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Instrumente Structurale
2014-2020

Description and execution of data processes in Cloud infrastructures



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Context

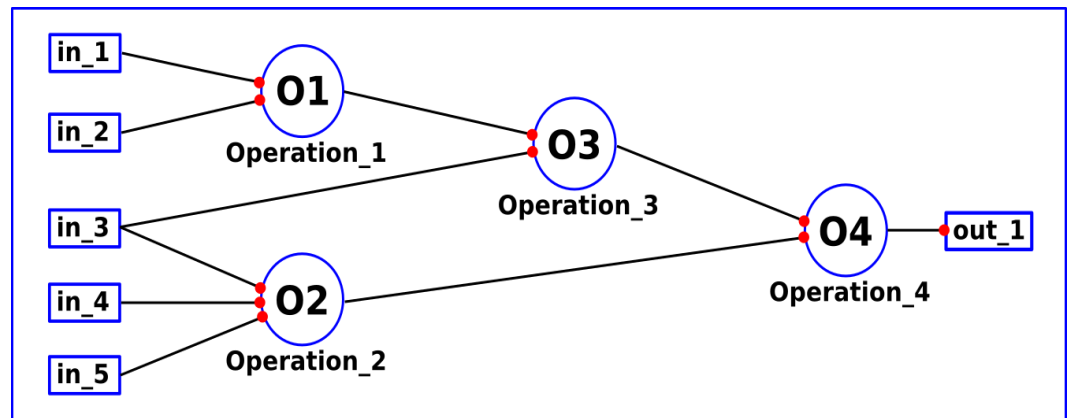
- Effective utilisation of high-performance computing (HPC) typically requires a great deal of expertise from the user
 - Software development
 - Parallel programming
 - Distributed systems
- This limits the pool of potential users or requires close collaboration between experts from various fields and those with a computer science background
- Improve the accessibility of Cloud resources – increase the pool of potential users
 - reduce the required skill set by abstracting away some of the more complex concepts

Objectives

- Facilitate access to HPC computing capabilities in the Cloud
 - Provide distributed data processing services to users with no computer science background
 - Simple and intuitive interface
 - Parallel processing of data in a user-transparent manner
- Reduce the overall processing time – exploit parallelism
 - Complex, multi-step and multi-layer data processing algorithms
 - Repetitive application of a process on multiple data sets or subsets
 - Serving multiple users, with multiple processes at the same

Process representation model

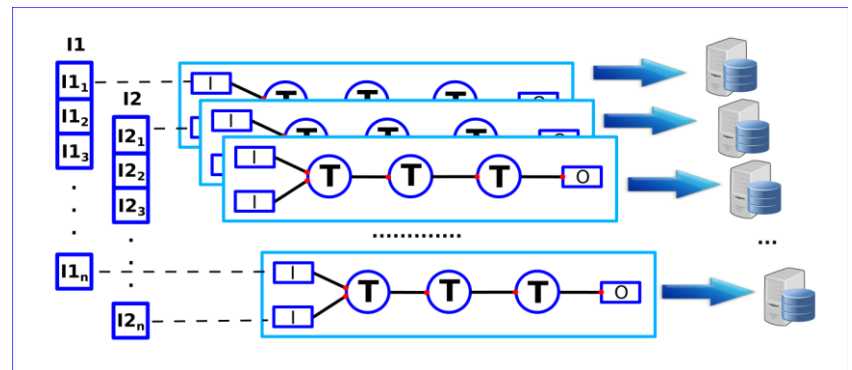
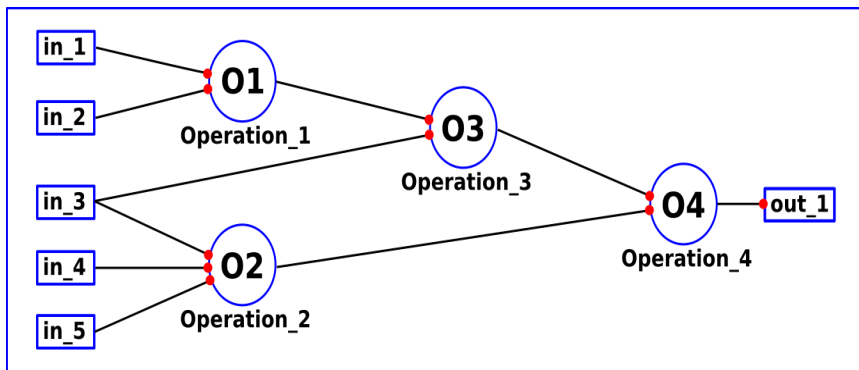
- Utilize a workflow-based model for representing data processing algorithms
 - Processing nodes
 - Input/Output ports
 - Data connections



- Workflow composed of atomic processing steps - operators
 - Based on predefined sets of operators, implemented as wrappers over domain-specific software applications
 - Coarse grained operations vs. simplified, abstract representation

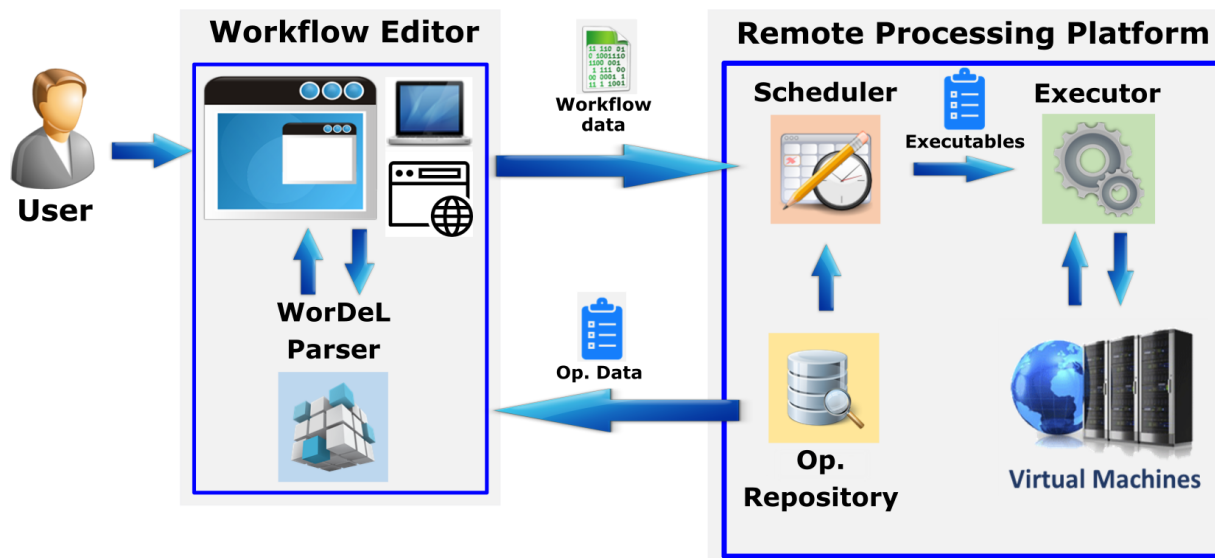
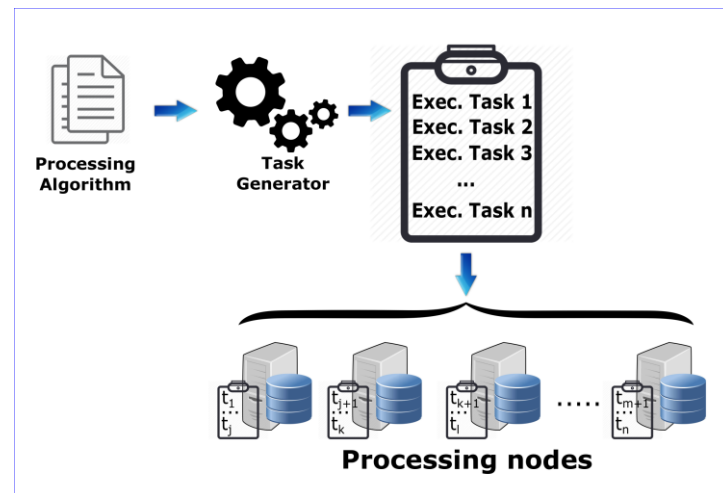
Process representation model

- Benefits of the workflow model:
 - Clean, intuitive and easy to follow visual representation
 - Effective means of design encapsulation and reuse
 - Standard interface for interconnecting workflows and operators
 - Simplifies the identification of parallelism opportunities:
 - Task level parallelism -> for complex, multi-step processes
 - Data level parallelism -> repeated application of a process on data subsets



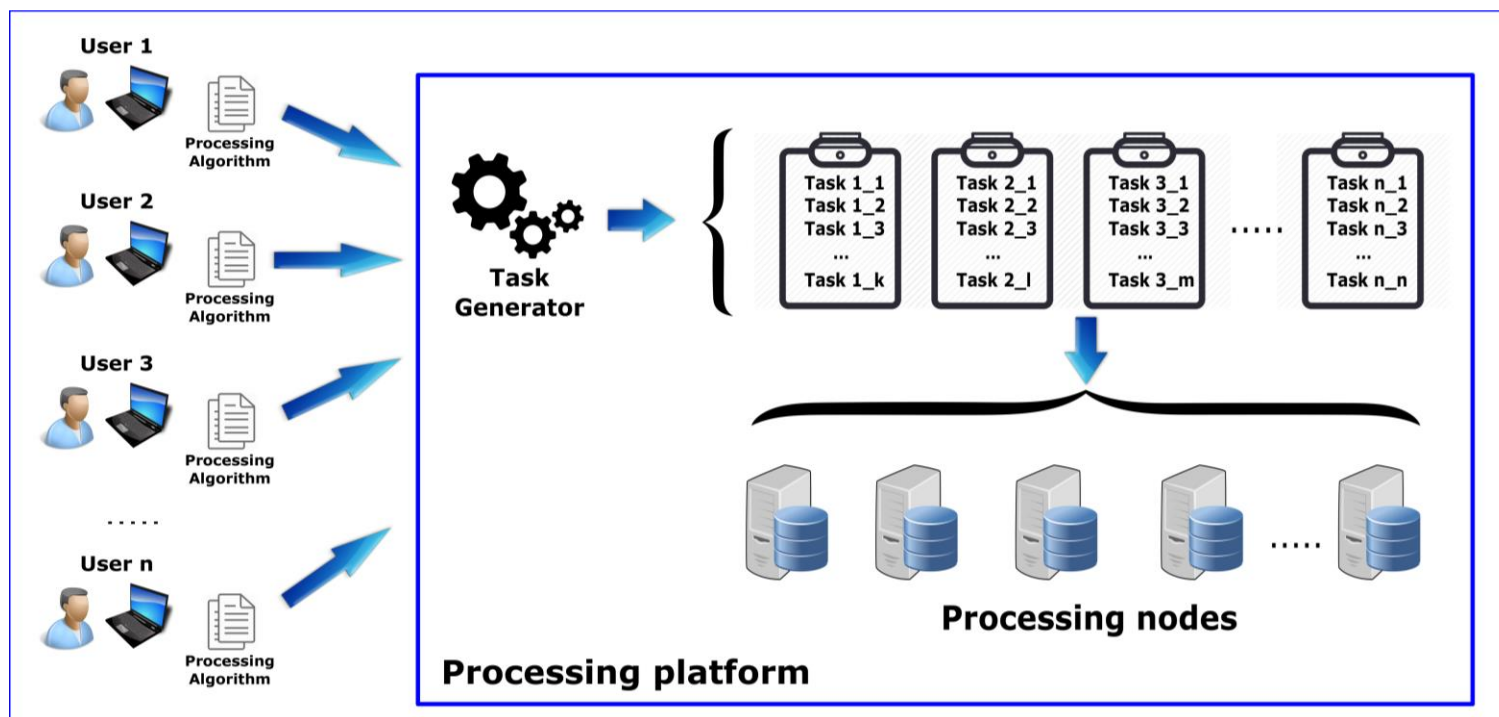
Implemented solution

- BigEarth Platform
 - Workflow Editor(WorDeL Parser)
 - Task Scheduler
 - Operator Repository (KEOPS)
 - Task Executor



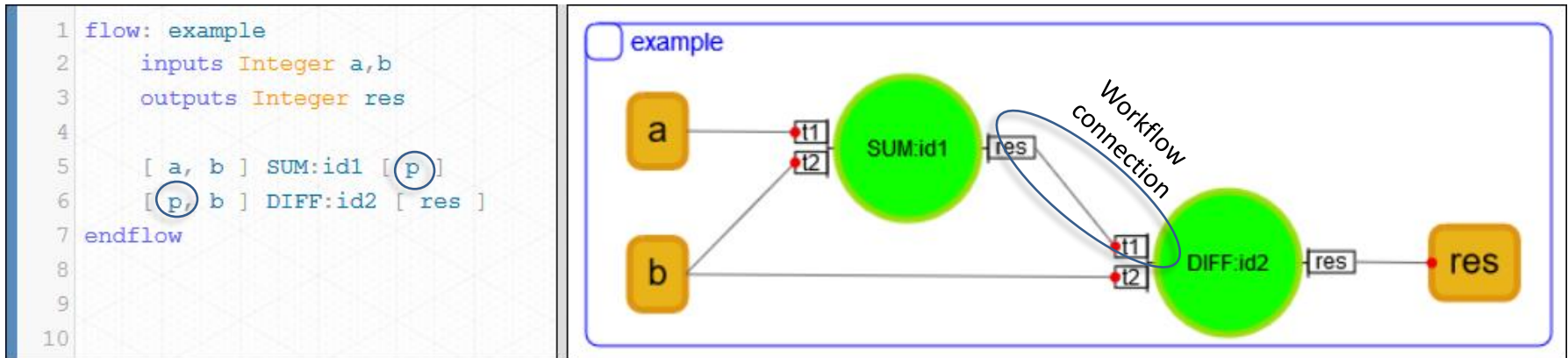
Implemented solution

- BigEarth Platform
 - Execute independent tasks in parallel
 - Handle tasks from multiple users
 - Increased system throughput



Workflow Topology

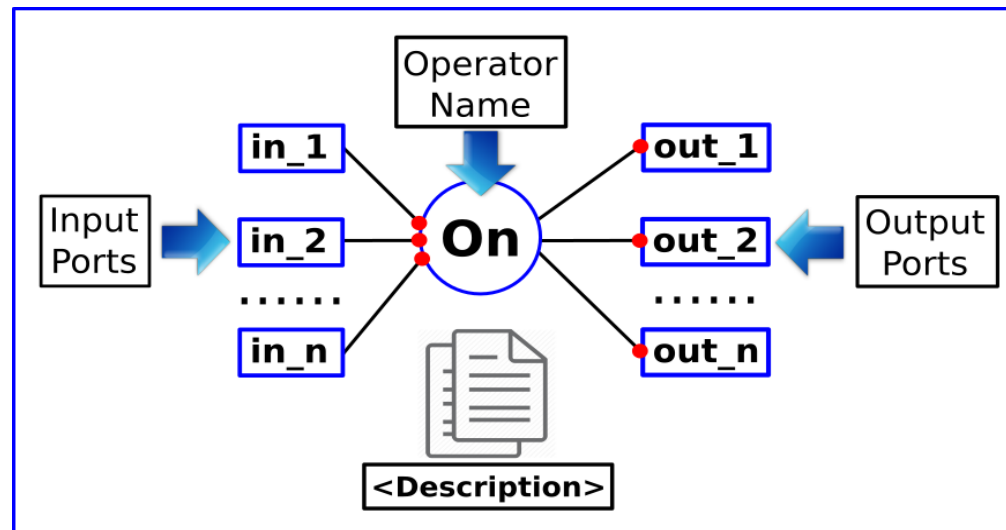
- Workflow Description Language -> **WorDeL**
 - Dedicated description language
 - Simple syntax to allow novice users to define linear workflows with little effort and minimal training [1]
 - Synchronized graphical representation



[1] Nandra C. and Gorgan D., „Usability evaluation of a domain-specific language for defining aggregated processing tasks”, in Proceedings of the 15th Intelligent Computer Communication and Processing (ICCP), September 2019, DOI: 10.1109/ICCP.2018.8516594

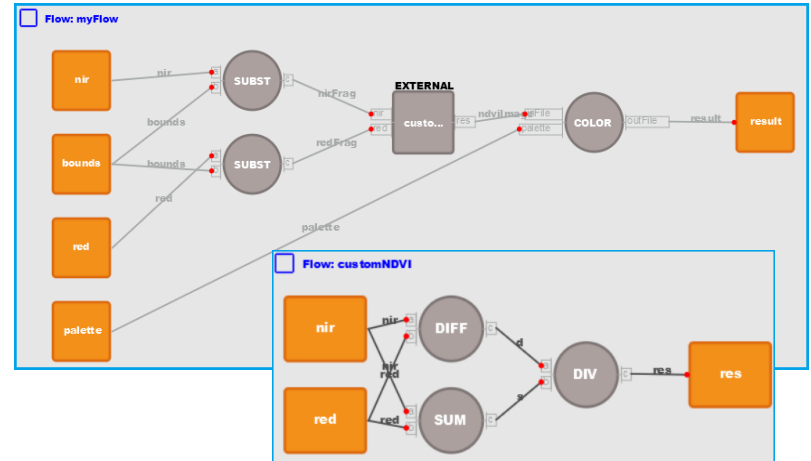
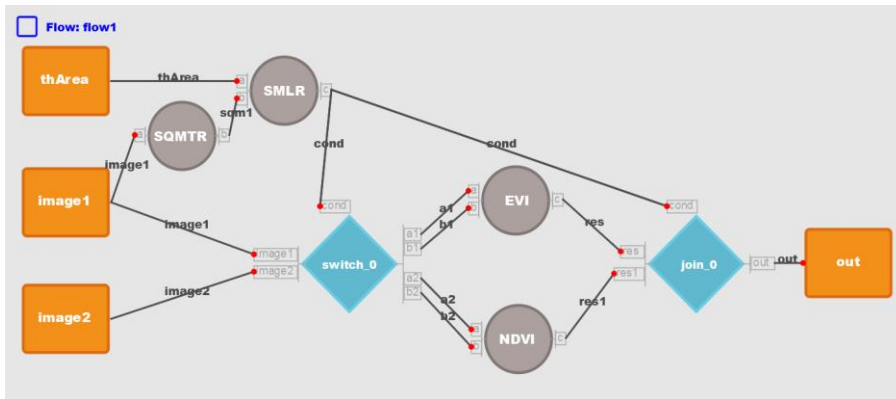
Workflow Topology - operators

- Abstraction mechanism
 - Provides the means of building a standardized interface for the various specialized software tools employed by users
 - Black-box view -> allows their incorporation into workflows

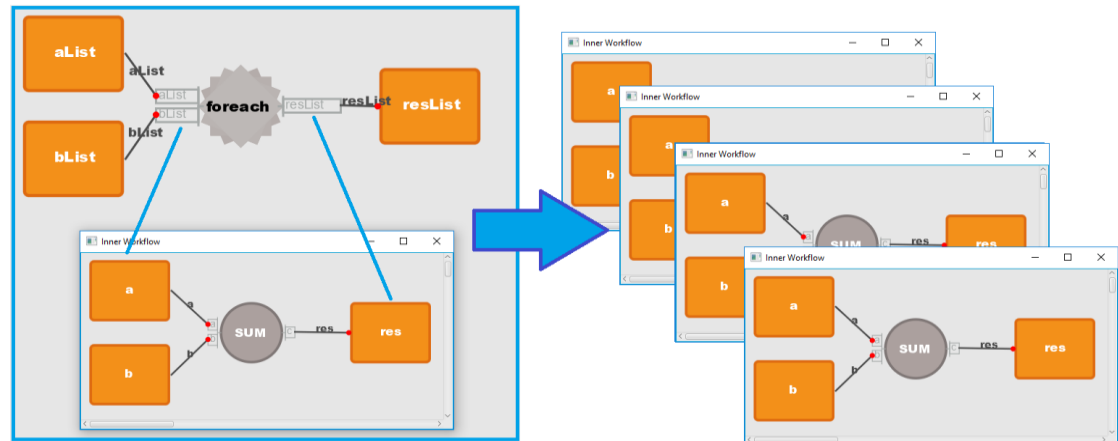


WorDeL Features

Workflow incapsulation



Conditional structures



Repetitive structures

Use case – satellite image processing

- Compute Normalized Vegetation Index (NDVI)

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

- Use standalone application *GRASS GIS* as a processing software
 - Operators – shell scripts accessing GRASS functions

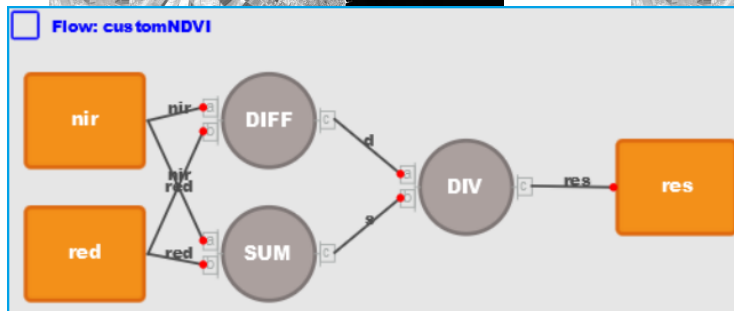
NIR (Near-Infrared) Band



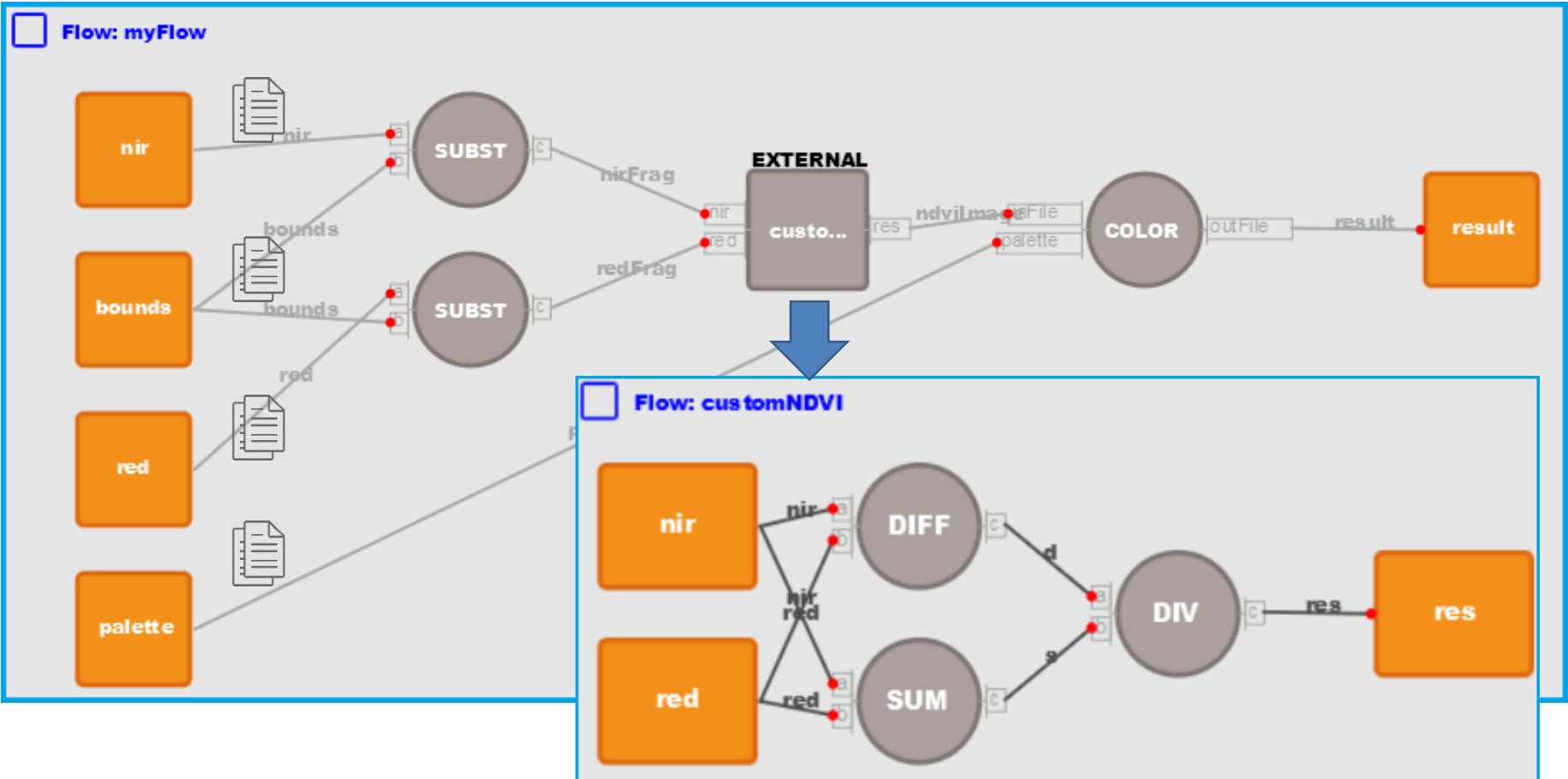
Red Band



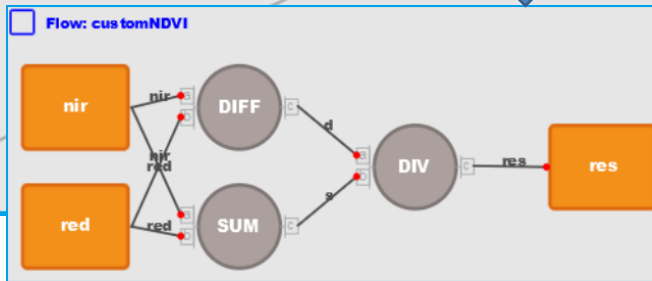
NDVI (Pseudo-color)



Use case – satellite image processing

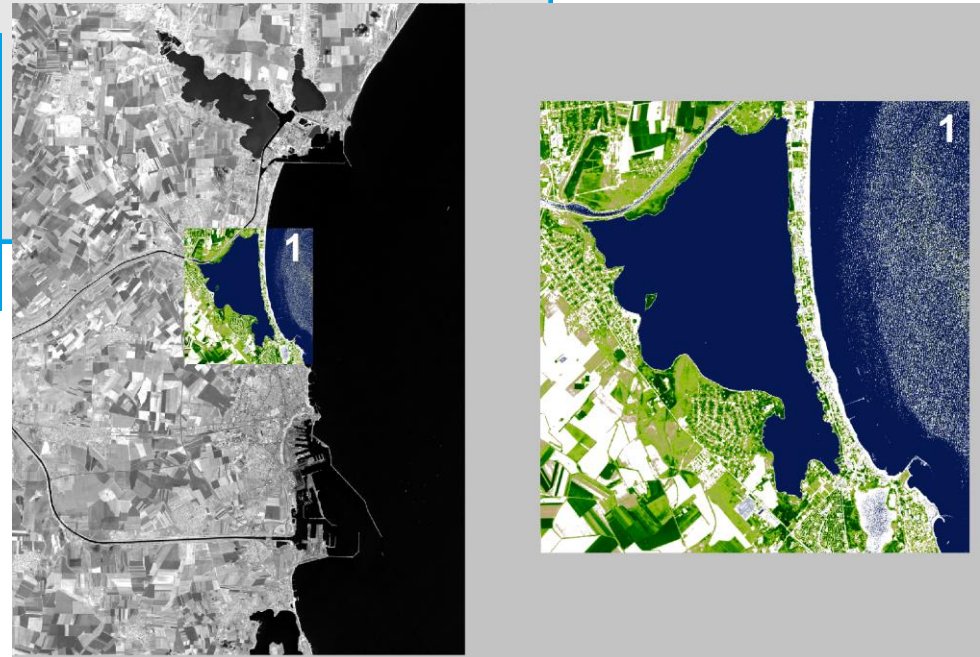


Use case – satellite image processing



```

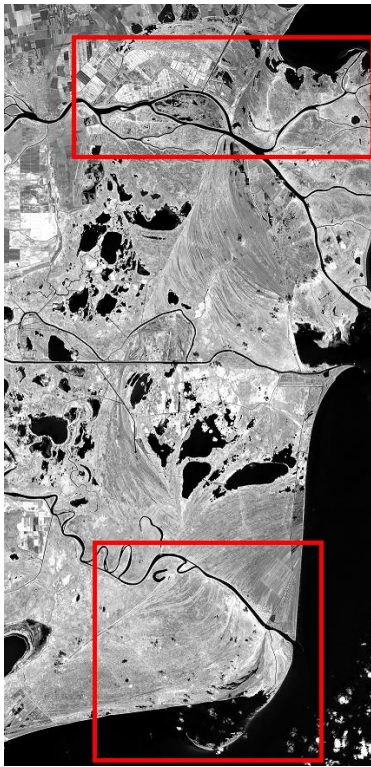
1 flow: customNDVI
2   inputs File nir, red
3   outputs File result
4
5   [ nir, red ] DIFF:op1 [ d ]
6   [ nir, red ] SUM:op2 [ s ]
7   [ d, s ] DIV:op3 [ result ]
8 endflow
  
```



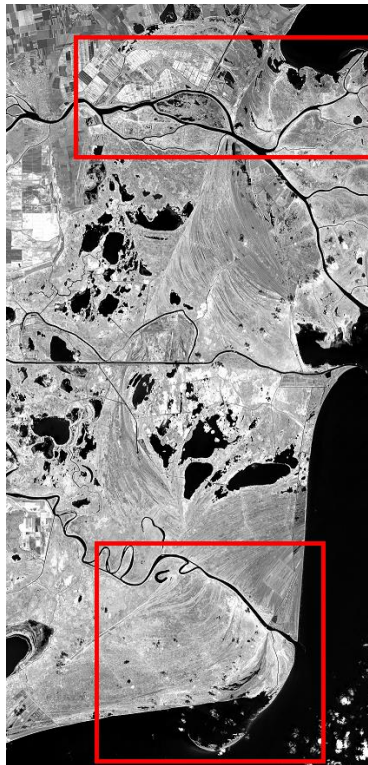
Use case – satellite image processing

- Repeated application of NDVI on a set of image regions

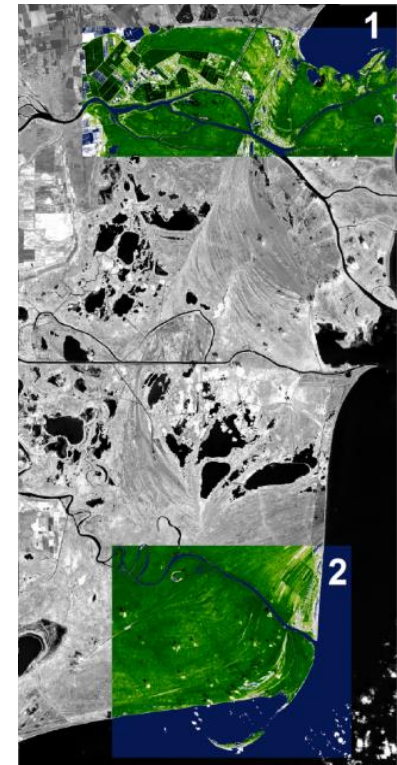
NIR (Near-Infrared) Band



Red Band

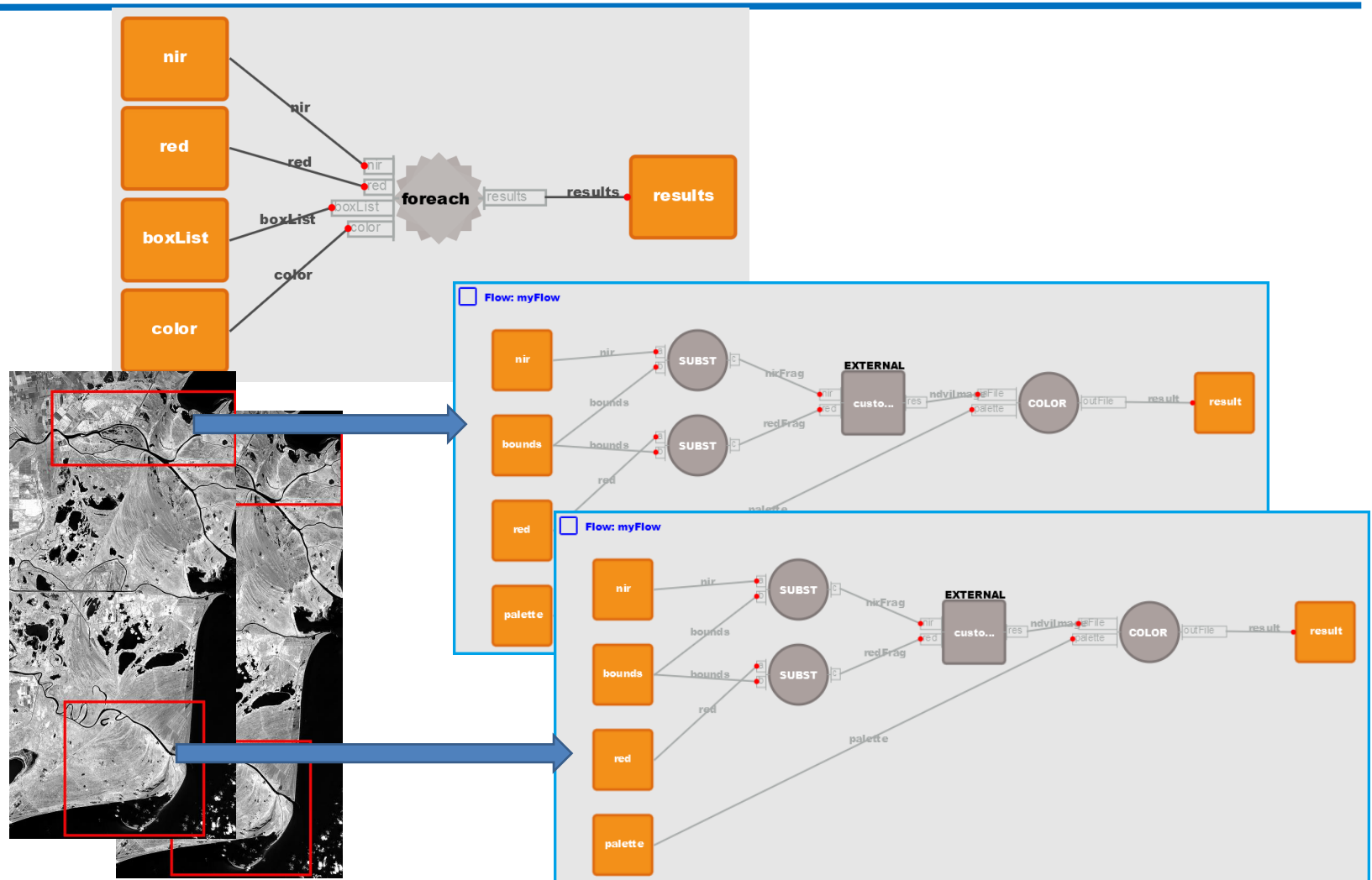


NDVI (Pseudo-color)

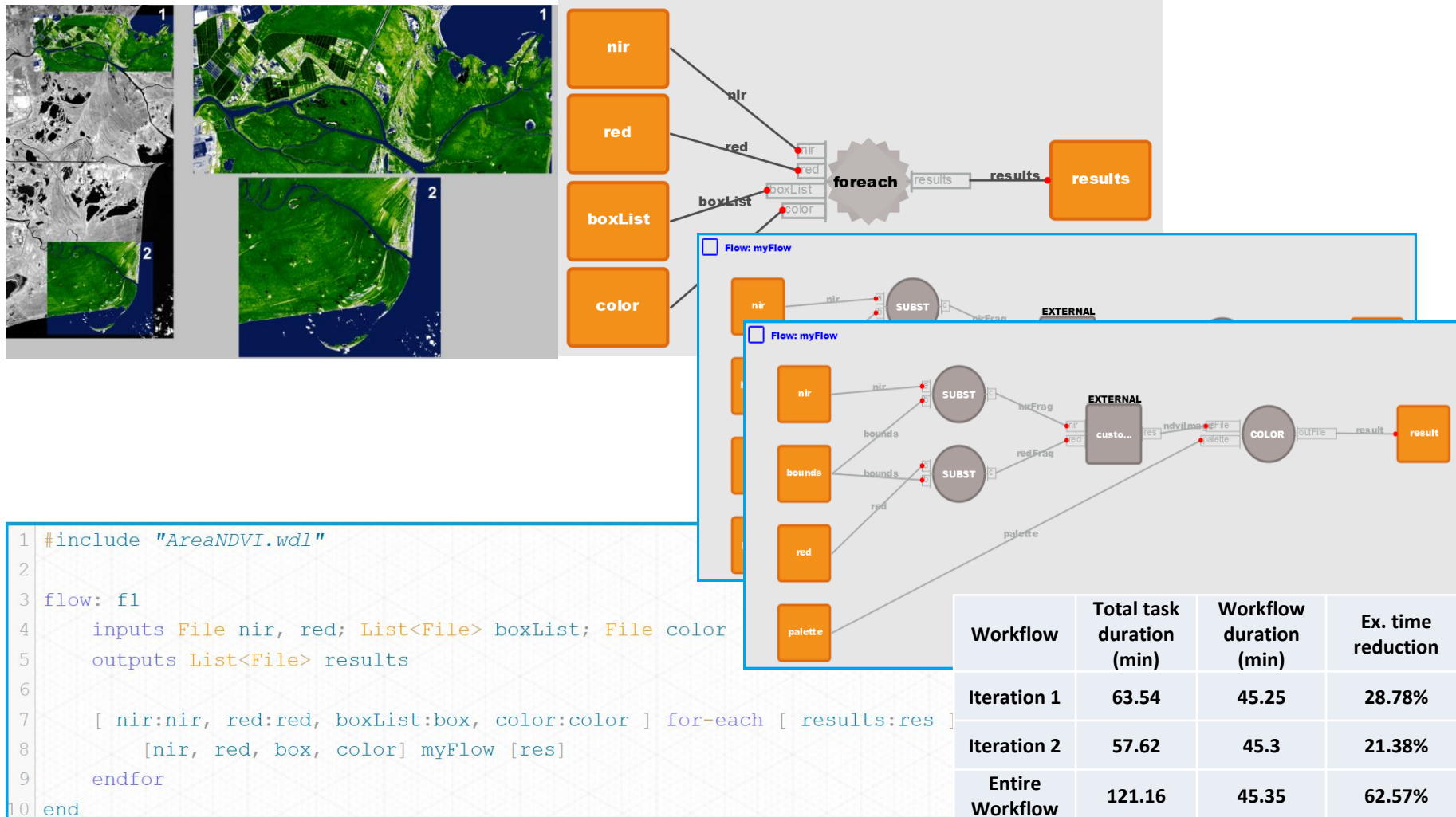


Nandra C., Bacu V., Gorgan D. "Parallel Earth Data Tasks Processing on a Distributed Cloud Based Computing Architecture", in Proceedings of the 21st International Conference on Control Systems and Computer Science (CSCS), May 2017, pp 677-684, DOI: 10.1109/CSCS.2017.104, ISBN: 978-1-5386-1839-4

Use case – satellite image processing



Use case – satellite image processing



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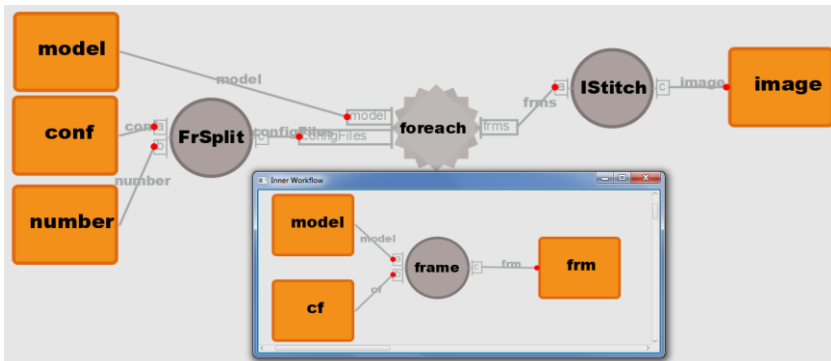
Use case – 3D scene rendering

- Parallel rendering of images and image series (movie frames) from a demo 3D scene built in *Blender*
 - Built operators as wrappers around Blender – call rendering engine
 - Extra operators for splitting the input domain and stitching the partial results



Nandra C., Bacu V., Gorgan D., „Distributed, Workflow-Driven Rendering of 3D Object Scenes on a Big Data Processing Platform”, Proceedings of 2018 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR), May 2018, pp 1-6, DOI: 10.1109/AQTR.2018.8402773, ISBN: 978-1-5386-2205-6

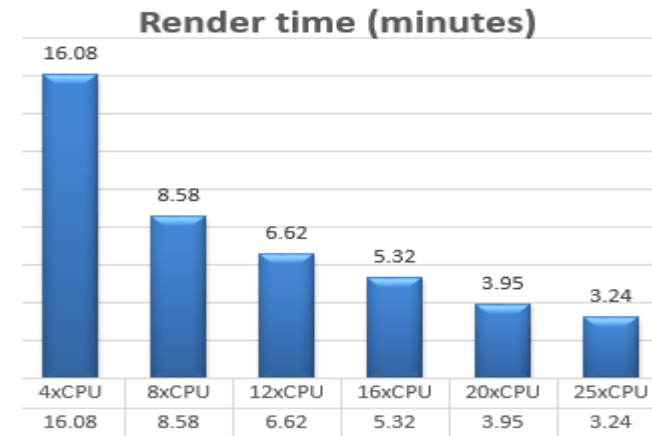
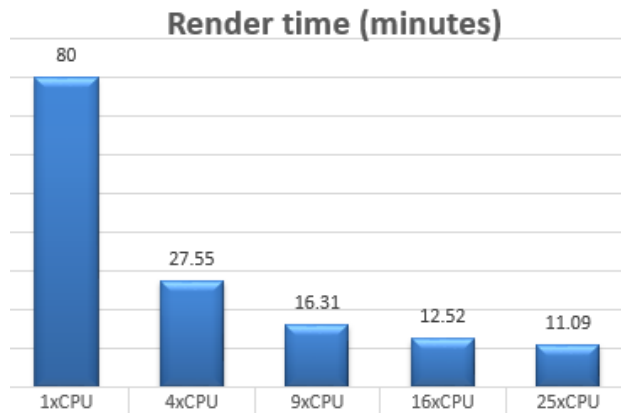
Use case – 3D scene rendering



```
1 flow: render
2   inputs File model, conf, number
3   outputs File image
4
5   [ conf, number ] FrSplit:o1 [ configFiles ]
6
7   [ model:model, configFiles:c ] for-each [ fragments:frag ]
8     [ model, c ] frame:o2 [ frag ]
9   end
10
11   [ frag ] IStitch:o3 [ image ]
12 endflow
```

Nandra C., Bacu V., Gorgan D., „Distributed, Workflow-Driven Rendering of 3D Object Scenes on a Big Data Processing Platform”, Proceedings of 2018 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR), May 2018, pp 1-6, DOI: 10.1109/AQTR.2018.8402773, ISBN: 978-1-5386-2205-6

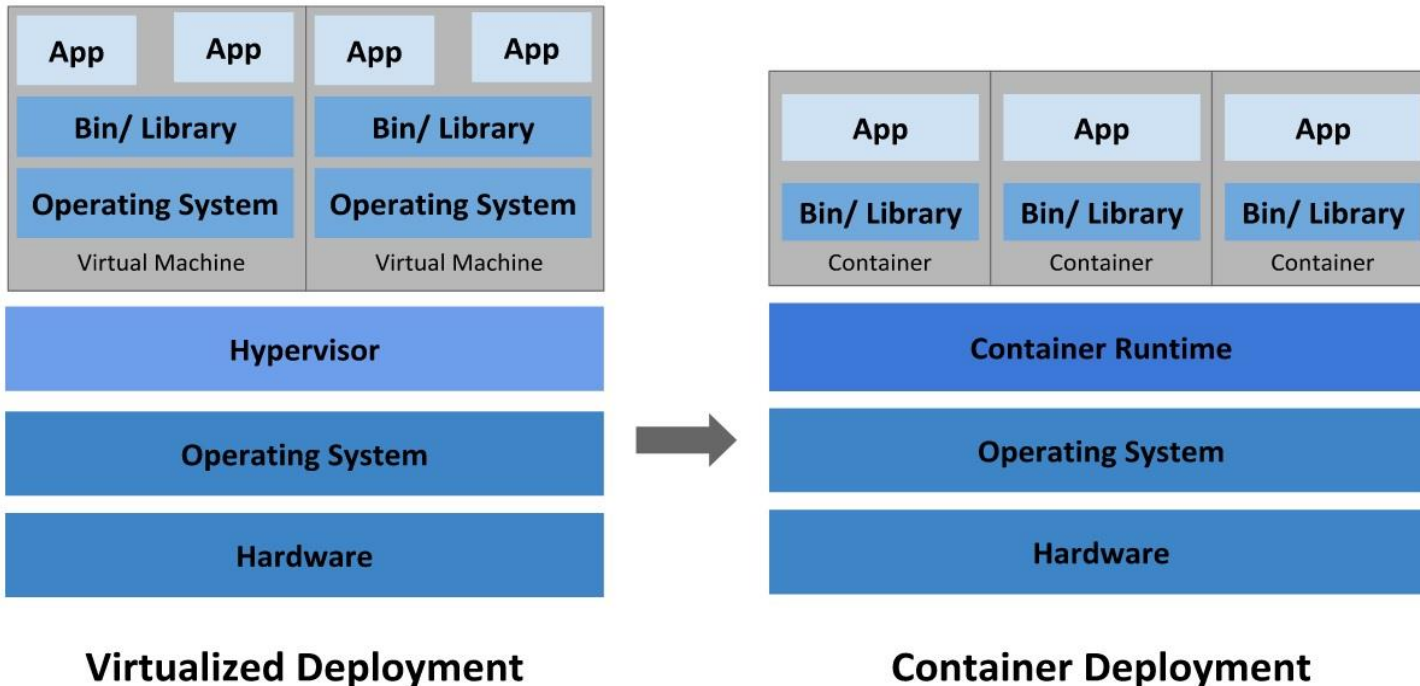
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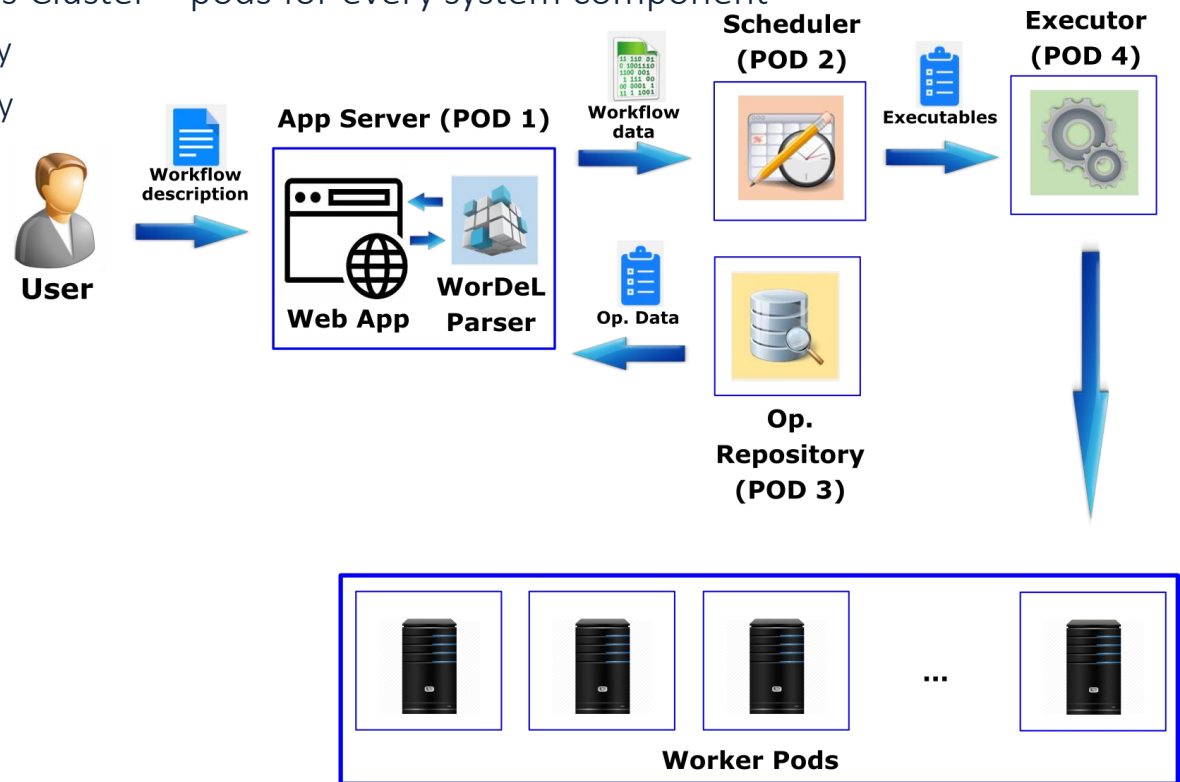
In development

- Migrate the old VM-based solution to a container-based environment
 - Flexible application modules (operators), ready to deploy
 - User-provided software tools (new operators)



In development

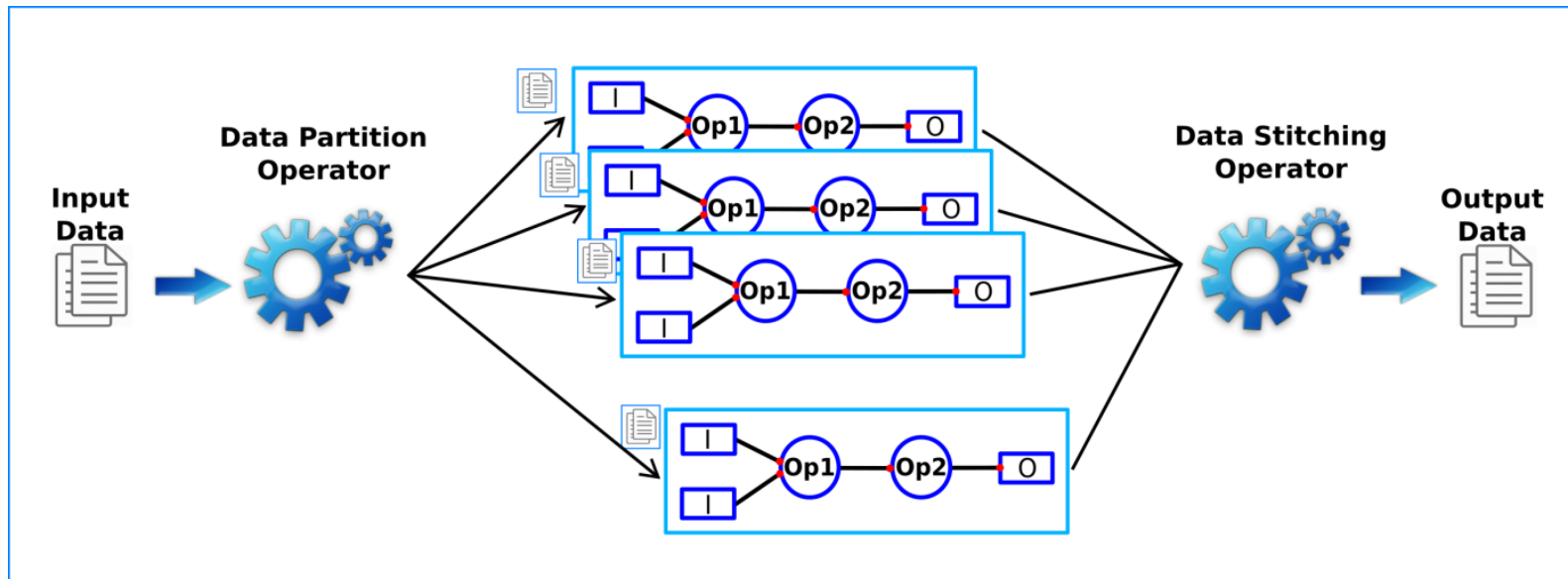
- Define, execute and monitor workflows within a network of worker nodes
 - The main system components first developed for BigEarth → incapsulate and deploy on Docker containers
 - Use docker containers for the software tools behind the operators
 - Configure a Kubernetes Cluster – pods for every system component
 - Improved scalability
 - Software availability



Future developments

1. Map-Reduce processing mechanism

- Automated deployment of the process repetition mechanism
 - On multiple sets of data
 - On subsets of the original data



Future developments

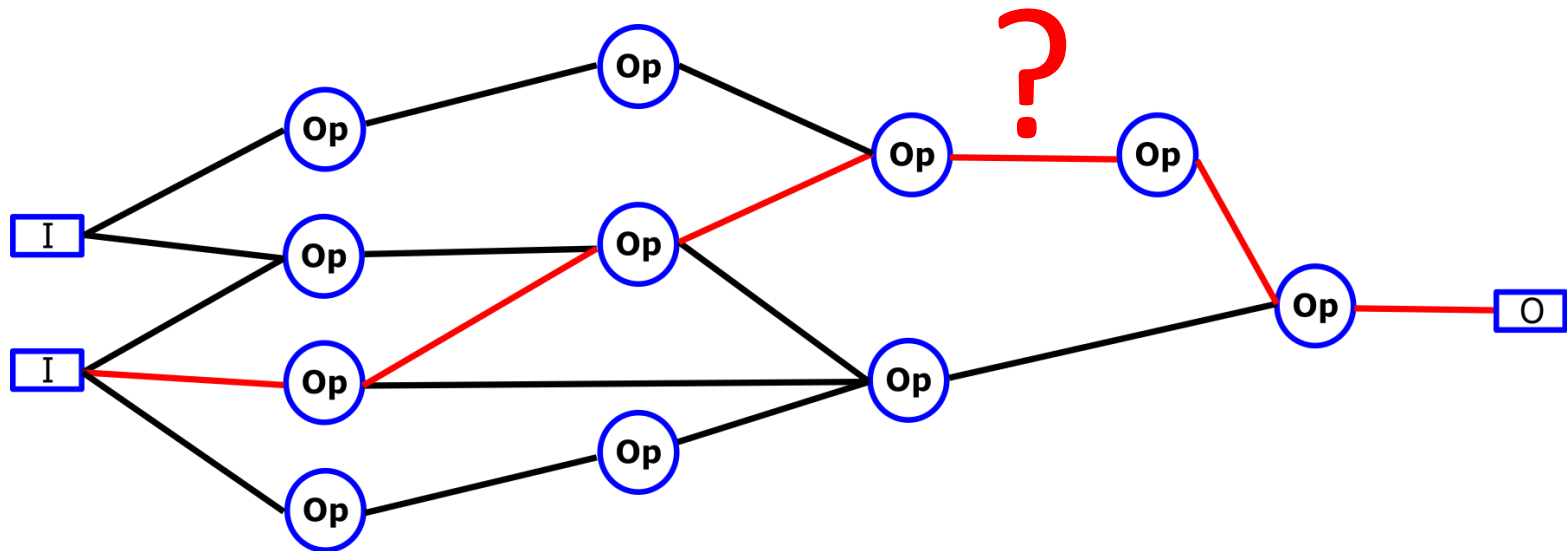
1. Map-Reduce processing mechanism

- Eliminate the need for user-defined “for-each” nodes
 - Can be complex for novice users
 - Should be handled by the system where possible
- Challenges
 - Rely on specially designated operators for data partitioning/aggregation
 - Mark out the processes (workflows/operators) that can be applied on data subsets without altering the final result
- Benefits
 - Simplified workflow structure
 - User-transparent handling of data-level parallelism
 - Employ existing functionality for dynamic workflow generation/execution

Future developments

2. Task scheduling and execution optimization

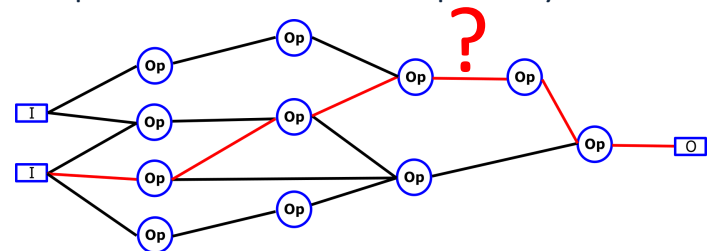
- Find critical path in workflow – what operations to prioritize?
 - Operations can vary wildly in complexity and execution time
 - Should rely on a time estimate for each operator instance



Future developments

2. Task scheduling and execution optimization

- Build a prediction model for operator execution time
 - Account for operator's algorithmic complexity
 - Factor in the input data size
 - Gather data on previous operator performance
 - Correlations: Data set size ➡ Execution time
- Machine learning techniques
 - Regression – compute execution time estimate
 - Neural Networks – classify black-box operations into complexity categories



Conclusions

- Solution for mass processing of data within a Cloud
 - Leverage the Cloud's resources to reduce processing time
 - Addressed to users lacking advanced programming knowledge
 - Can automate the distribution and execution of processing tasks within a network of nodes => transparent setup and management
 - Can incorporate any software tools as “black-box” operators
 - As long as they provide a command-line interface

Conclusions

- Solution for mass processing of data within a Cloud
 - Proof-of-concept => the BigEarth platform
 - Applications in the area of Earth data processing
 - Extensible by means of new operators
 - Wrappers around use-case specific software tools
 - Operators deployable by means of containers (in development)
 - Planned features:
 - Map-reduce mechanism => automated generation of parallel tasks
 - Scheduling optimization => prediction of operator execution time



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Thank you for your attention!



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