



DISPEL introduction

Malcolm Atkinson <u>Malcolm.Atkinson@ed.ac.uk</u> 16th July 2012 **NSF PIRE Open Science Data Cloud** workshop Informatics Forum Edinburgh

FP7-INFRASTRUCTURES-2011 project# 283543

Outline

- Data Intensive
 - What is it?
 - Why use it?
- DISPEL
 - What is it?
 - Why design it?
 - Is it different?
- A simple example
- Summary and Conclusions



picture from Erica Salmon Cornish Coast Path where I call home

Data-Intensive Thinking



Data-Intensive Thinking





Computing over data pedigree!

• Tycho Brahe and Johannes Kepler

1546-1601 & 1571-1630



Dennis Noble uses Mercury

- The London University Computer in 1959
- to demonstrate heart beats as emergent behaviour
- by simulating two ion channels
- 2 papers in Nature 1960
 - read "The Music of Life" by Dennis Noble



edinburgh

research

data-intensive

Gray's Laws of Data Engineering

Jim Gray:

- Scientific computing is revolving around data
- Need scale-out solution for analysis
- Take the analysis to the data!
- Start with "20 queries"
- Go from "working to working"



Tuesday, 17 July 12

From: Alex Szalay, JHU

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- Need s
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From: Alex Szalay, JHU

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FOURTH PARADIGM

DATA-INTENSIVE SCIENTIFIC DISCOVERY

CITED BY TONY HEY, STEWART TANSLEY, AND KRISTIN TOLLS

Defining "Data-Intensive"

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Generally

- A computational task is data-intensive if you have to think hard about an aspect of data handling to make progress
 - distribution, permissions and rules of use, complexity, heterogeneity, rate of arrival, unstructured or changing structure, long tail of small and scattered instances, size of data, number of users
 - often in combination

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Quantitatively

- The computation's Amdahl numbers are close to 1
 - CPU operations : bits transferred in or out of memory
 - ▶ 1000 CPU operations : 1 I/O operation
- Total volumes expensive to store

Total requests/unit time hard to accommodate

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- So that you can afford a lot of them
- Balanced for data-intensive work
- Treat memory bandwidth as a scarce resource

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Work on small chunks of data

- as small as logically possible
- a column of a table
- a row of a table
- a file
- data unbundled, in computational format & compressed

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- multiple derivatives in one pass
- pipelining
- re-use of intermediate data, caching and forwarding

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- pipelining
- re-use of intermediate data, caching and forwarding
- Use directories and indexes to avoid revisiting data randomly

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 - many subtasks at modest rate per task in large numbers
 - NOT tightly coupled parallelism!!!
 - distribution for availability, ownership & persistence
 - proximity to data sources or destinations for speed

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 - distributed shared structures
 - just enough synchronisation

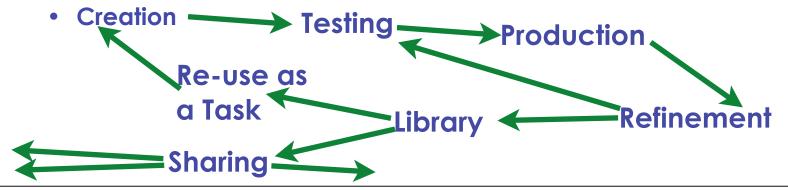
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- Statistical and quantised accounting

- High-level notations for describing methods /composing tasks
 - with well-developed optimised transformations before execution
 - query languages: SQL/AQL, (Xquery & SPARQL), ...
 - workflow languages: Kepler, Pegasus, DISPEL, ...
 - MapReduce: PigLatin, ZigZag, ...

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- Support for the query & workflow lifetime: new research objects



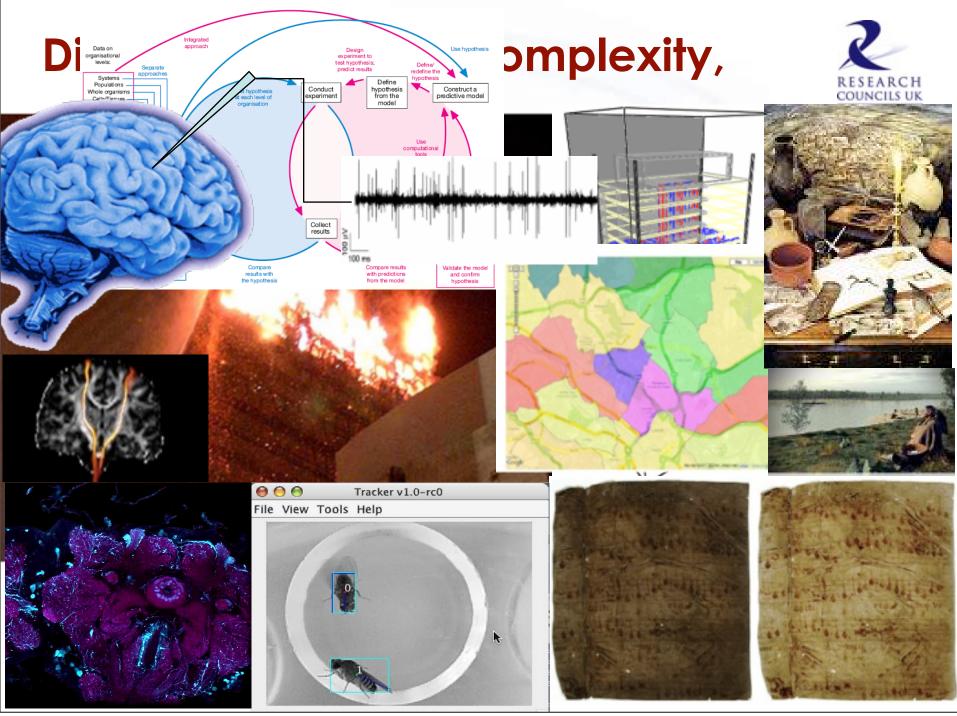
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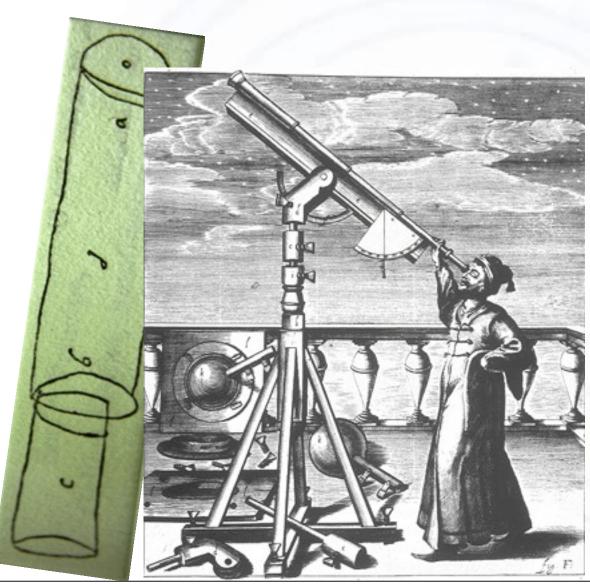




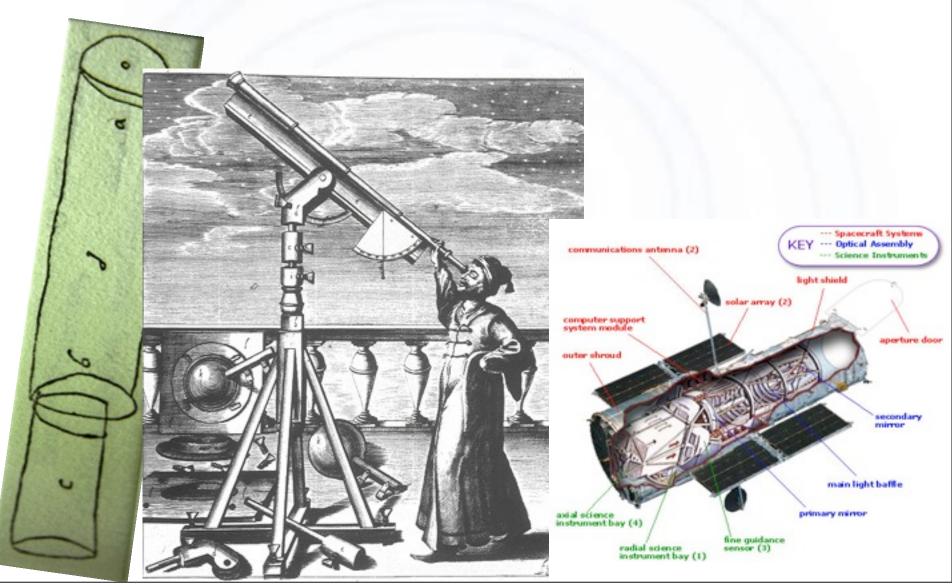




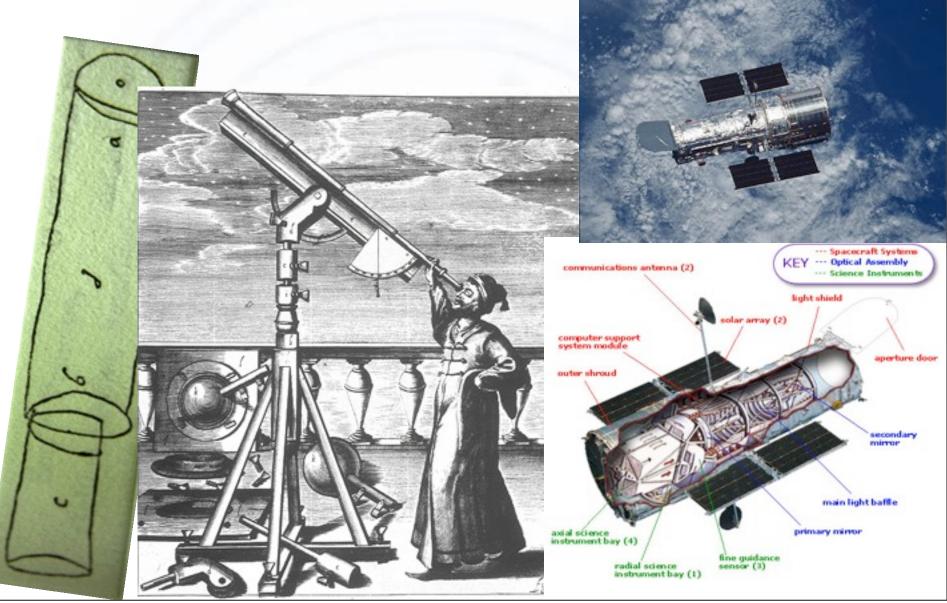




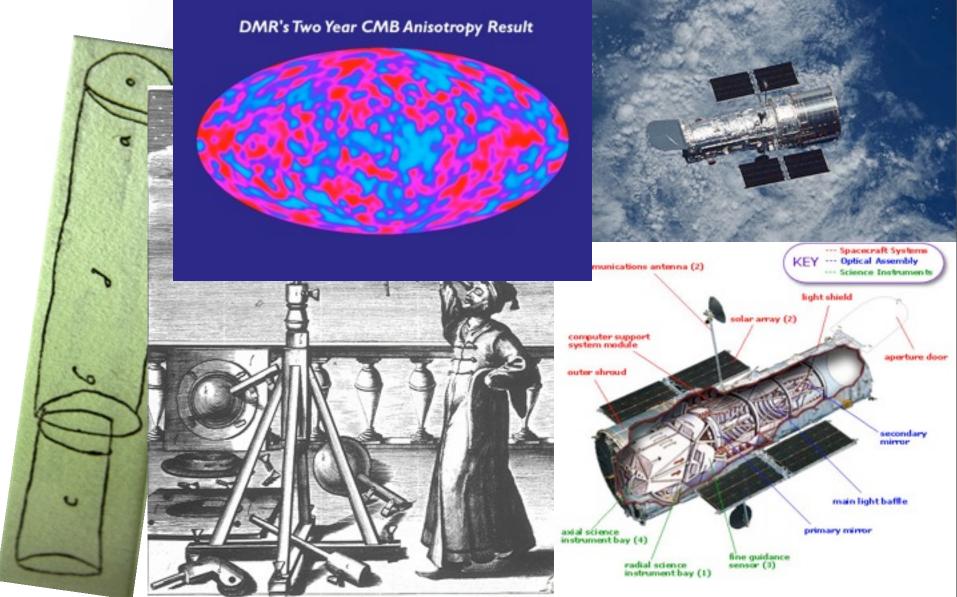




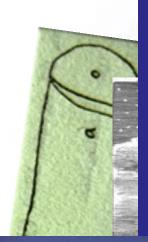


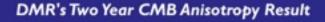


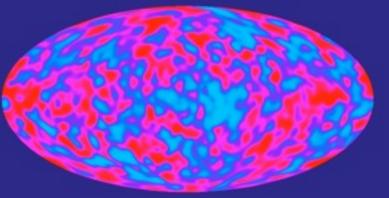




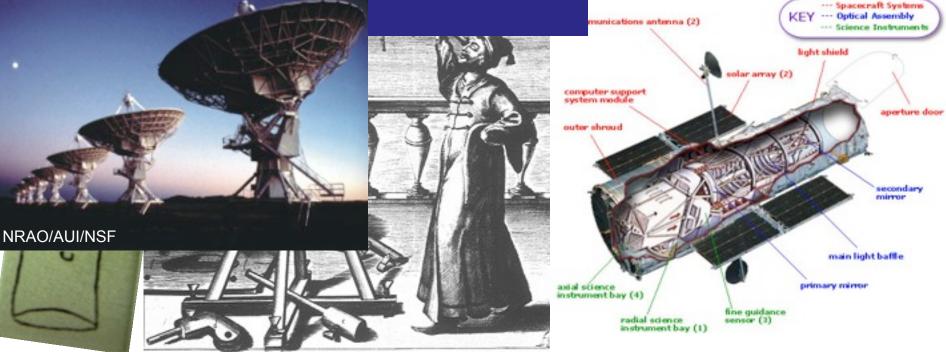




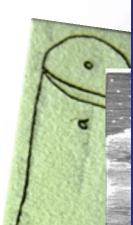


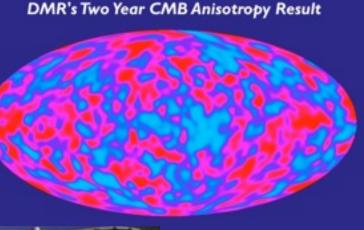










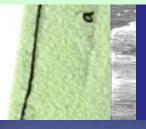


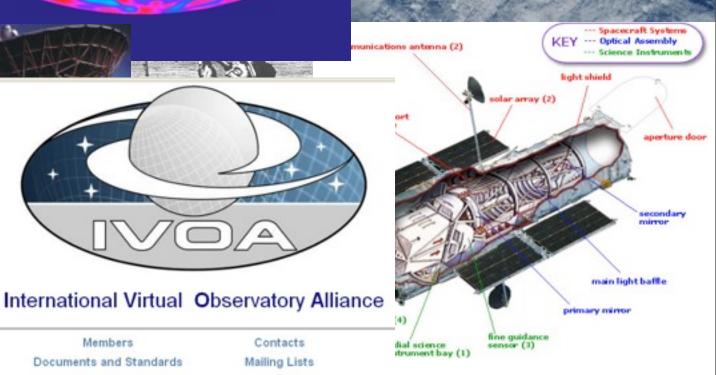




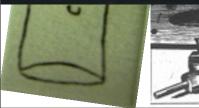


To reveal evidence in data you could never see before





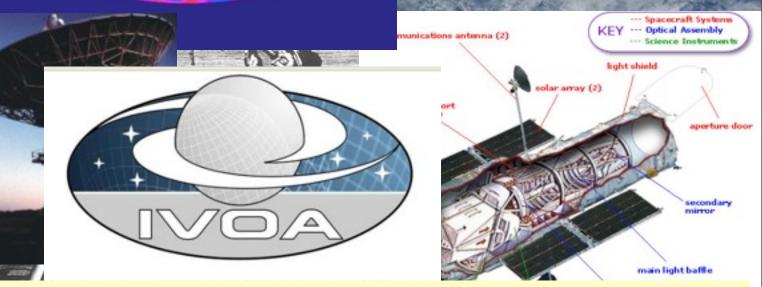






To reveal evidence in data you could never see before





Changed our place in the universe

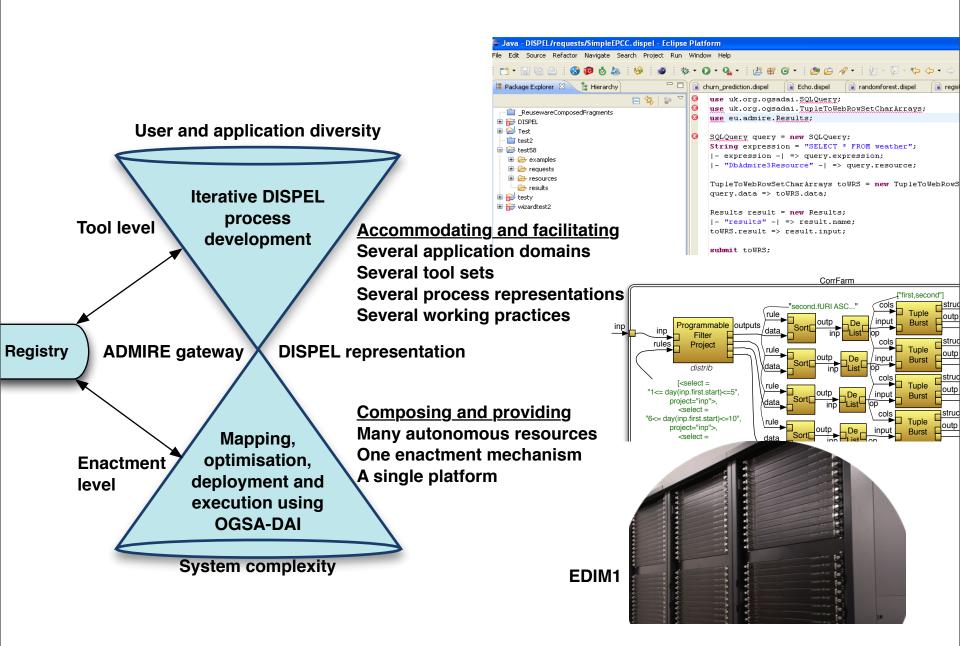
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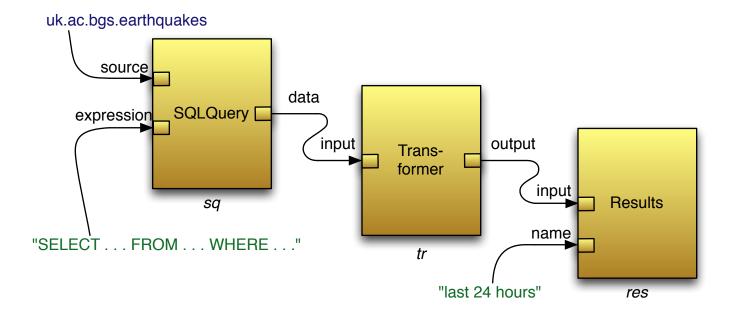


Data-Intensive Process Engineering Language

- A language for constructing data-flow graphs
 - Nodes are processing elements
 - Arcs are data-flow paths
- A language for generating data-flow patterns
 - Functions hide detail of graphs
 - Functions generate graphs
- A language for discussing data-flow engineering
 - Designed to be read and written by humans
 - As well as by programs
 - Supports validation and optimisation



A simple DISPEL graph



The DISPEL to Generate it

```
package book.examples.seismology {
  use dispel.db.SQLQuery;
  use book.examples.seismo.Transform;
  use dispel.lang.Results;
```

```
SQLQuery sq = new SQLQuery;
Transform tr = new Transform;
Results res = new Results;
```

```
sq.data => tr.input; // set up data flow from sq to tr
tr.output => res.input; // set up data flow from tr to res
|- "uk.ac.bgs.earthquakes" -| => sq.source; // URI of source of data
|- "SELECT ... FROM ... WHERE ..." -| => sq.expression; //query gets traces
|- "last 24 hours" -| => res.name; //name of results for user
```

submit res;

// submit for enactment

//set working context

//import PE SQLQuery

//import PE Transform

// new instance of SQLQuery

// new instance of Transform

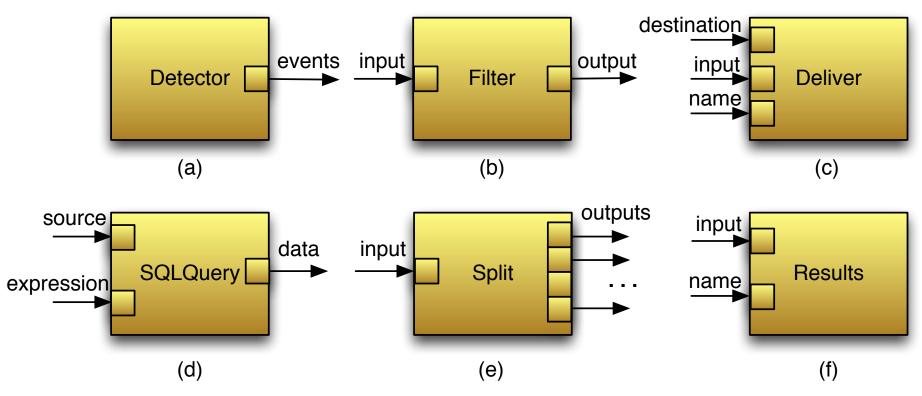
// new instance of Results

//import PE Results

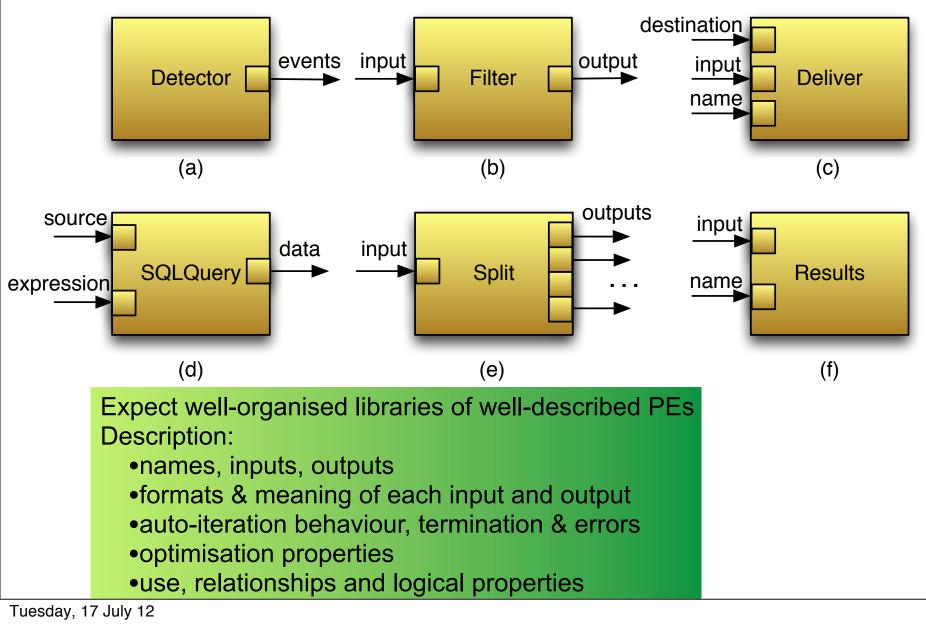
Who 'speaks' DISPEL

	Architectural Level		
	Tool	Gateway & DISPEL	Enactment
Domain Experts			
Data-Analysis Experts			
Data-Intensive Engineers			

Processing Elements



Processing Elements



Functions

- Algorithms to generate graphs
 - parametric variation
 - patterns
 - parameters
 - subgraphs
- Abstraction and Optimisation
 - smart methods for common patterns
 - hiding pattern implementation for stability
 - late evaluation permits contextual optimisation

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Expect well-organised libraries of well-described Functions Description:

•names, type signature

Enactment Model

1. DISPEL language processing

- 1.1. Validation & Import from Registry
- 1.2. Format & Meaning mis-match handling
- 1.3. Interpretation to generate graph

2. Graph optimisation & mapping

- 2.1. Re-ordering & Parallelisation
- 2.2. Identification of target locations
- 2.3. Selection of PE implementations / instances
- 2.4. Partitioning into co-located subgraphs

3. Deployment

4. Execution, Monitoring & Clean up







Ian J. Taylor, Ewa Deelman, Dennis B. Gannon, and Matthew Shields. Workflows for e-Science: Scientific Workflows for Grids. Springer London, 2007.



DISPEL is Different 1

• Spanning Distributed Independent Hosts

- Fragments of one workflow can run in different regimes
- Different security models
- Different file systems
- Different DBMS
- Different Operating Systems
- Different DISPEL implementations
- Agnostic about Size & Scale
 - Processing Elements of any size
 - Data values in streams of any size
 - Streams of any length
 - Graphs of any size

DISPEL is Different 2

- Patterns & Pattern Composition
 - Functions define & generate patterns
 - Higher-order functions compose patterns
 - Functions can be refined to optimise
- Component-Description Driven
 - Rich description of components
 - Capturing logical properties
 - Collecting component-builders' hints
- Restricted language for workflow longevity
 - Only hints and no WF-definition time concrete mappings
 - Late mapping permits optimisation and enactment, for the system is at execution time much different from definition time!

Summary and Conclusions



- DISPEL is an experimental data-intensive language
 - draws on workflows & database query internals
 - auto-iteration over values flowing through connections
 - agnostic about value sizes implementation challenge
 - controlled access to system information
 - optimisation based on description & operation
 - distributed termination protocol

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 - seven different application domains

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- Differences
 - functional pattern handling
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- Status
 - two implementations: to OGSA-DAI & to Java
 - much still to do to fully explore the ideas

www.verce.eu

research.nesc.ac.uk/node/828

www.ogsadai.org.uk

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ADMIRE - Framework 7 ICT

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Picture composition by Luke Humphry based on prior art by Frans Hals