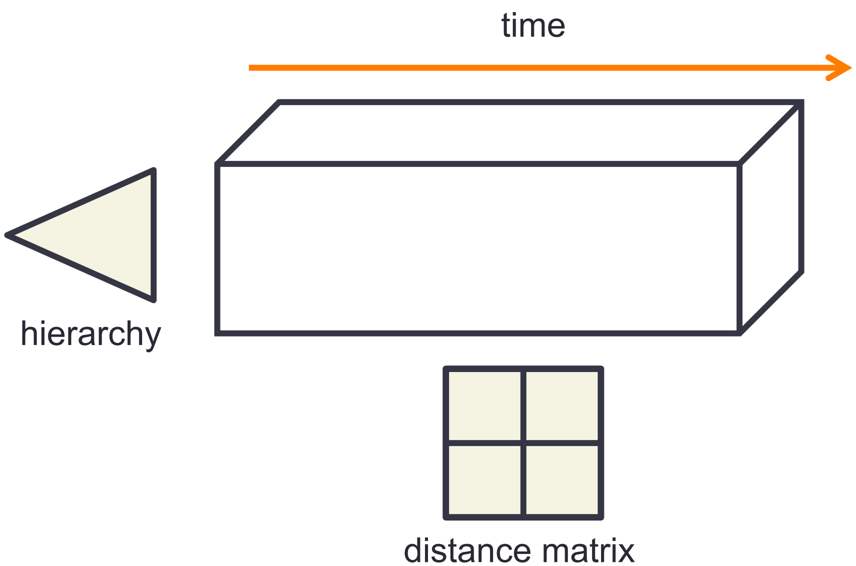
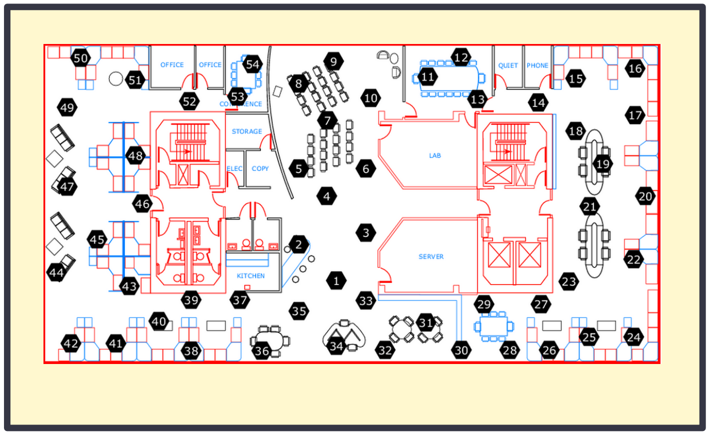




..and the metadata……

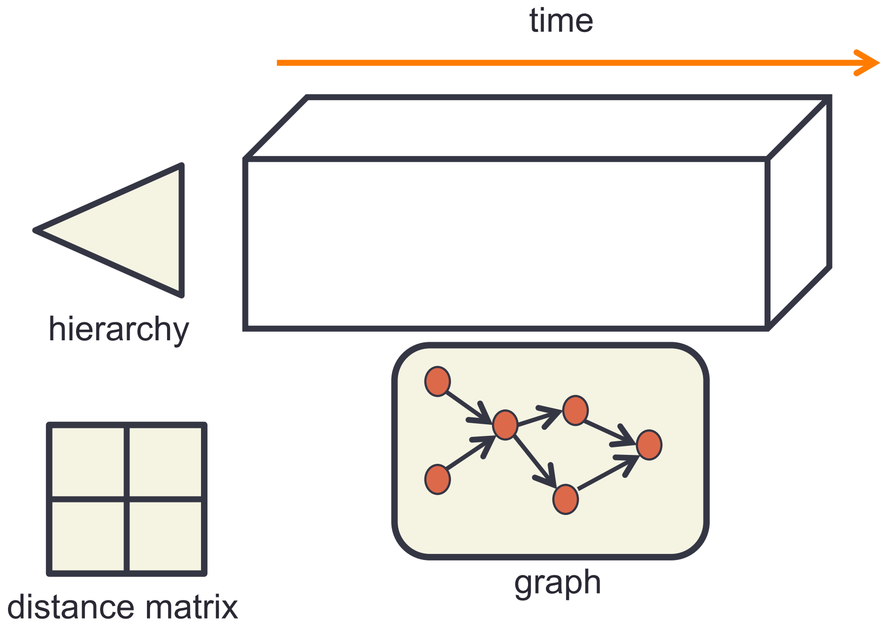
- Different modes of the tensor can have different types of metadata..

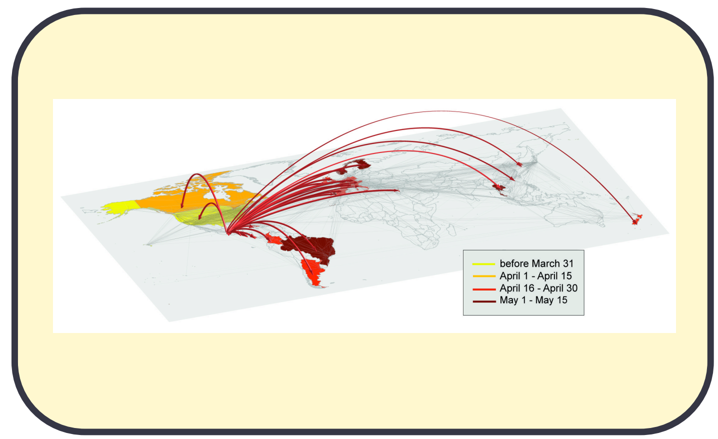




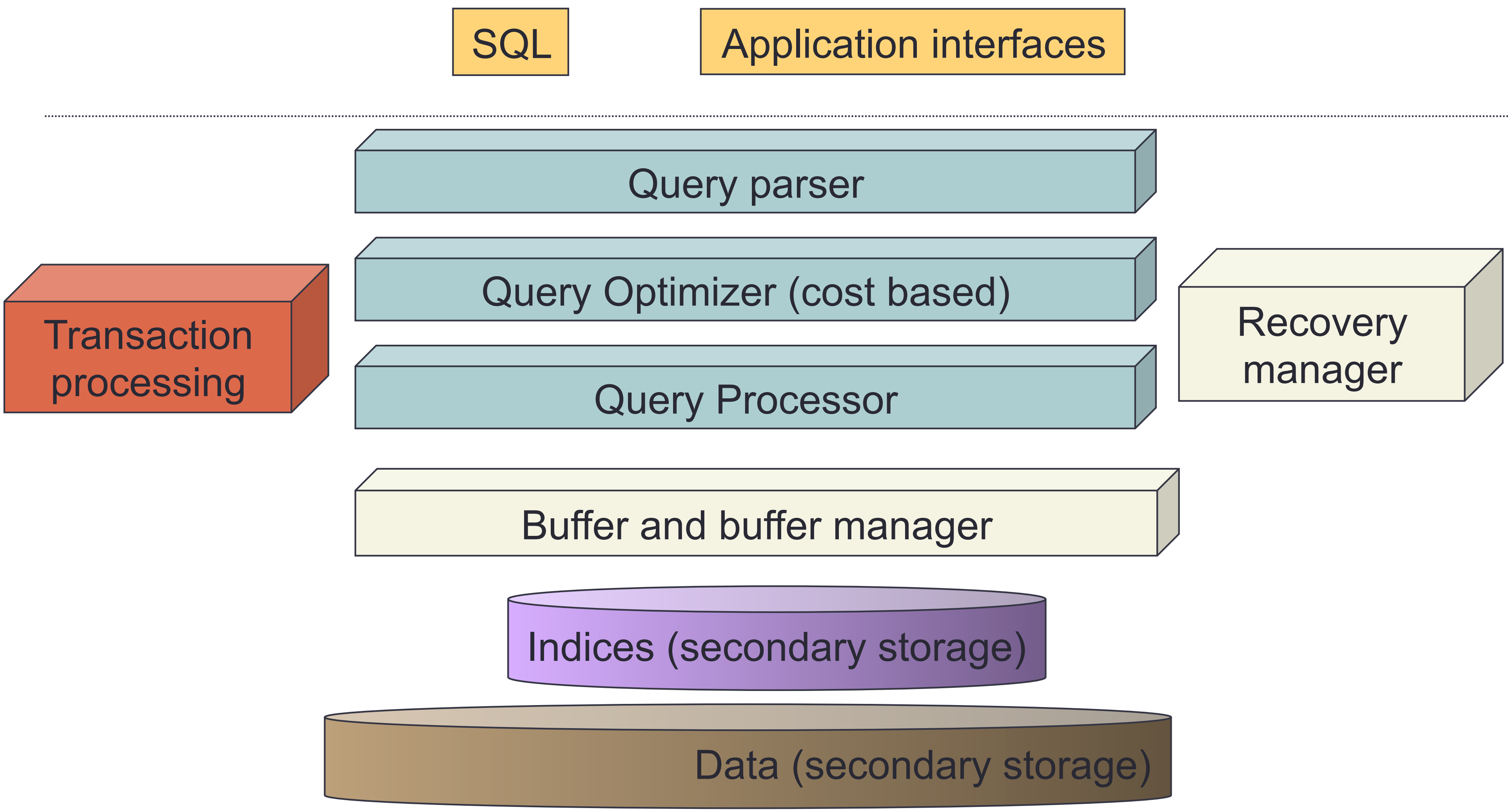
..and the metadata……

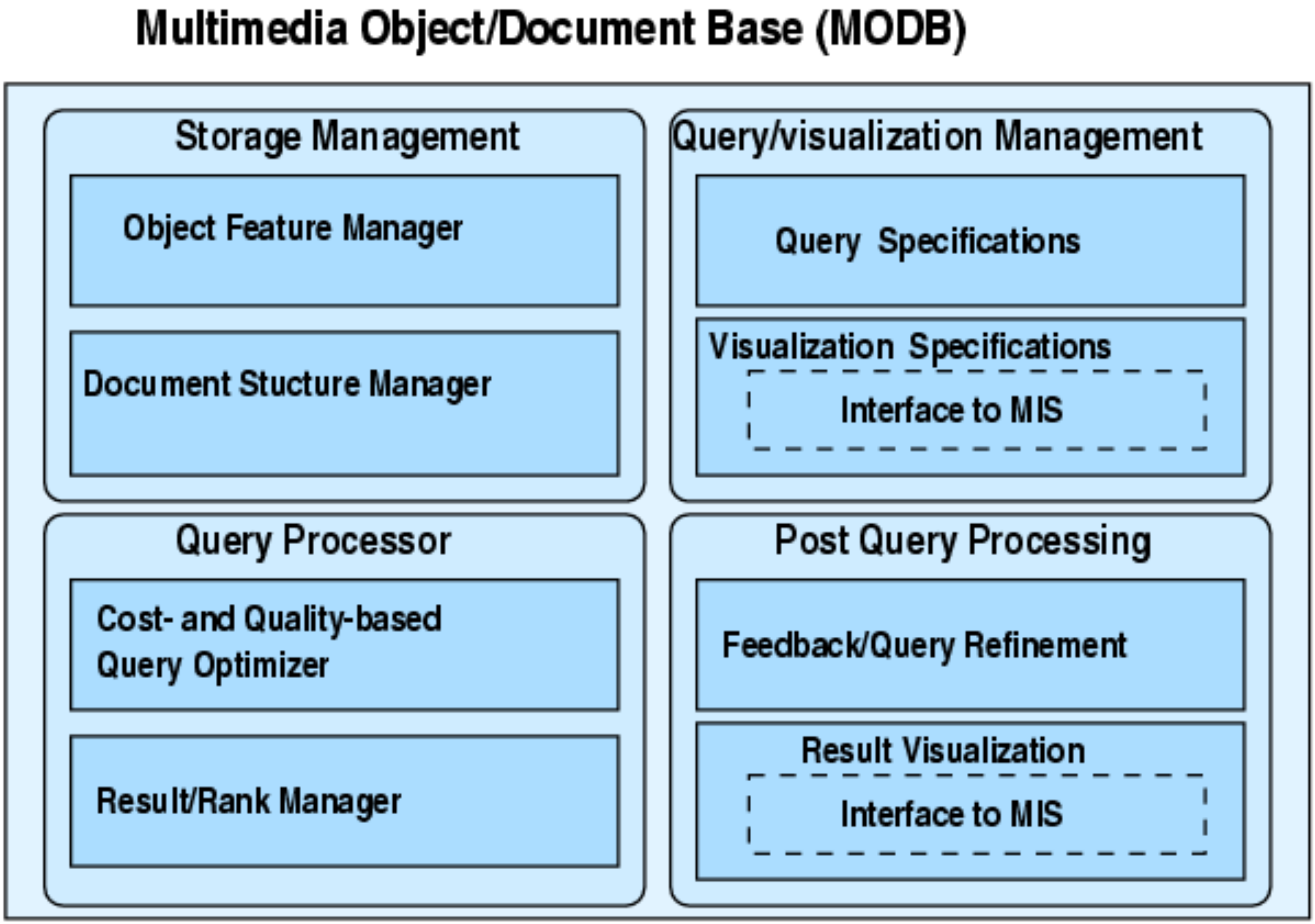
Differently-Modal Tensors (DMT)

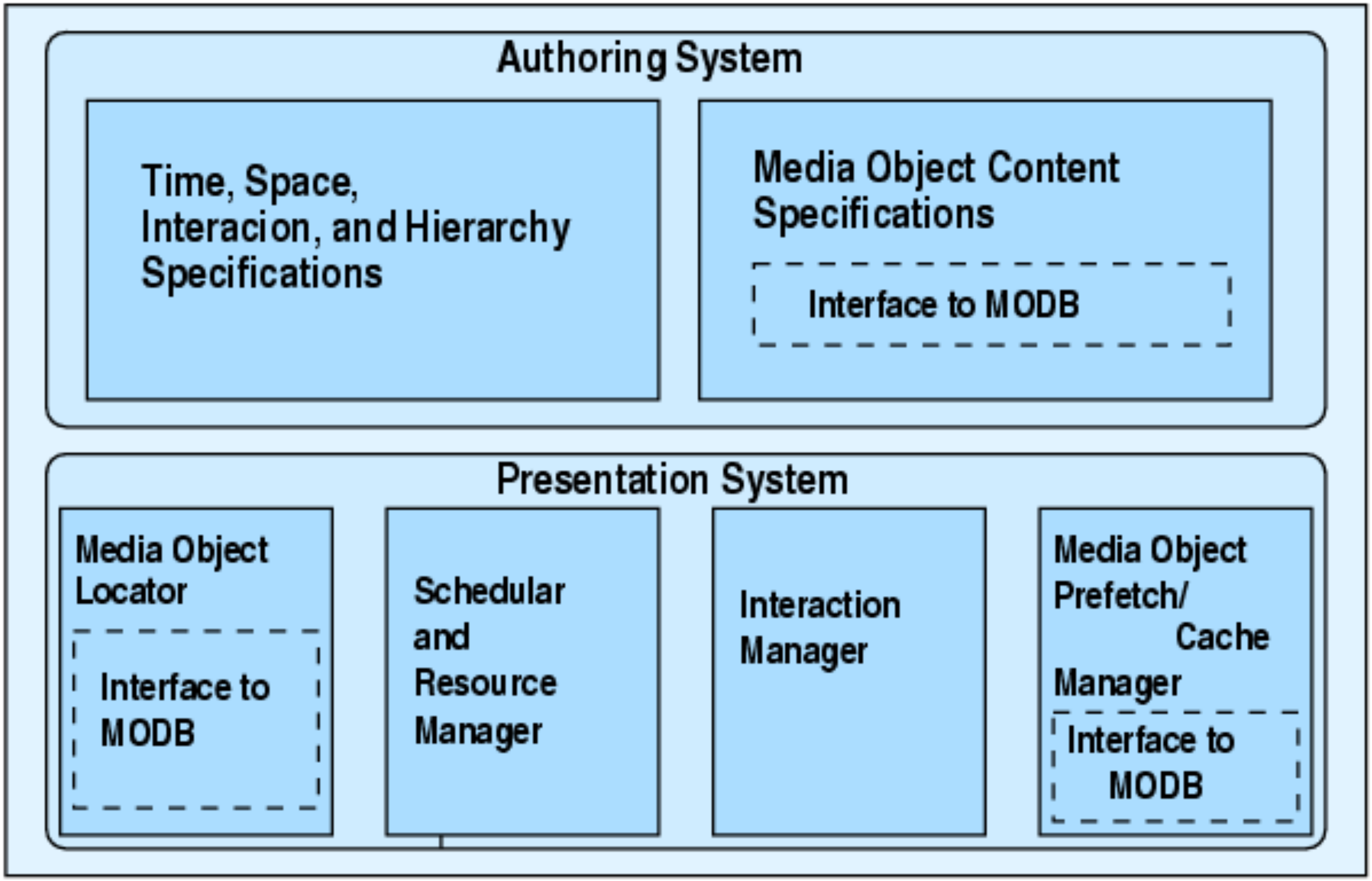




How does a traditional database engine look like?




Multimedia Object/Document Base (MODB)
Storage Management
Object Feature Manager
Document Stucture Manager
Query/visualization Management
Query Specifications
Visualization Specifications
Interface to MIS
Query Processor
Cost- and Quality-based
Query Optimizer
Result/Rank Manager
Post Query Processing
Feedback/Query Refinement
Result Visualization
Interface to MIS


Authoring System
Time, Space, Interacion, and Hierarchy Specifications
Media Object Content Specifications
Interface to MODB
Presentation System
Media Object Locator
Interface to MODB
Schedular and Resource Manager
Interaction Manager
Media Object Prefetch/ Cache Manager
Interface to MODB