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Rhea: Automatic Filtering for Unstructured Cloud Storage

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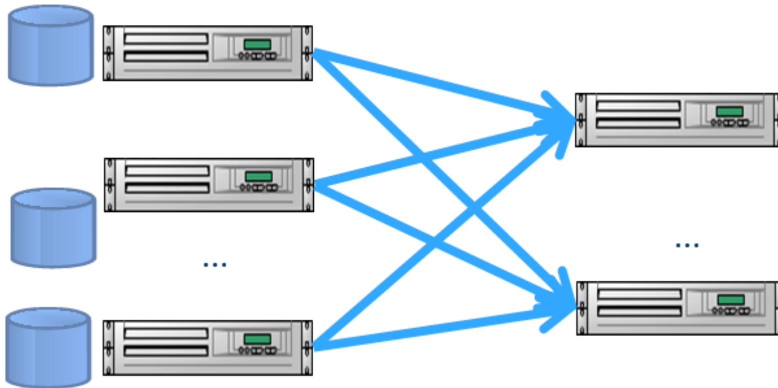
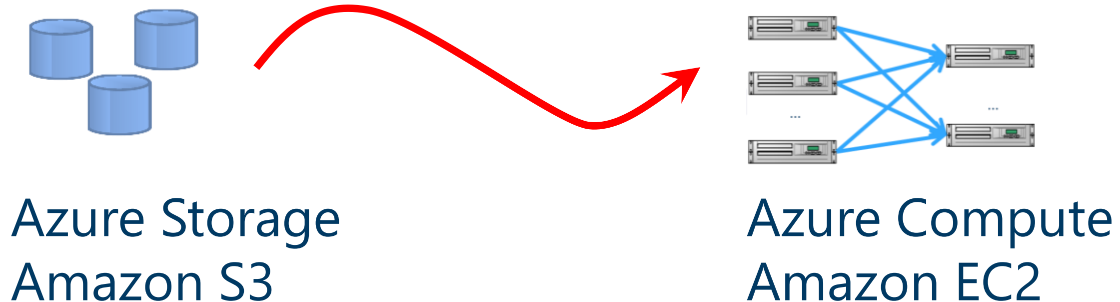
Cluster design for data analytics: [Traditional] Collocate storage & compute



- Hadoop & MapReduce, Dryad/DryadLinq, Scope, etc

Cloud Analytics: Hadoop in the Cloud

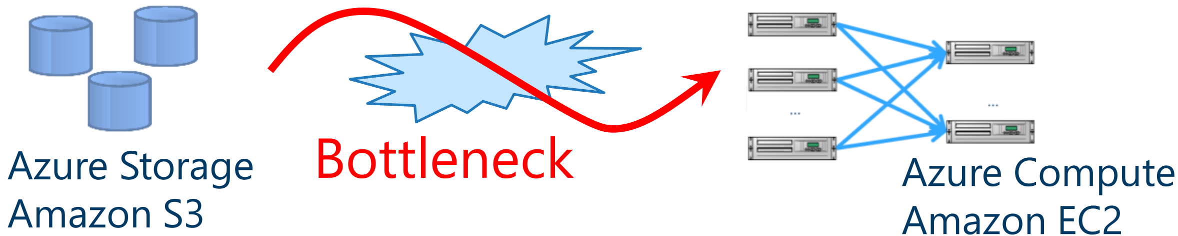
Separate storage and compute



Examples:

- ❑ Hadoop on Azure
- ❑ Amazon's Elastic MapReduce

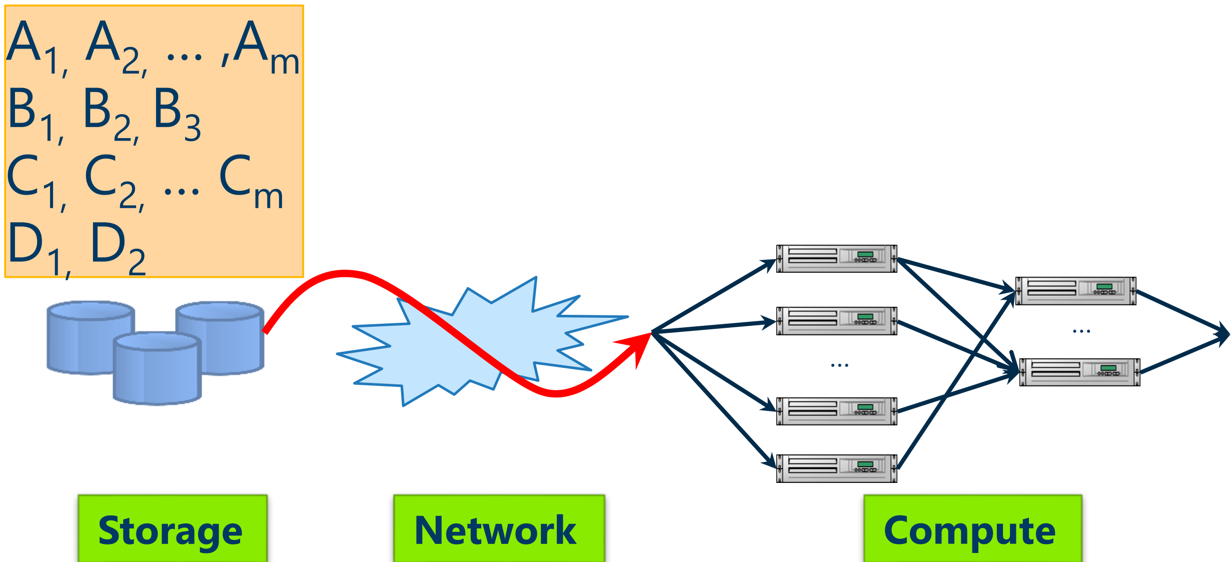
Cloud Analytics: Hadoop in the Cloud
Separate storage and compute



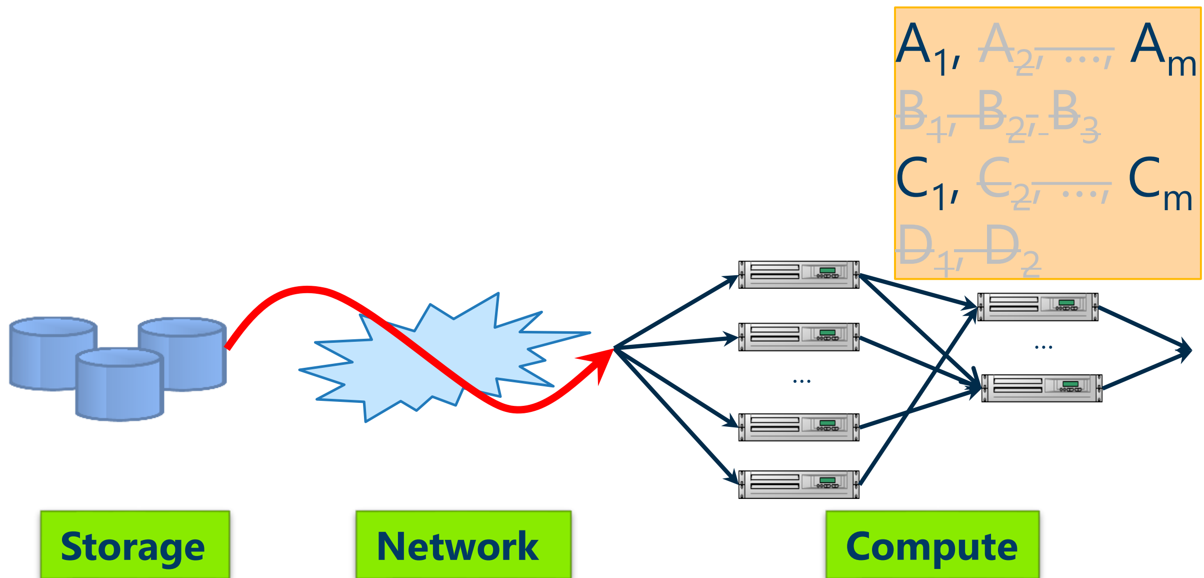
Why separate storage from compute?
+ (User) Don't pay for compute just to keep data alive
+ (User) Offload storage management to operator
+ (Operator) Evolve compute & storage independently
+ (Operator) Offer services that do not require both

- **Network between storage and compute is limited**
  (see paper for details)

Problem: Transfer lots of data …



Problem: Transfer lots of data …
… even when only a subset is needed



Problem: Transfer lots of data …
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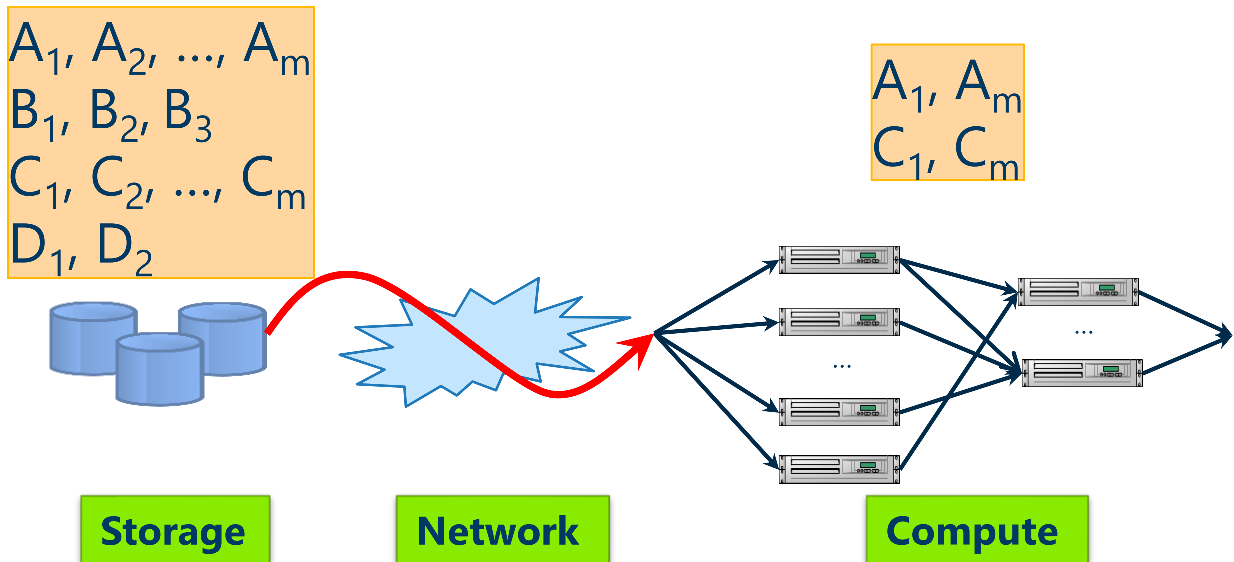


Scenario

- Apache Hadoop (Map/Reduce)
- Input data in storage service
- Hadoop running in compute service
- Unstructured data:
  - **text, log files, etc**

Goal

Transparently reduce data transfers from storage to compute

How to minimize transfers?

- Strawman: Can we execute mappers on storage nodes?
  - Intuition: Mappers throw away a lot of data
  - ☹ Data reduction not guaranteed
  - ☹ Difficult to stop mappers during storage overload
  - ☹ Storage nodes have to execute complicated logic (Hadoop system & protocol)
  - ☹ Dependencies on runtime environment, libraries, etc

- Better approach: Filter unnecessary data at storage nodes
  - Filters need to be **opportunistic and transparent** i.e. can kill/restart at any time (e.g. during overload)
  - Filters need to be **correct** i.e. always preserve correctness of computation

Challenge: How to filter the data?

Recall: data are typically unstructured text

- No external source of structure/schema

Insight:

- The data analytic job knows structure
- … and what needs to be filtered

Idea: static analysis of job bytecode

```
public void map(... value ...)
{
String[] entries = value.toString().split("\t");
String articleName = entries[0];
String pointType = entries[1];
String geoPoint = entries[2];

if (GEO_RSS_URI.equals(pointType)) {
    StringTokenizer st = new StringTokenizer(geoPoi
    String strLat = st.nextToken();
    String strLong = st.nextToken();
    double lat = Double.parseDouble(strLat);
    double lang = Double.parseDouble
    String locationKey = .........
    String locationName = .........
    geoLocationKey.set(locationKey);
    geoLocationName.set(locationName);
    outputCollector.collect(geoLocationKey, geoLocationName);
} }
```

Input Value

Projection operation
- 3 "columns" interesting (out of 4 for this job)

Selection operation
- roughly 1/3 of rows are of the interesting type

"selects"/"projects" implicit in Java byte code

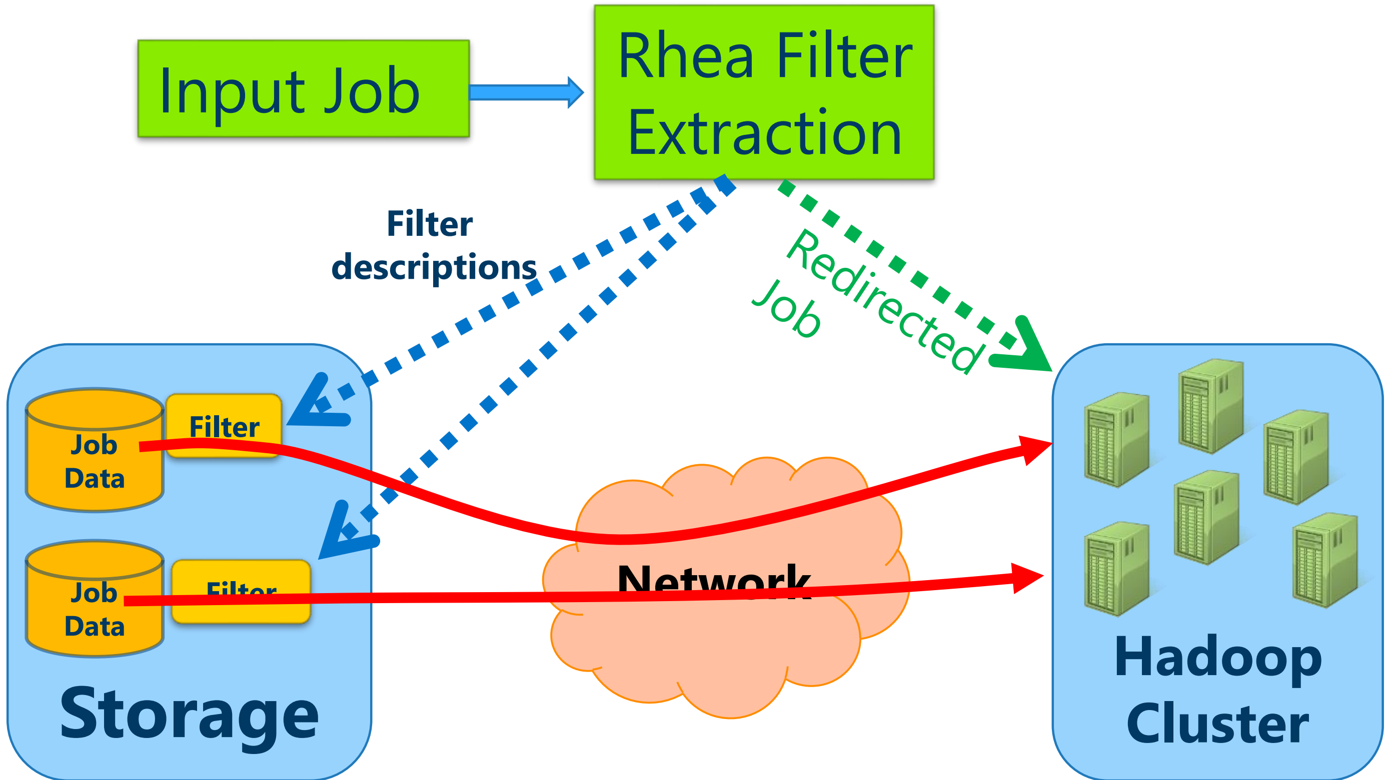
Output operation

Rhea

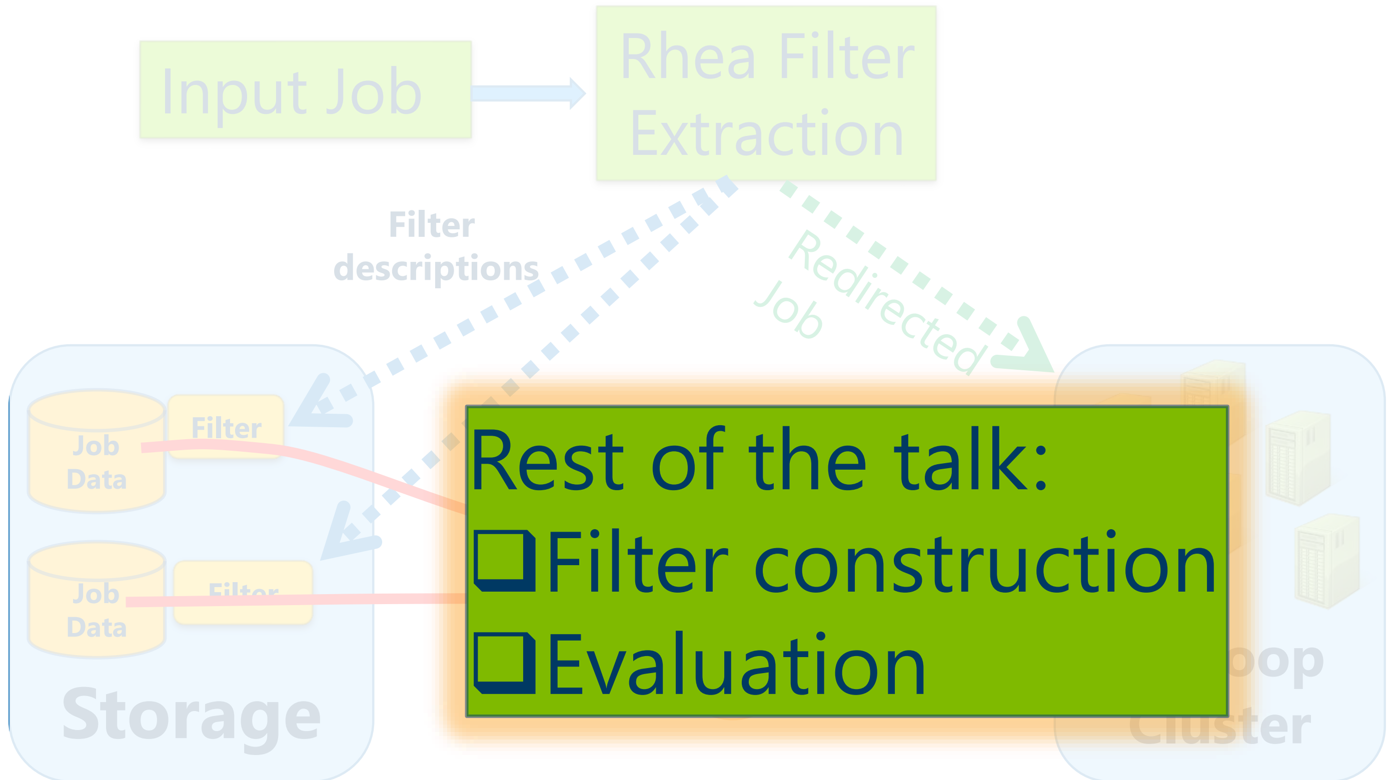
- Static analysis of Java byte code
- Extract row (select) & column (project) filters
  - as **executable** Java methods
  - column filters can also be C, regular expressions, etc.

- Filters are **conservative**:
  - May accept more data than strictly necessary
- Filters are **opportunistic**
  - kill/restart at any time (e.g. during storage overload)
- Filters are **transparent**
  - no change to Hadoop job

Rhea's Architecture



Rhea's Architecture



Filters: Identify bits of data that affect output of mapper

- Row Filters:
  - Given an input row:

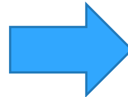
    Does it lead to output?
  - Row corresponds to one invocation of map
  - Approach: Path Slicing
  - Challenge: Deal with mutable state
- Column Filters:
  - Given a row that leads to output:

    Which substrings of the row affect output?
  - Approach: Abstract interpretation
  - Challenge: Deal with loops

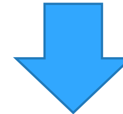
Row Filter Generation via Path Slicing

```
public void map(... value ...)
{
String[] entries = value.toString().split("\t");
String articleName = entries[0];
String pointType = entries[1];
String geoPoint = entries[2];

if (GEO_RSS_URI.equals(pointType)) {
    StringTokenizer st = new
    StringTokenizer(geoPoint, " ");
    String strLat = st.nextToken();
    String strLong = st.nextToken();
    double lat = Double.parseDouble(strLat);
    double lang = Double.parseDouble(strLong);
    String locationKey = .........
    String locationName = .........
    geoLocationKey.set(locationKey);
    geoLocationName.set(locationName);
    outputCollector.collect(geoLocationKey,
    geoLocationName);
} }
```



1. Tag "observable" instructions
2. Identify path conditions that lead to observable instructions
3. Perform dataflow analysis to identify all instructions that affect path conditions
4. Emit code



```
public boolean filter(Text bcvar2) {
    String[] bcvar5 = bcvar2.toString().split("\t");
    String bcvar7 = bcvar5[1];
    boolean irvar0_1 =
GEO_RSS_URI.equals(bcvar7);
    if (irvar0_1 == 1) { return true; }
    return false;
}
```

Challenge: Taming State

- Map-Reduce program are often NOT pure functions
  ➔ M/R programmers use state (i.e. objects in heap):
  - … to avoid frequent initializations
  - … to pass job parameters
  - … to optimize temporary storage (e.g. with dictionaries)
- Filters cannot rely on mutable state:
  - Recall: output of filtered data = output of original data
- Solution: Tag all access to mutable fields as “observable” (i.e. output) instructions.

Column Filter Generation (aka projects)

- Goal: Identify substrings that affect output
- Based on *abstract interpretation*
  - Captures common patterns for "reading" fields: e.g. string tokenizers, regular expressions, etc.
  - Guarantees termination by using numerical constraints
    - Important to deal with loops
- Output:
    - Tokenization method and sep
    - List of indices of interesting to

Rest of the talk:

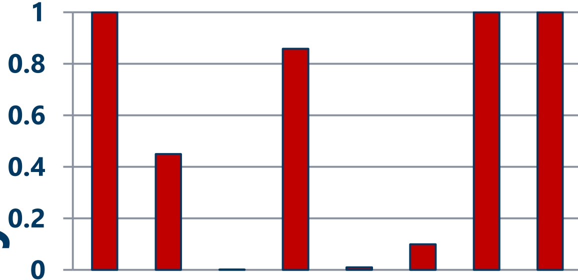
❑ Filter construction

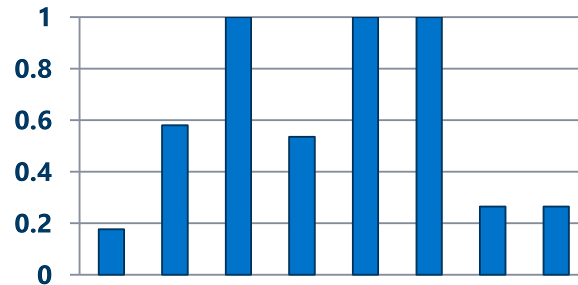
❑ **Evaluation**

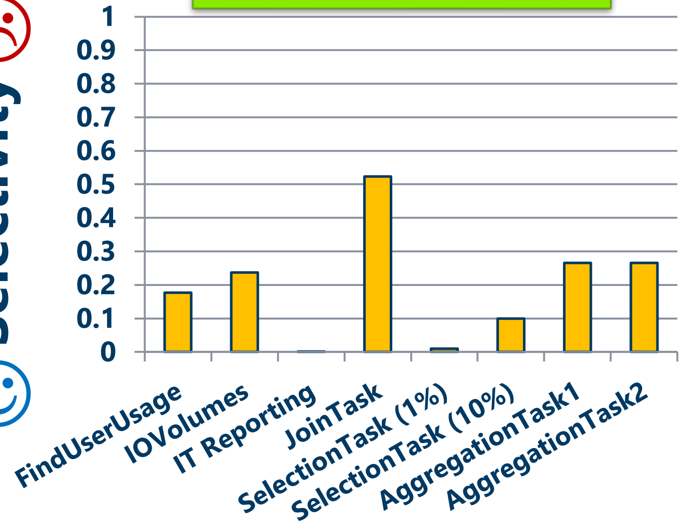
Experimental setup

- Hadoop on Azure:
- Input data in Azure Storage
- Compute on Azure Compute
- 8 jobs with both code and data
  - **200 jobs code only (in paper)**
- Same data-center
  - **Also, cross data-center (in paper)**

Job Selectivity





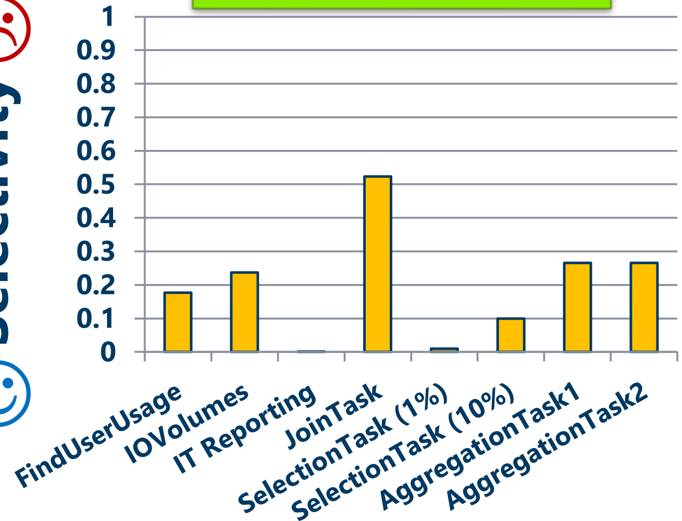


Many jobs are very selective …
either on rows, columns, or both

Job Selectivity

High selectivity ➔
less bytes to transfer
✓ Good for operators
✓ Cheaper for users
for cross-data centers
scenarios [see paper]

reduce runtime
✓ Good for users



Many jobs are very selective …
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Measuring runtime benefits

- We cannot extend Azure Storage or Amazon S3 with filters ☹
- Instead, **we use pre-filtered data** and compare with unfiltered data
- We assume storage with: (a) scalable I/O, and (b) enough processing power for filtering

Diversion:
Do we have enough processing power?

- Row & Column filtering in **Java**: **~100MBytes/sec per core**
- Scales linearly with multiple cores

- ≤2 cores for filtering enough for all but 1 job
- Runtime **always reduces** runtime, even with fewer cores

- Performance dominated by string input/output, not filter
- Column filtering in optimized **C**: **5-17x faster** than Java

Runtime benefits

Normalized runtime

1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

FindUserUsage
IOVolumes
IT Reporting
JoinTask
SelectionTask (1%)
SelectionTask (10%)
AggregationTask1
AggregationTask2

- **30-80% reduction in runtime**
- **Runtime reductions less than selectivity due to Hadoop overheads**

Conclusions

- Hadoop in the cloud:
  separation of storage and compute.

- Rhea minimizes transfers from
  storage to compute
  - Uses static analysis on the job bytecode
  - Extracts **selection** and **projection** operators from code
  - Generates filters to run in the storage layer
  - Runs transparently to user (and is safe for provider)
  - Potential benefits to the user (time, money) and
    cloud provider (bandwidth)

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