

Accelerating Data-driven Science using the Cyberinfrastructure Continuum

Manish Parashar, Ph.D.

Director, Rutgers Discovery Informatics Institute RDI²
Distinguished Professor, Department of Computer Science

Yubo Qin, Anthony Simonet, Juanjo Villalobos, Ivan Roderio

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Outline

- Facilities-based, data-driven science: Opportunities & challenges
- The Virtual Data Collaboratory (VDC) project: Leveraging the computing continuum for facilities-based science
Data discovery, **data access**, data integration
- Conclusion and next steps

Science & Society Transformed by Data & Computing

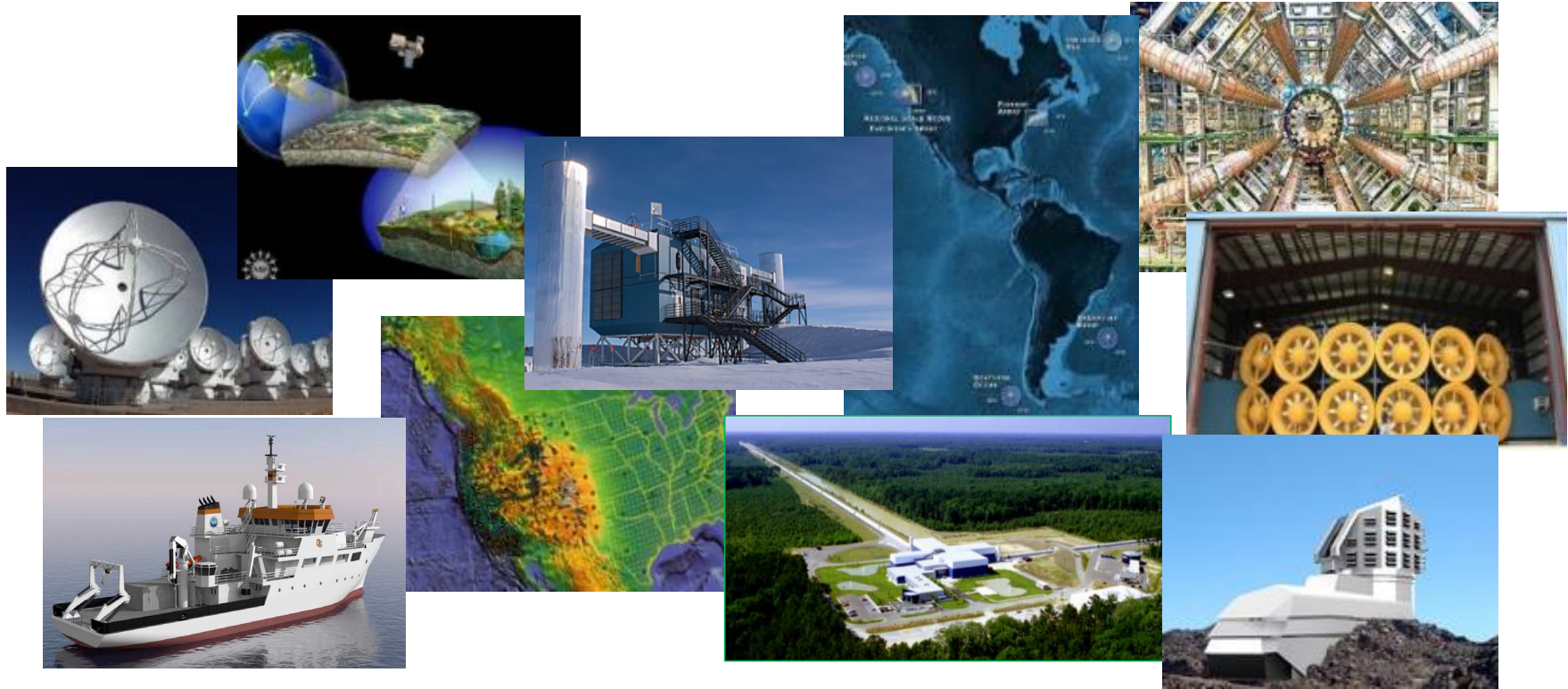


- *Nearly every field discovery is transitioning from “data poor” to “data rich”*
- *The **scientific process** has evolved to include **computation & data***

Science and Engineering in 21st Century

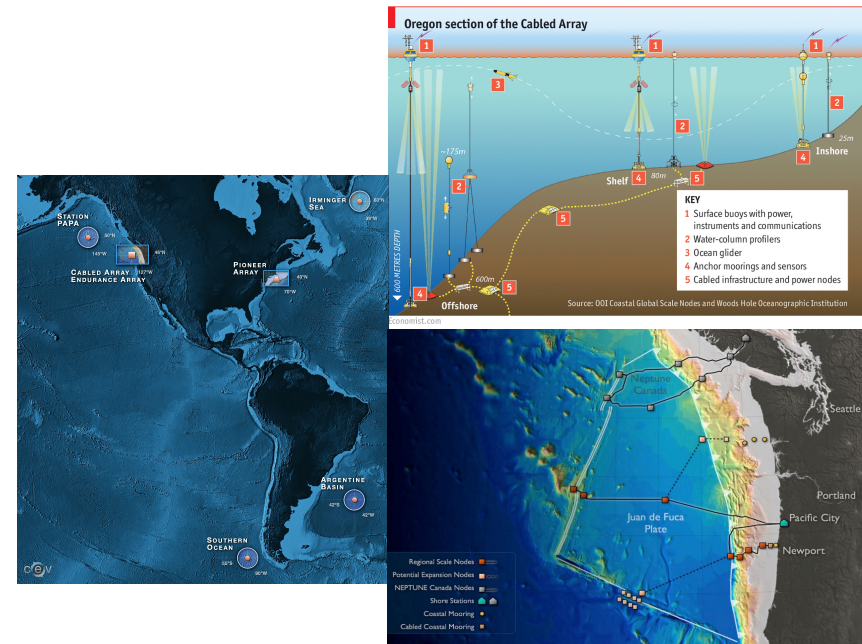
- New paradigms and practices in science and engineering
- Inherently multi-disciplinary
- Extreme scales, data-driven, data and compute-intensive
- Collaborative (university, national, global)

Large, Shared-use Facilities can Transform S&E Research





NSF Ocean Observatories Initiative (OOI)





7 Arrays

57 Stable Platforms
Moorings, Profilers, Nodes

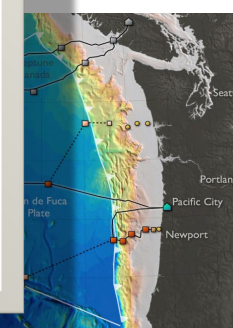
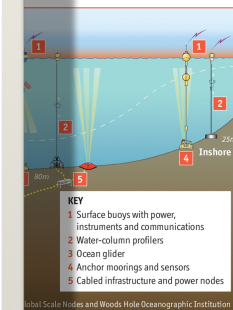
31 Mobile Assets
Gliders, AUVs

1227 Instruments (~850 deployed)

>2500 Science Data Products

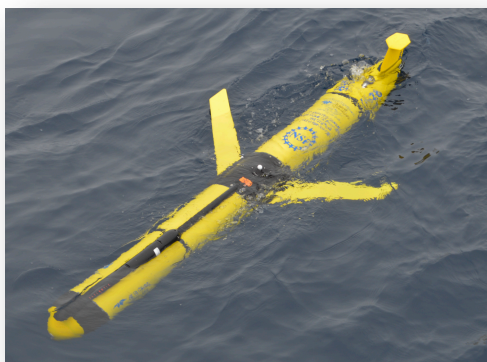
>100K Science/Engineering Data Products

Observatories



Types of Data

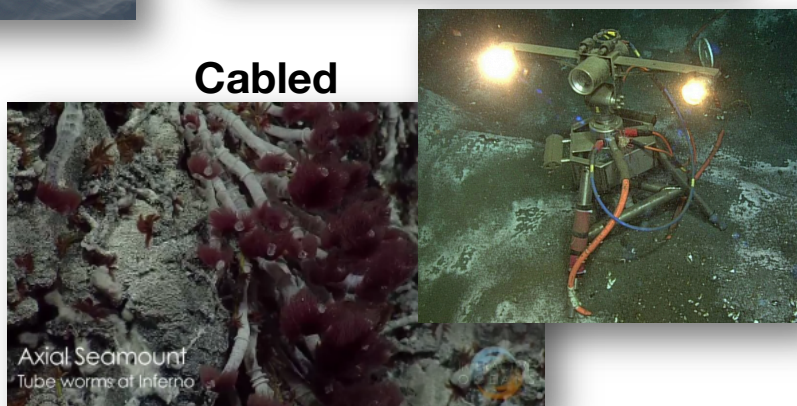
Telemetered



Recovered

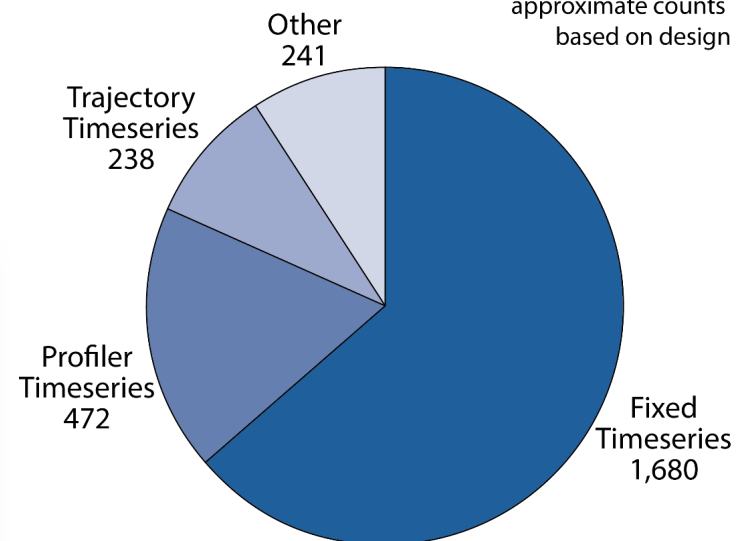


Cabled



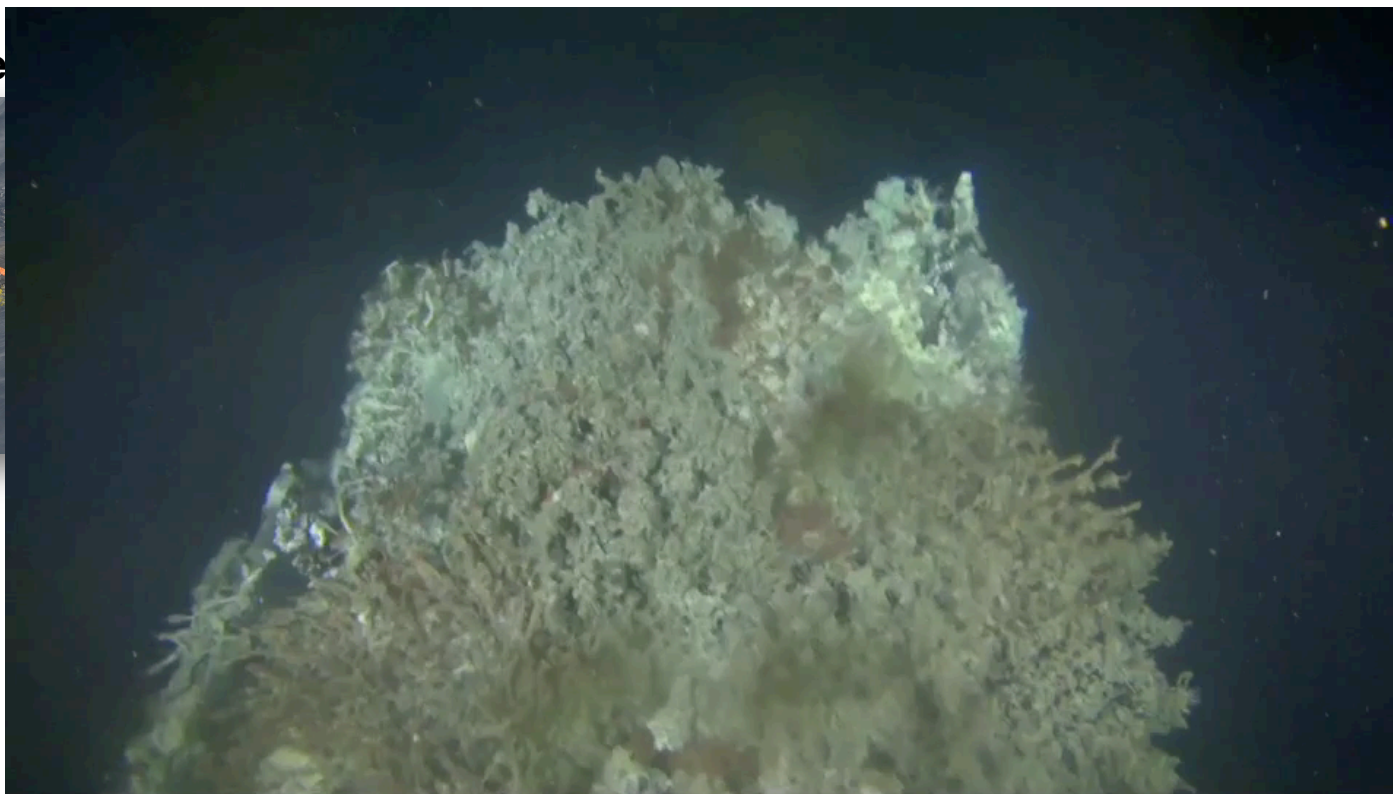
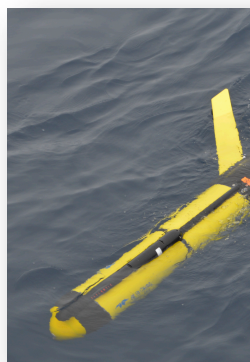
Data Product Types

approximate counts
based on design



Types of Data

Teleme



Tube worms of Inferno

Product Types

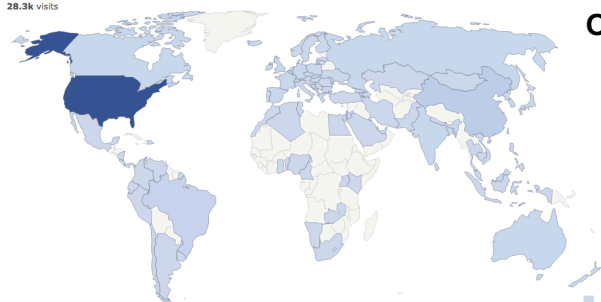
approximate counts
based on design

Fixed
Timeseries
1,680

Data Download Statistics (Jun'16 – Jun'17)

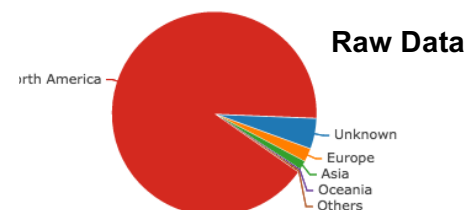
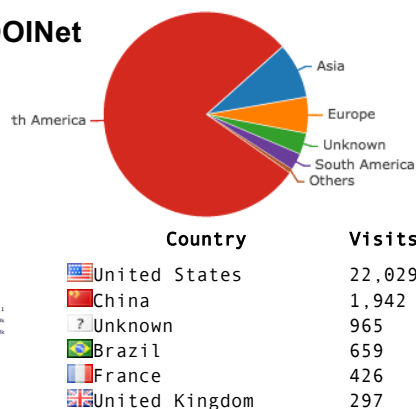
	OOINet (UI Portal)	THREDDS Server	Raw Data Server
Visits	28,341	3,681	18,829
Distinct countries	104	36	57
Direct entries	22,446 (79%)	3,324 (90%)	17,021 (90%)
Search engines	227(1%)	51 (1%)	(<1%)
From websites	3,228 (26%)	306 (8%)	1,792 (10%)
Distinct websites	131 (540 distinct URLs)	17 (92 distinct URLs)	30 (158 distinct URLs)
Data transferred	75.31 GB	923.3 GB	41.85 TB

28.3k visits



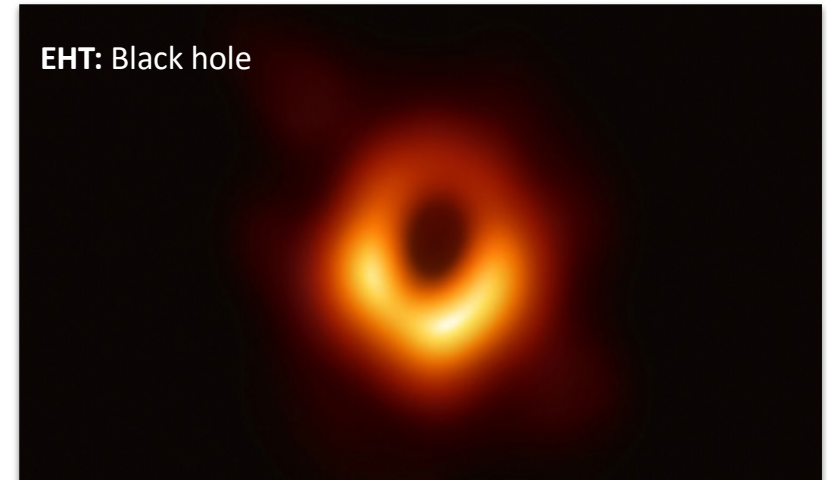
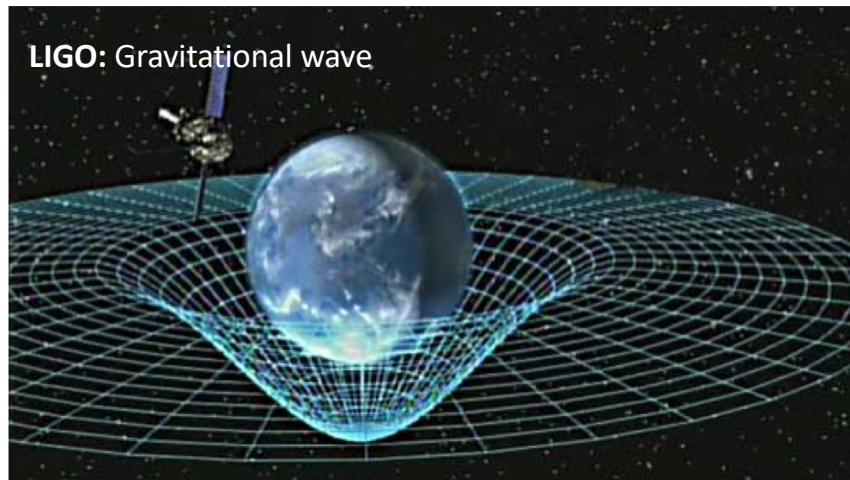
OOINet

OOINet



Raw Data

Large, Shared-use Facilities can Transform S&E Research



Observatory data repository



Scientific discovery



[EHT image] http://news.mit.edu/sites/mit.edu.newsoffice/files/styles/news_article_image_top_slideshow/public/images/2019/01-eso1907a_0.jpg?itok=LNUsoo9M

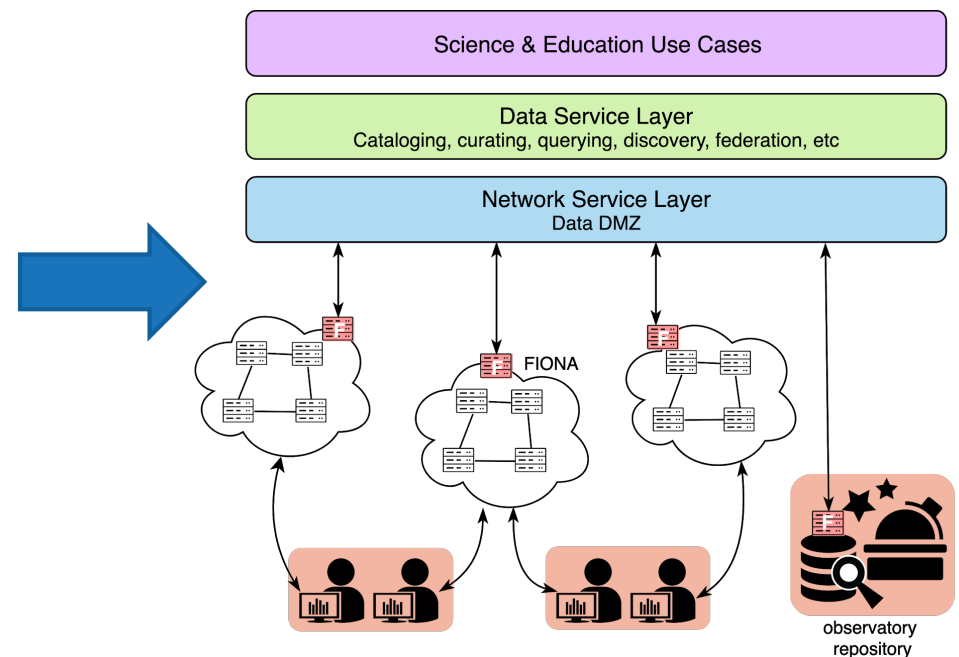
[LIGO image] https://www.ligo.caltech.edu/system/media_files/binaries/266/original/162571main_GPB_circling_earth3_516.jpg?1446243770

Virtual Data Collaboratory: Enabling The Large Facilities Science

- Data and services provided by large-scale instruments and observatories have become **important enablers** of scientific discoveries.
- The VDC project explores how the emerging cyberinfrastructures continuum can improve the performance, usability and science impact of data and services provided by facilities.

SYSTEM PLANE	Physical infrastructure (compute, storage, network, FIONAS), operating system and networking. Virtual infrastructure management: VMs, containers, etc.
DATA PLANE	Cross-repository data indexing and discovery, provenance records and other data-related services.
KNOWLEDGE PLANE	Data analytics, cross-repository data fusion, in-transit processing.
USER PLANE	Productivity tools, streaming-based interfaces, advanced caching and prefetching strategies.

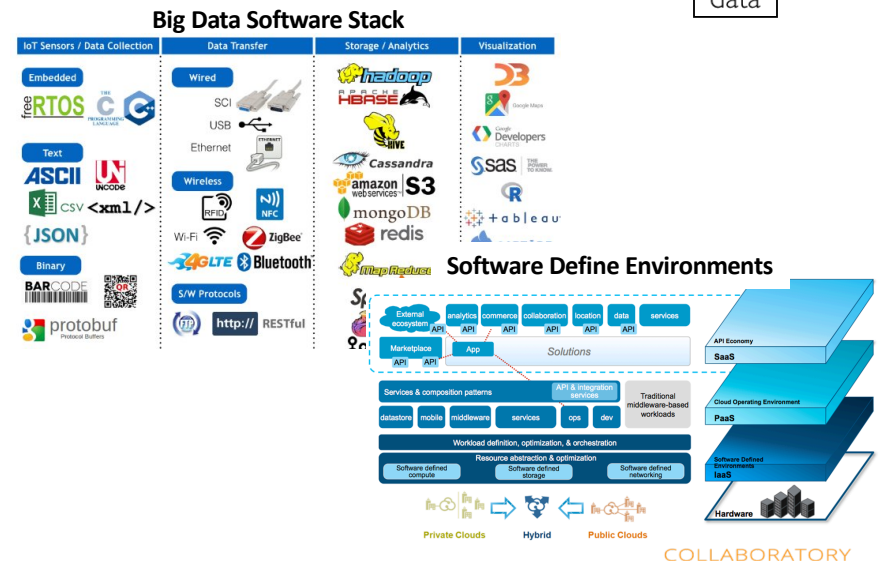
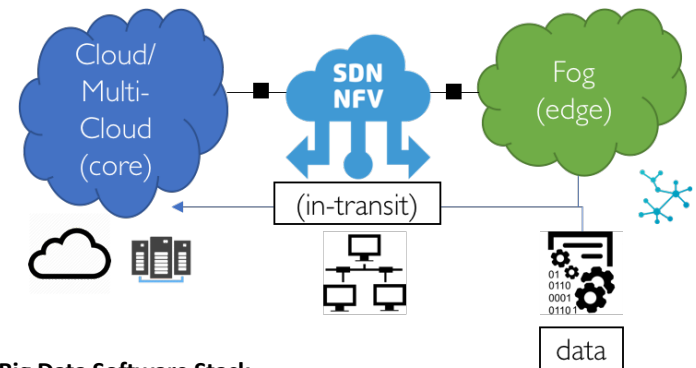
Collaborative data services to enable facilities' data to be **discovered, accessed, integrated** and **analyzed** in a timely manner



Leveraging the Computing Continuum

Emerging computing landscape

- Cloud
 - Hosted in data centers at the core
 - Relatively inexpensive; seemingly infinite
 - Far from data; data access expensive
- Fog/Edge
 - Computation/storage limited and expensive
 - Closer to the data; lower latencies
 - Limited and unreliable connectivity
- In-Transit
 - Distributed along the data path
 - Limited, but can be effective
 - Intermediate latency
 - Fewer guarantees



Leveraging the Computing Continuum

Emerging computing landscape

- Cloud

-

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Computing across the Continuum

- Fog

-

-

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- In-Edge

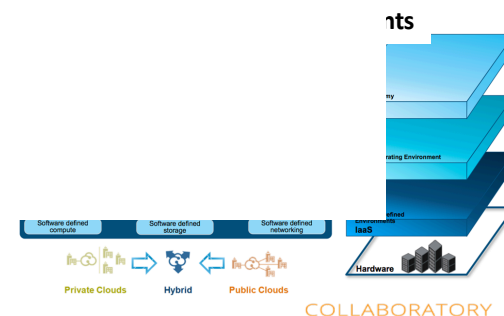
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- Fewer guarantees

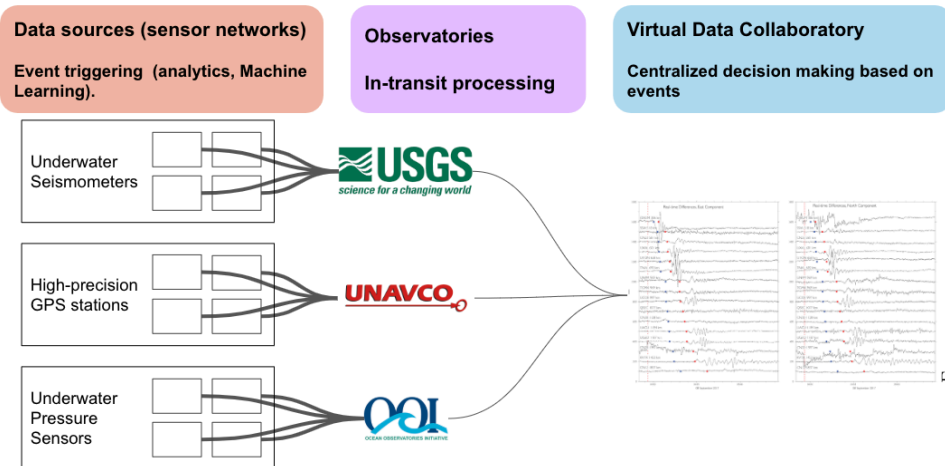
- Leverage resources and services at the logical extreme of the network and along the data path to increase the value of the data while potentially reducing costs
- Exploit the rich ecosystem of data and computation resources at the edge so that data is not moved



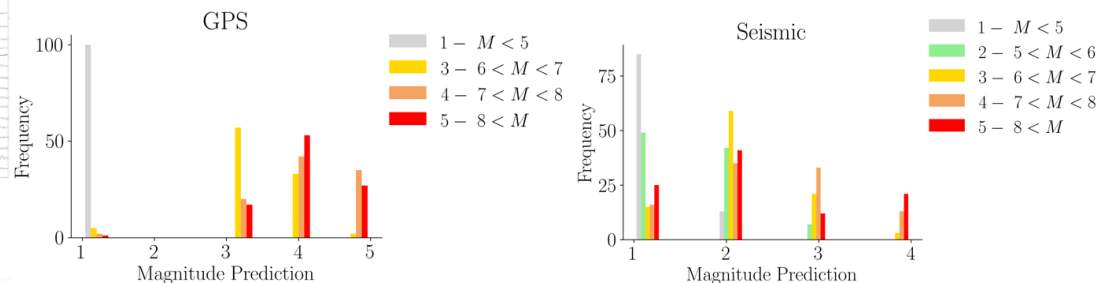
Driving Use-case: Tsunami Early Warning

Increase precision and timeliness of tsunami warning by analyzing multiple geo-graphically-distributed data sources simultaneously,

- **Tsunami Early Warnings** require earthquakes to first be characterized (magnitude, location, speed of displacement, etc.).
 - A **single data source** doesn't able to cover a whole spectrum of events. *Seismometers* are good for the *smaller* earthquakes (< 6.5), *high-precision GPS* are good for *larger* earthquakes.
 - **Centralized data processing** does not support *real-time* and *high volume* of data constraints of such system.
- Goal: Combine multiple data sources to cover the **whole spectrum** of events.
- **Decentralized Early Earthquake Magnitude (DEEM)**: A new two-step ensemble ML algorithm leveraging the two types of data for magnitude prediction using in-network resources



	# 60s MTS	GPS (# Events)	Seismic (# Events)
Magnitude < 5		7,718 (170)	1,038 (349)
$5 \leq \text{Magnitude} < 6$		3,859 (85)	None
$6 \leq \text{Magnitude} < 7$		991 (4)	266 (4)
$7 \leq \text{Magnitude} < 8$		432 (6)	249 (6)
Magnitude > 8		265 (4)	133 (4)
Total		13,265 (269)	1,686 (363)



Driving Use-case: Tsunami Early Warning

Increase precision and timeliness of tsunami warning by analyzing multiple geo-graphically-distributed data sources simultaneously,

- **Tsunami Early Warnings**
 - A **single data source** (e.g., earthquakes (< 6.5), high-speed GPS, etc.)
 - **Centralized data processing**
- Goal: Combine multiple data sources
- **Decentralized Early Earthquake Warning** (e.g., combining data for magnitude prediction)

Key requirements/challenges

- Data discovery
- **Data access**
- Data integration

, speed of displacement, etc.).
are good for the *smaller*

traits of such system.

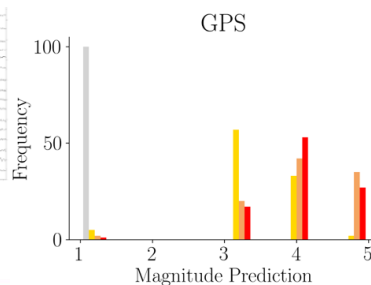
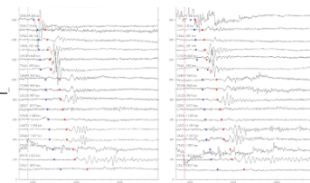
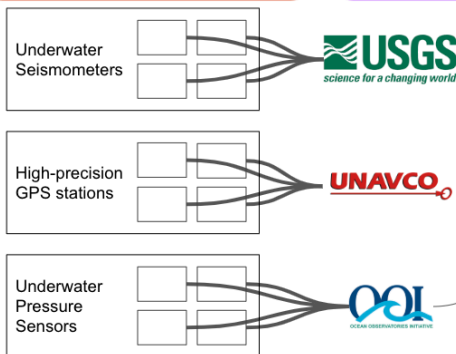
nm leveraging the two types of

Data sources (sensor networks)

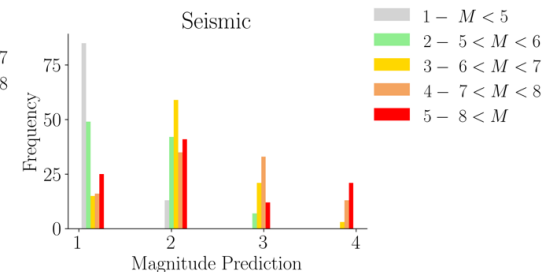
Event triggering (analytics, Machine Learning).

Observatories

In-transit processing



Events)	Seismic (# Events)
(170)	1,038 (349)
(85)	None
(4)	266 (4)
(6)	249 (6)
(4)	133 (4)
(269)	1,686 (363)

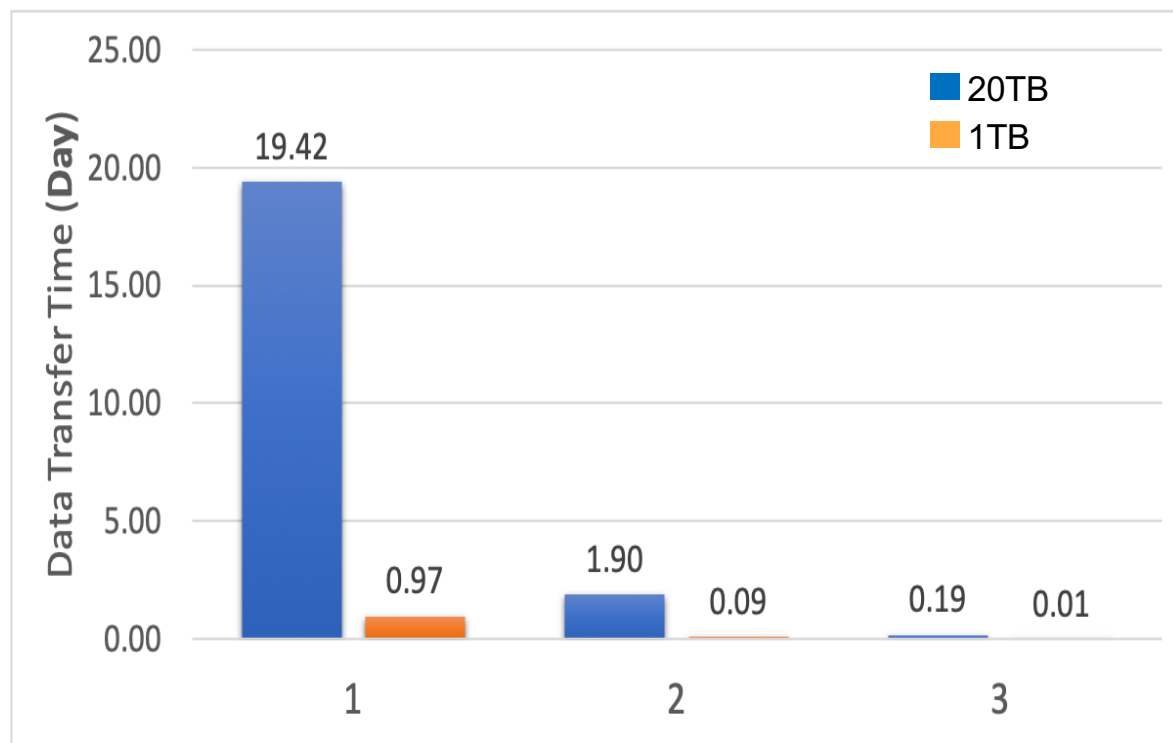


Facilities-based, Data-driven S&E: Data Access Challenge

Large volume, high data-rate, geographically distributed datasets

- Ocean Observatory Initiative
 - 1,227 instruments (~850 deployed)
 - 25,000 science data sets
 - 100,000 scientific data products
- LIGO: Generate TBs data per day, during 'observing' mode
- SKA: Estimate to generate an EB a day of raw data, which could be compressed to around 10 PB
- LSST: Produce 20 TB data per night

Large number of geographically distributed user communities with overlapping interests



Network bandwidth: 100Mbps, 1Gbps, 10Gbps

Addressing Data Access: Prefetching & Smart Caching

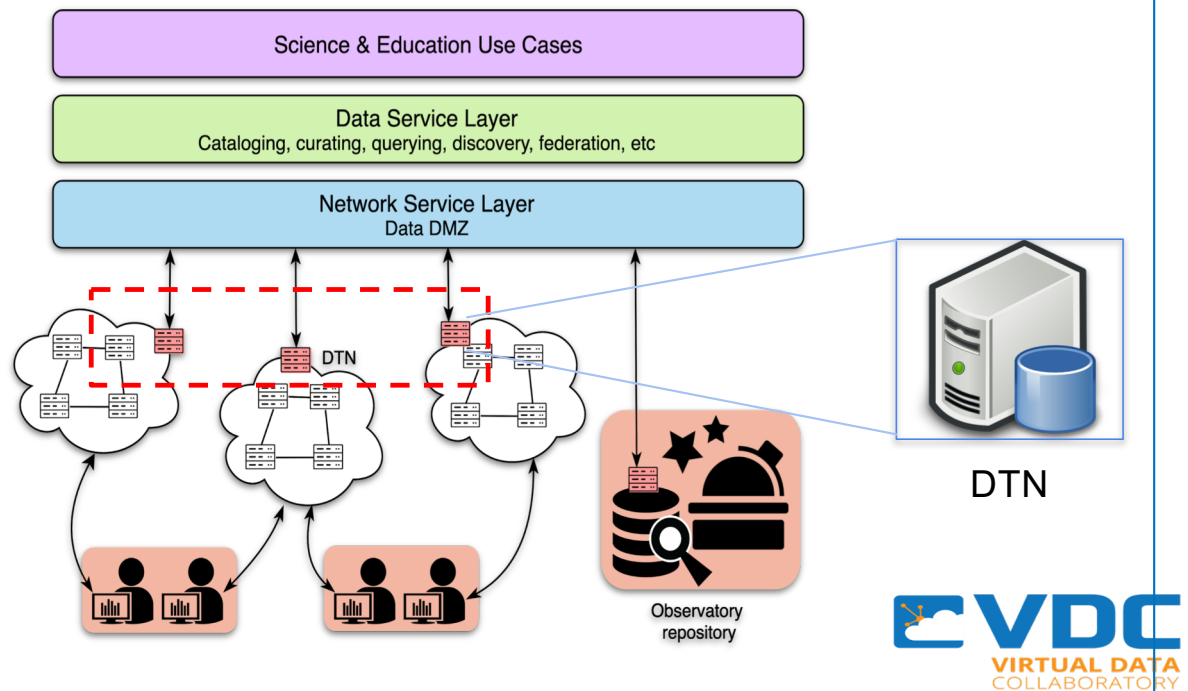
Objective: A *push-based* data delivery framework that leverages user access patterns and locality to accelerate the data delivery performance

Approach:

- Establish a distributed cache network using in-network DTNs
- Develop a hybrid prefetching model
 - Association-based model
 - Historical record-based model

Data sets:

- Ocean Observatory Initiative
 - Nov. 2018
 - 17.9 million records
- UNAVCO
 - One year of 2018
 - 77.8 million records



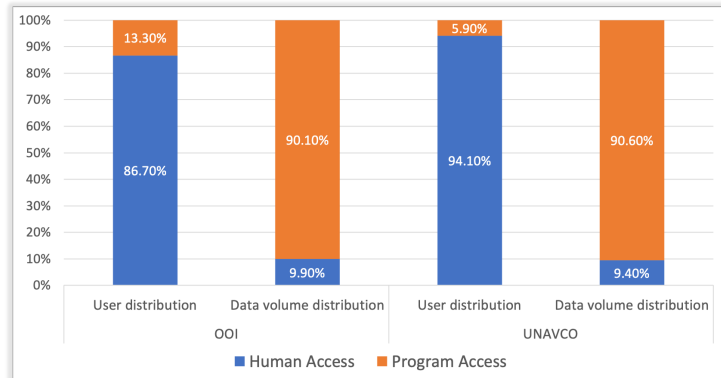
Addressing Data Access: Studying User Access Patterns

User access classification:

- **Interactive access:** users manually download data
- **Program access:** scripts automatically download data

Observations:

- Interactive users are the major users (~90%)
- Programs are the major data consumers (~90%)



Summary:

- Focus on the **program access**: ~90% of total data transfer
- Add a **cache layer** to alleviate redundant data transfers
- Implement **prefetching**: program accesses are predictable (~90%)

Program access classification:

- **Regular data download:** at regular intervals; no overlap
- **Overlapping access:** at regular intervals; large overlap with previous access
- **Real-time access:** high frequency access (e.g. every 5 sec); no overlap



Regular data download

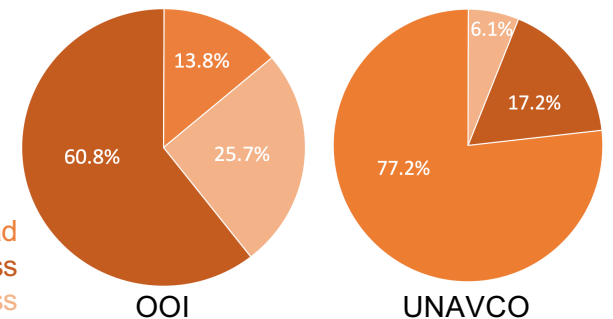
Overlapping access

Real-time access

Data usage pattern:

- Duplicated data transfer volume
 - OOI: 60.8%
 - UNAVCO: 17.2%

Regular data download
Overlapping access
Real-time access

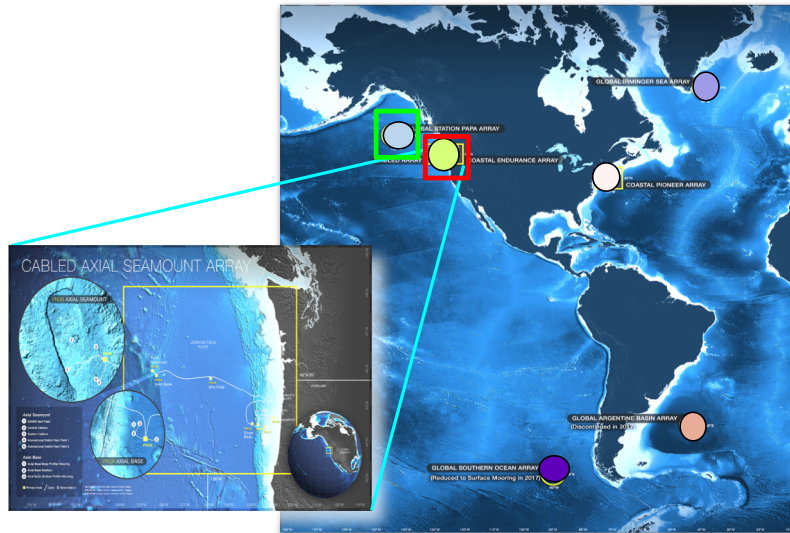


Addressing Data Access: Prefetching

A hybrid prefetching model:

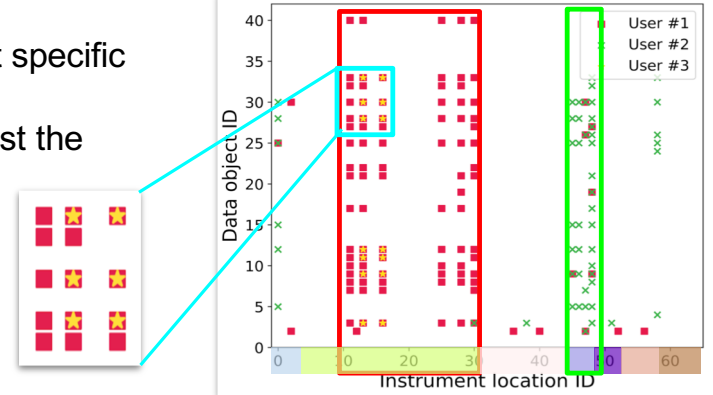
- Association-based prediction model
 - Spatial correlation
- Historical record-based prediction model
 - Temporal correlation

Example: OOI Instruments distributed across 7 platforms

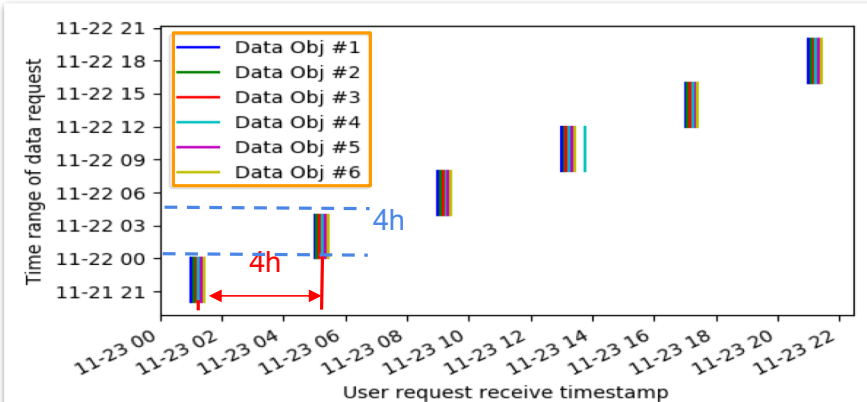


Spatial locality:

- User requests target specific locations
- Multiple users request the same data



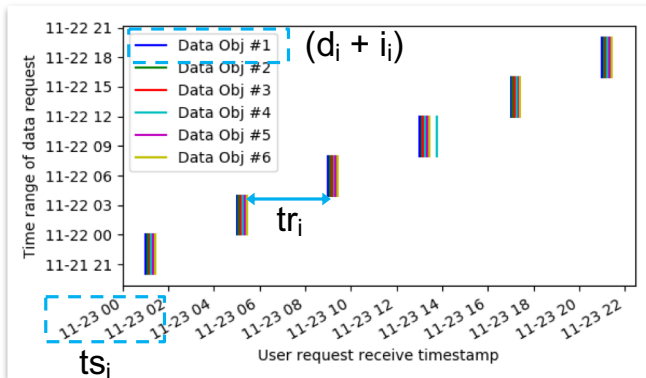
Temporal locality:



Prefetching Approach

Modeling the request sequence

Request: $R = \langle TS_n, D_n, I_n, TR_n \rangle$
 Timestamp: $TS_n = \langle ts_1, ts_2, \dots, ts_n \rangle$
 Data stream ID: $D_n = \langle d_1, d_2, \dots, d_n \rangle$
 Instrument ID: $I_n = \langle i_1, i_2, \dots, i_n \rangle$
 Time range: $TR_n = \langle tr_1, tr_2, \dots, tr_n \rangle$



Association-based prediction model

- Exploit spatiotemporal correlation
- Use the Frequent Pattern growth algorithm (FP-growth) to predict next request
 - Construct the frequent-pattern tree (FP-tree)
 - Prefetch the data with confidence $\phi_j > \text{threshold}$
 - $(d_1, d_2, \dots, d_{i+m-1}) \rightarrow \langle d_{i+m}, \phi_j \rangle$, ϕ_j is confidence value

Historical record-based prediction model

- Identifying program-based access (PA)
 - Maintain a detection time window (e.g. 2 weeks)
 - Check repetition patterns for a user's request R
- Once PA is identified
 - Determine $\langle D_n, I_n, TR_n \rangle$
- Use ARIMA to predict TS_n

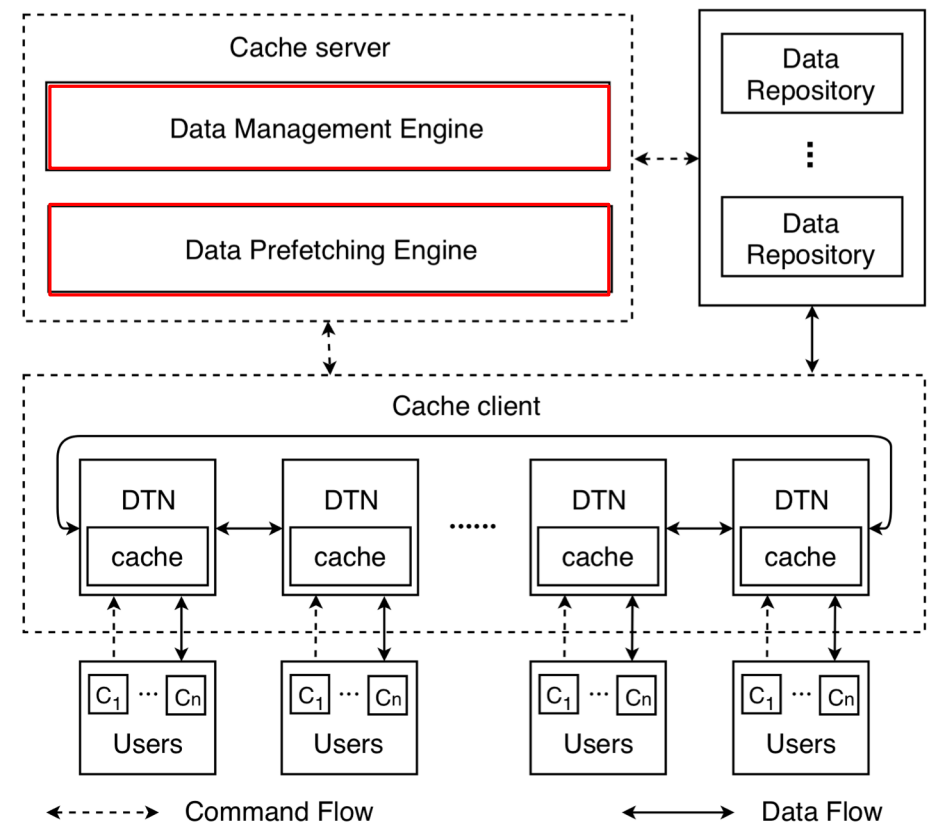
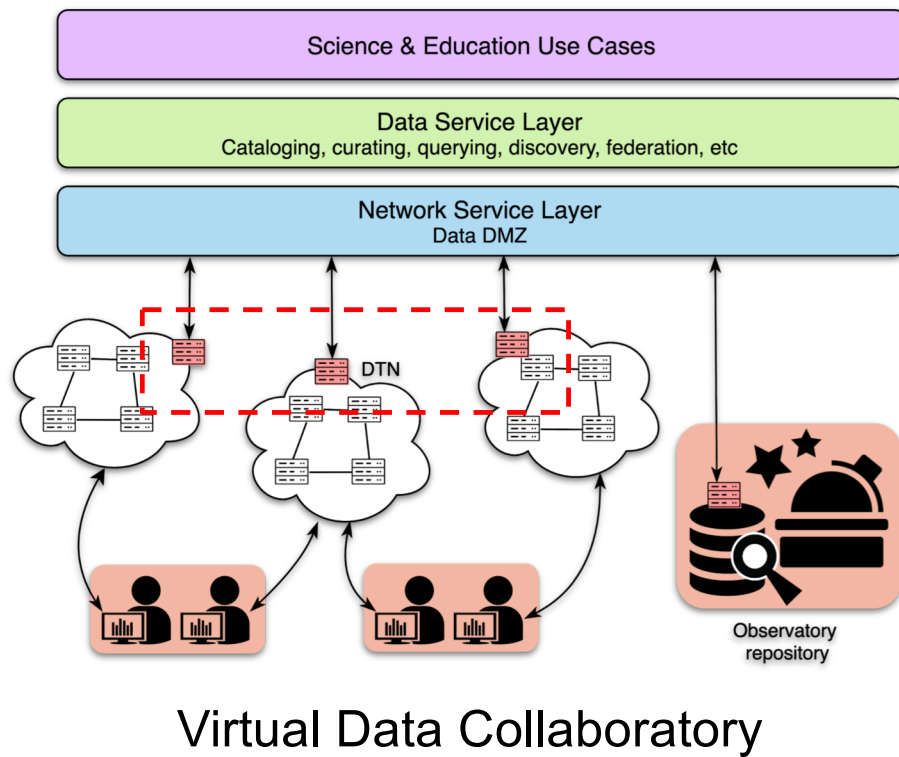


Beer and Diapers

UNIVERSITY OF CALIFORNIA
COLLABORATORY

Image: <http://myshopdiscountsblog.com/wp-content/uploads/2014/06/dad-shopping.jpg>

System Architecture

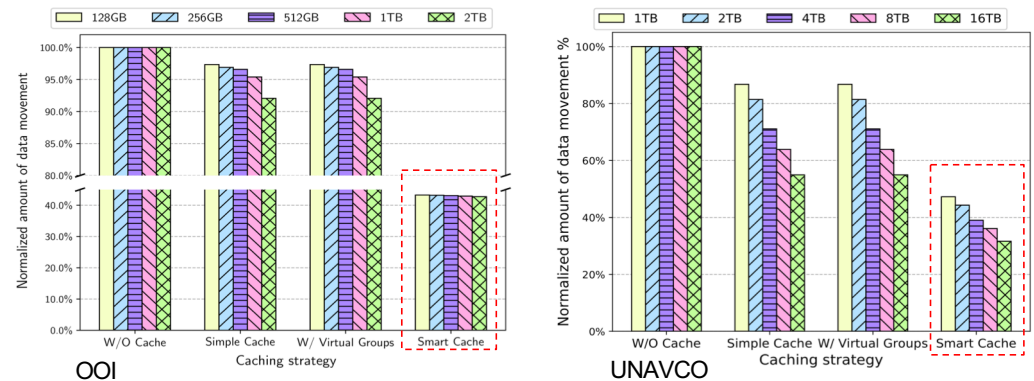


Experimental Evaluation

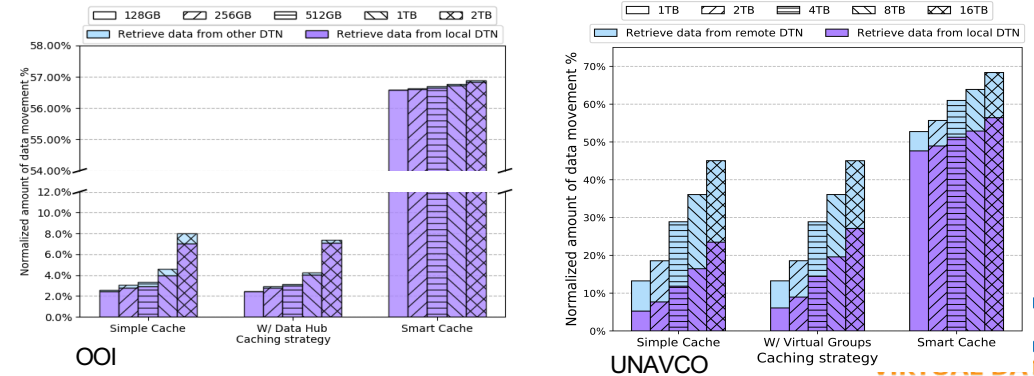
- System setup emulated:
 - 8 DTNs based on parameters obtained from the PRP Dashboard (Feb. 13, 2019 at 15:39:00)
 - Cache sizes: 128GB, 256GB, 512GB, 1TB, 2TB; LRU cache eviction
- Data source: OOI access log from November 2018 (17 Million records)
- Four scenarios:
 - W/O Cache
 - Simple Cache (LRU)
 - Simple Cache W/ Virtual Group
 - Smart Cache (including prefetch)

The **Smart Cache** enables users get more than **56% data** from their **local DTN cache**

The volume of data retrieved from the repository



The volume of data retrieved from the local DTN cache



Facilities-based Data-driven S&E: Challenges

#1 Data access

#2 Data discovery

- Users typically manually explore data via a web portal

The screenshot shows the OOI Data Portal interface. The navigation menu on the left includes links for Home, Sites, Research, and Assets. The main content area displays a search results table with columns for Name, Location, and Depth. The table lists several research arrays, including Coastal Endurance, Coastal Pioneer, Global Argosy, Global Irminger, Global South, and Global Station. The table is filtered by 'Time Range' (2015-01-01 to 2015-08-31) and 'Depth Range' (10 to 4500). The 'Assets' column shows a list of assets with their respective locations and depths. The interface also includes a 'Quick Table' section with a 'Reset Table' button and a 'Global search' bar.

#1: Select research arrays

#2: Select the facility site

#3: Select the instrument

#4: Select the data stream

#5: Specify the data time range and click download

#6: Receive the data download link and Done!

Manually searching for data/data products is not efficient (feasible)

Remember, OOI has:

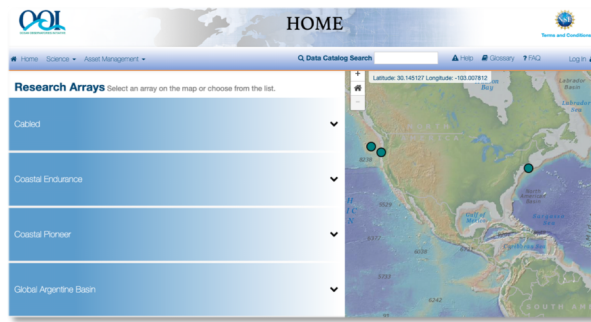
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Facilities-based Data-driven S&E: Challenges

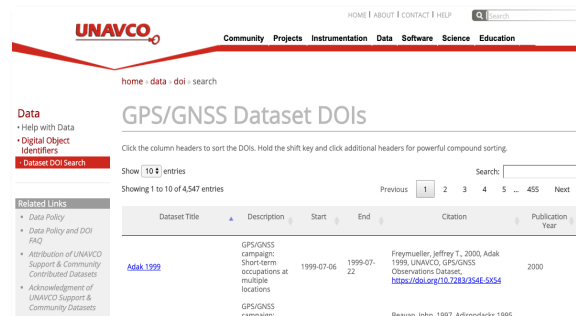
#1 Data access

#2 Data discovery

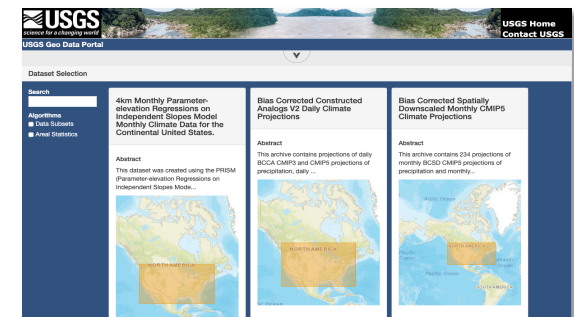
- Users have to manually explore data from the observatory data web portal
- Gets even more tedious when exploring data across multiple repositories



OOI



UNAVCO



USGS



Facilities-based Data-driven S&E: Challenges

#1 Data access

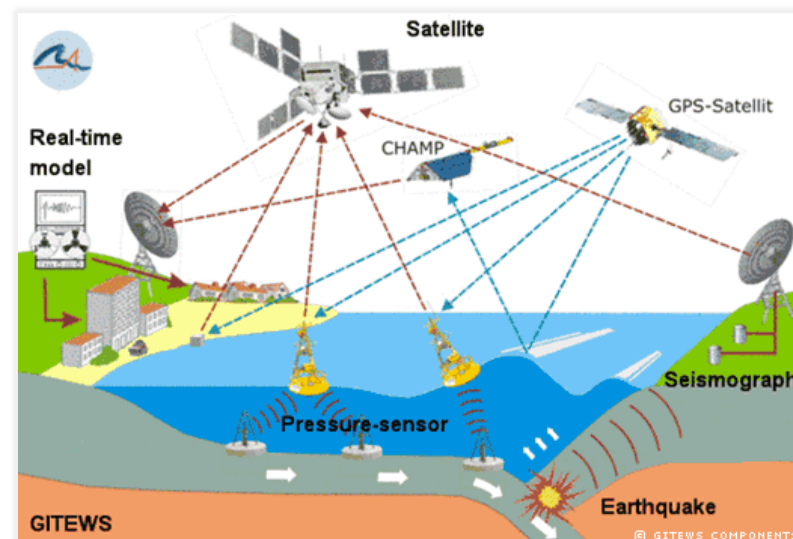
#2 Data discovery

#3 Data integration

Enable data from multiple data sources to be dynamically (opportunistically) integrated as part of support data-driven workflows

Example: Tsunami early warning system

- Integrate three data sources:
 - GPS (UNAVCO)
 - Seismograph (USGS)
 - Underwater pressure (OOI)



Tsunami early warning system [1]

[1] https://www.dhigroup.com/presences/nala/usa/news/2006/9/27/~media/Images/News/2006/20060927_GITEWS.ashx

Summary

Data-driven science and engineering research enabled by large-scale, shared-use experimental and observational facilities presents new opportunities for discovery

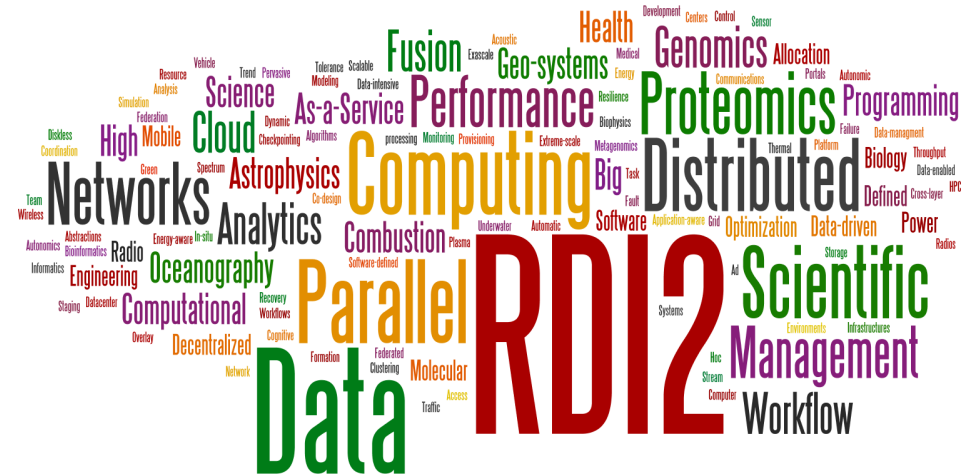
Data distribution, size, heterogeneity presents discovery, access, integration, processing challenges

- Large scale, heterogeneous in nature and geographic location

- Data needs to be processed by complex application workflows in a timely manner

The VDC project aims to provide data services that can leverage the computing continuum to address the needs for facilities-based data-driven science

Thank you!



Manish Parashar

Rutgers Discovery Informatics Institute (RDI²)

Rutgers, The State University of New Jersey

Email: parashar@rutgers.edu

WWW: <http://parashar.rutgers.edu/>

