

# Challenges for Scheduling Scientific Workflows on Cloud Functions

Joanna Kijak, Piotr Martyna, Maciej Pawlik, Bartosz Balis and **Maciej Malawski** 

> Department of Computer Science, AGH University of Science and Technology al. Mickiewicza 30, 30-059 Kraków, Poland





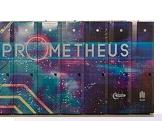
#### Outline

- Motivation: scientific workflows in clouds
- Experiments with HyperFlow
- Scheduling challenges
- Experiments with SDBWS algorithm
- Results on AWS Lambda
- Conclusions



#### **DICE Team**

- Investigation of methods for building complex scientific collaborative applications
- Elaboration of environments and tools for e-Science
- Integration of large-scale distributed computing infrastructures
- Knowledge-based approach to services, components, and their semantic composition





**AGH University of Science and Technology (1919)** 

16 faculties, 36000 students; 4000 employees <a href="http://www.agh.edu.pl/en">http://www.agh.edu.pl/en</a>





120 employees

http://www.cyfronet.pl/en/



2000 students, 200 employees

http://www.iet.agh.edu.pl/



http://dice.cyfronet.pl

**Department of Computer Science AGH (1980)** 



800 students, 70 employees

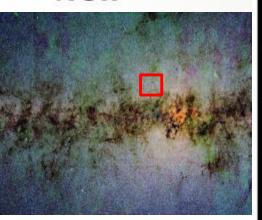
http://www.ki.agh.edu.pl/uk/index.htm

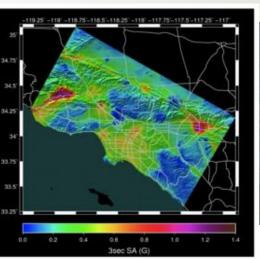
Other 15 faculties

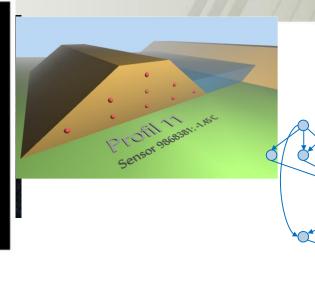




#### Motivation: Scientific Workflows

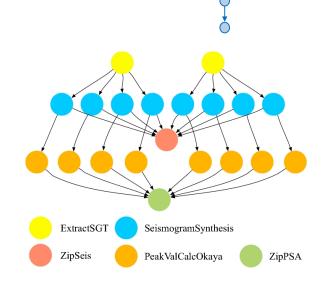






 Astronomy, Geophysics, Genomics, Early Warning Systems ...

- Workflow = graph of tasks and dependencies, usually directed acyclic graph (DAG)
- Granularity of tasks
  - Large tasks (hours, days)
  - Small tasks (seconds, minutes)





# Infrastructure – from clusters to clouds

- Traditional HPC clusters in computing centers
  - Job scheduling systems
  - Local storage





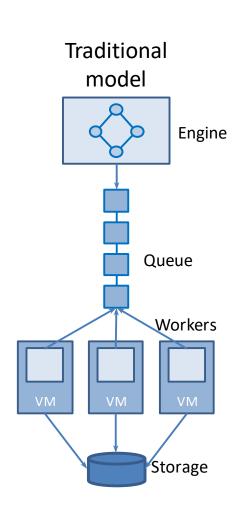
- Infrastructure as a service
- Globally distributed
- Virtual machines (VMs)
- On-demand
- Cost in \$\$ per time unit





# Workflow execution model in (traditional) clouds

- Workflow engine manages the tasks and dependencies
- Queue is used to dispatch ready tasks to the workers
- Worker nodes are deployed in Virtual Machines in the cloud
- Cloud storage such as Amazon S3 is used for data exchange
- Examples
  - Pegasus, Kepler, Triana, Pgrade,
     Askalon, ...
  - HyperFlow (AGH Krakow)

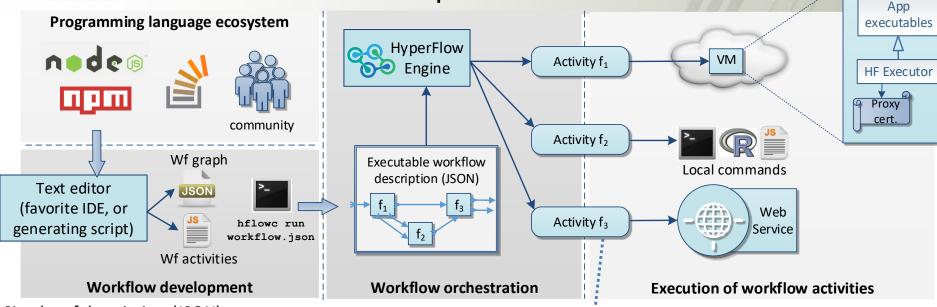




HyperFlow

Lightweight workflow programming and execution

environment developed at AGH



Simple wf description (JSON)

```
"name": "PlotDataStatistics".
"processes": [ {
  "name":
              'ComputeStats",
 "ins":
             [ "data.csv" ],
  "outs":
               "stats.txt" ]
  "config":
    "executor": {
     "executable": "cstats.sh",
     "args": "data.csv -o stats.txt"
}, {
  "name":
              "PlotChart",
              [ "stats.txt" ],
  "outs":
               "stats.png" ].
 "config":
     "executor": {
       "executable": "plot.sh",
       "args": "stats.txt"
 } ]
```

Advanced programming of wf activities (JavaScript)

```
function getPathWayByGene(ins, outs, config, cb) {
  var geneId = ins.geneId.data[0],
    url = ...

http({"timeout": 10000, "url": url },
  function(error, response, body) {
    ...
    cb(null, outs);
  });
}
```

Running a workflow – simple command line client

hflowc run <workflow\_dir>

<workflow dir> contains:

- File workflow.json (wf graph)
- File workflow.cfg (wf config)
- Optionally: file functions.js (advanced workflow activities)
- Input files



# New challenges – serverless architectures

- Serverless no traditional VMs (servers)
- Composing of applications from existing cloud services
  - Typical example: web browser or mobile device interacting directly with the cloud
- Examples of services:
  - Databases: Firebase, DynamoDB
  - Messaging: Google Pub/Sub
  - Notification: Amazon SNS
- Cloud Functions:
  - Run a custom code on the cloud infrastructure



#### Cloud Functions – good old RPC?

- Examples:
  - AWS Lambda
  - Google Cloud Functions (beta)
  - Azure Functions
  - IBM Bluemix OpenWhisk
- Functional programming approach:
  - Single function (operation)
  - Not a long-running service or process
  - Transient, stateless
- Infrastructure (execution environment) responsible for:
  - Startup
  - Parallel execution
  - Load balancing
  - Autoscaling



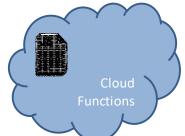
deploy

execute

- Triggered by
  - Direct HTTP request
  - Change in cloud database
  - File upload
  - New item in the queue
  - Scheduled at specific time



- Node.js, Java, Python
- Custom code, libraries and binaries can be uploaded
- Fine-grained pricing
  - Per 100ms \* GB (Lambda)







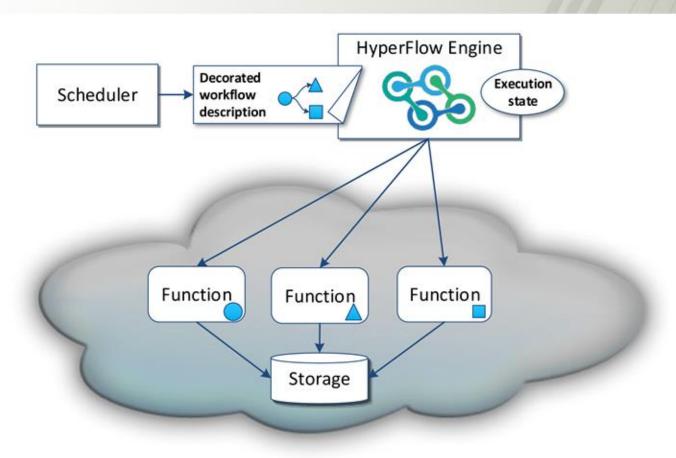


### Scheduling challenges

- Which size of cloud functions should be allocated to each task of a workflow?
- Which tasks should be executed on FaaS and which ones on IaaS?
- What is the performance variability of the cloud functions infrastructure and how to deal with it?
- What are the limits of concurrency that we can expect when running multiple tasks as cloud functions in parallel?
- How to address the problem of data transfer between tasks?



#### **Execution model**



[9] B. Baliś. Hyperflow: A model of computation, programming approach and enactment engine for complex distributed workflows



# Serverless Deadline-Budget Workflow Scheduling

- Adaptation of existing DBWS[2] heuristic for serverless model
- Finds mapping between tasks and resources (cloud functions) to meet the deadline constrait and tries to meet the budget constraint
- Assumes the knowledge of task runtime estimates on each resource type



## Idea of algorithm

 For each workflow level compute the maximum execution time

$$Level_{execution}^{j} = \max_{l(t_i)==j} \{ET_{max}(t_i)\}$$

• We divide the deadline into sub-deadlines for each level:

$$Level_{DL}^{j} = Level_{DL}^{j-1} + D_{user} * \frac{Level_{execution}^{j}}{\sum_{1 \leq j' \leq l(t_{exit})} Level_{execution}^{j'}}$$



#### Resource selection

Resource selection is based on the time and cost:

$$Time_{Q}(t_{cur}, r) = \frac{\xi * S_{DL}(t_{cur}) - FT(t_{cur}, r)}{FT_{max}(t_{cur}) - FT_{min}(t_{cur})}$$

$$Cost_{Q}(t_{cur}, r) = \frac{Cost_{max}(t_{cur}) - Cost(t_{cur}, r)}{Cost_{max}(t_{cur}) - Cost_{min}(t_{cur})} * \xi$$

$$\xi = \begin{cases} 1 & \text{if } FT(t_{cur}, r) < S_{DL}(t_{cur}) \\ 0 & \text{otherwise} \end{cases}$$



## Resource selection (2)

We select the resource which maximizes the quantity:

$$Q(t_{cur}, r) = Time_Q(t_{cur}, r) * (1 - C_F) + Cost_Q(t_{cur}, r) * C_F$$

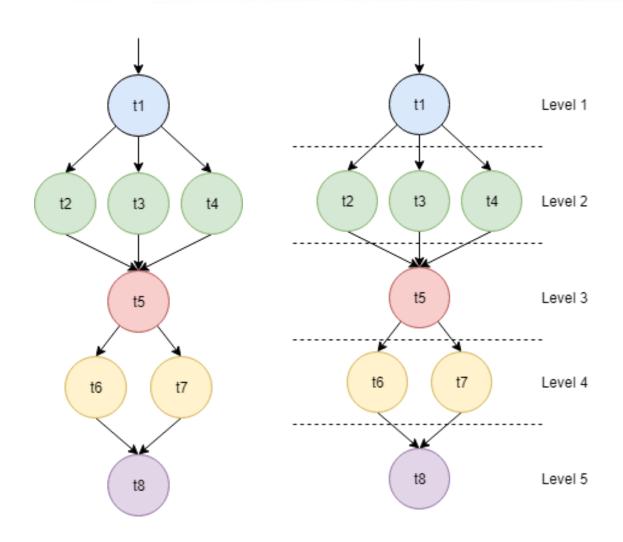
Where CF is a cost factor:

$$C_F = \frac{Cost_{low}(DAG)}{B_{user}}$$

- It represents user preferences:
  - Lower value means we prefer to pay more for faster execution
  - Higher value means we prefer cheaper and slower solutions



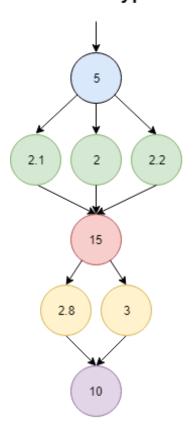
# Example DAG



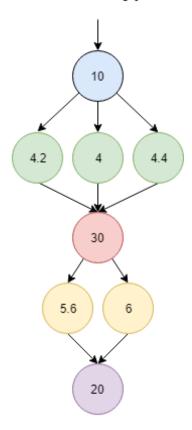


#### Task runtime estimates

#### Function Type 1

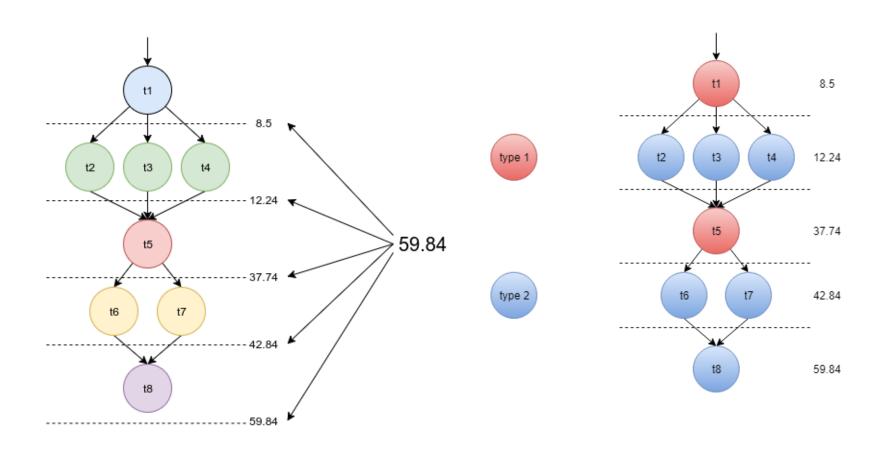


#### Function Type 2

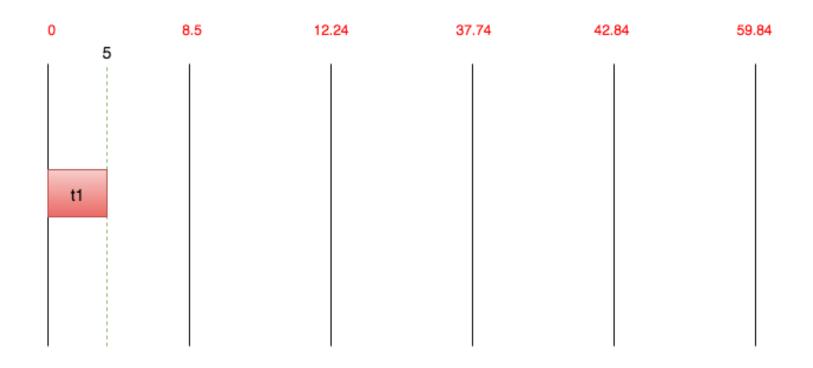




# Sub-deadlines and resource allocation



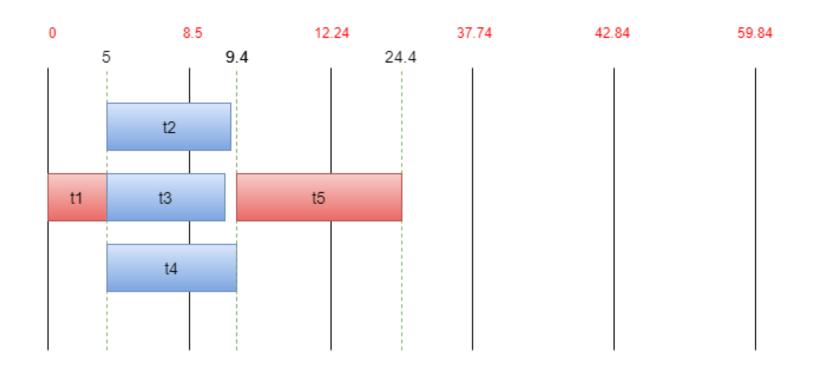




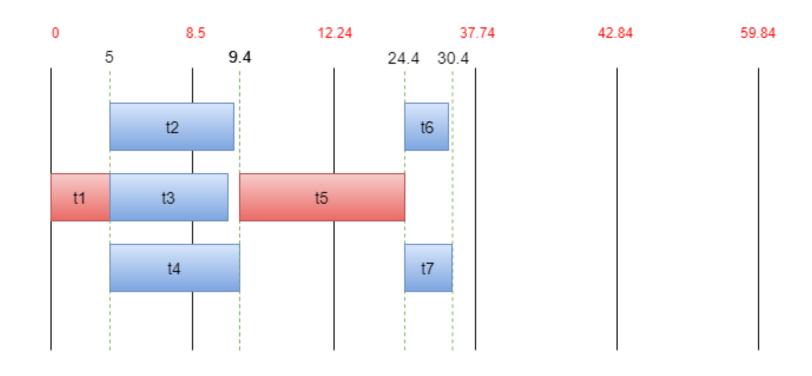




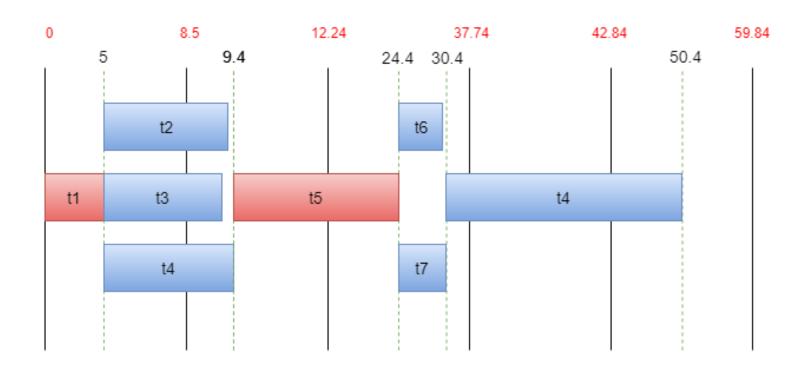












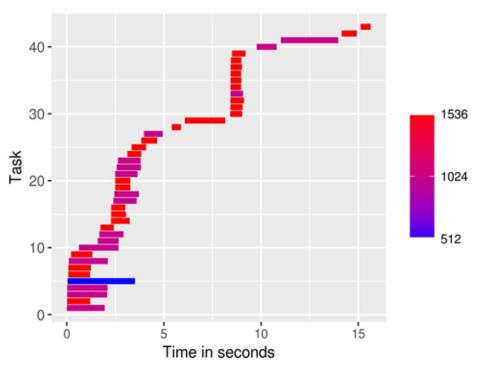


#### Tests on AWS Lambda

- Montage workflow, 43 tasks
- Function size: 256, 512, 1024, 1536 MB
- Execution times estimated based on runs on homogeneous resources
- Limits adjusted to fit between minimum and maximum measured values

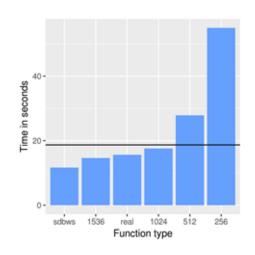


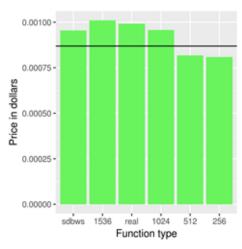
### Experiment 1





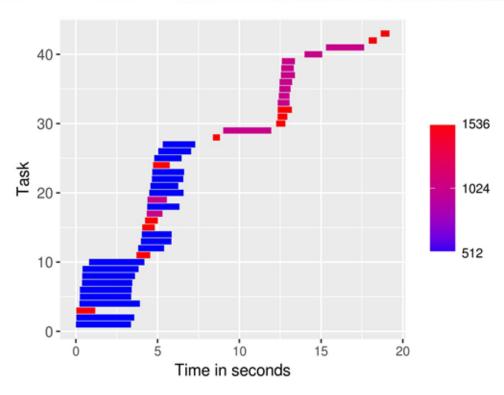
- •Budget: \$0,00086
- •10,8% fastert han 1024MB
- •3,6% more expensive than 1024MB







#### Experiment 2

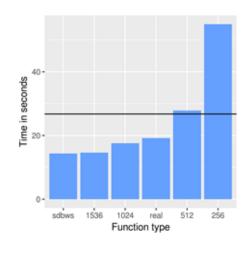


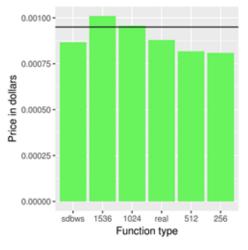
•Deadline: 26,7s

•Budget: \$0,00094

•30,9% faster than 512MB

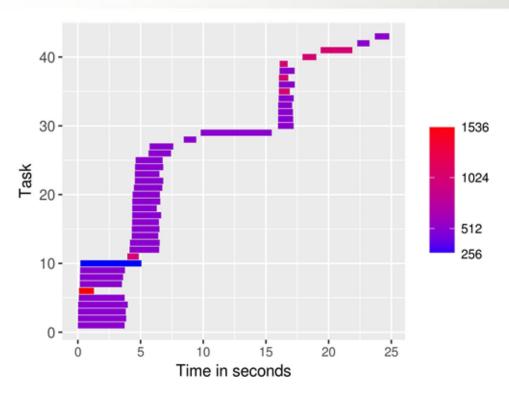
•7,4% more expensive than 512MB







### Experiment 3

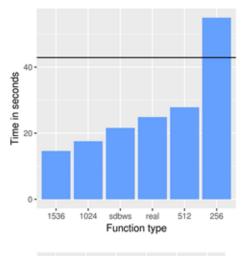


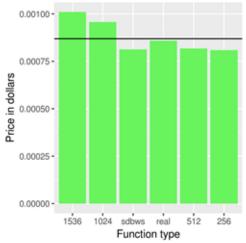
•Deadline: 42,8s

•Budżet: \$0,00086

•10,6% szybciej niż 512MB

•4,9% drożej niż 512MB







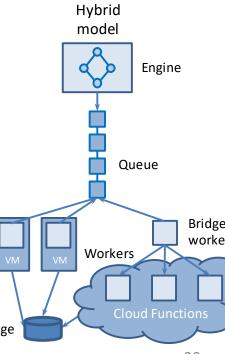
#### Conclusions

- Serverless and other highly-elastic infrastructures are interesting options for running high-throughput scientific workflows
- Cloud functions are heterogeneous
  - Technologies, APIs
  - Resource management policies (over/under provisioning)
  - Performance variations and guarantees
- Their provisioning model may change the game of resource management
- Experiments with SDBWS show that heterogeneous execution may have advantages, but more tests are needed



#### Future Work

- Evaluation of parallelism limits and influence of delays
- Key parameter: elasticity
  - How quickly the infrastructure responds to the changes in workload demand
  - How fine-grained pricing can be?
  - Granularity of tasks vs. granularity of resources
- Example questions:
  - Which classes of tasks/workflows are suitable for such infrastructures?
  - How to dispatch tasks to various infrastructures?
  - Can we actually save costs when using such resources (e.g. for tight deadlines/high levels of parallelism)?





## Thank you!

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  - Marian Bubak, Piotr
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    - Ewa Deelman & Pegasus Team
  - Notre Dame:
    - Jarek Nabrzyski

- Projects & Grants
  - National Science Center (PL)
  - ISMOP (PL)
- References:
  - HyperFlow:<a href="https://github.com/dice-cyfronet/hyperflow/">https://github.com/dice-cyfronet/hyperflow/</a>
  - DICE Team: <a href="http://dice.cyfronet.pl">http://dice.cyfronet.pl</a>





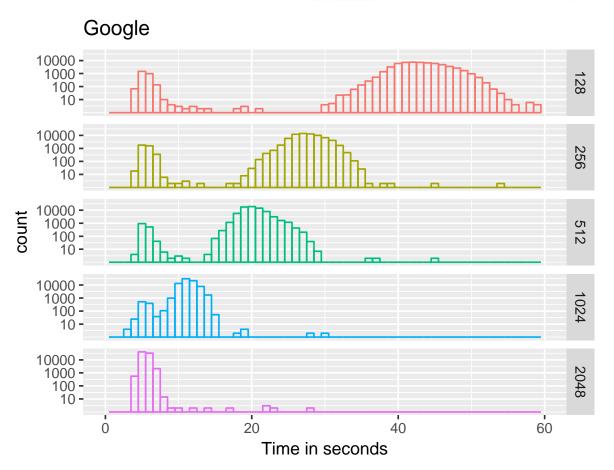


# Backup slides



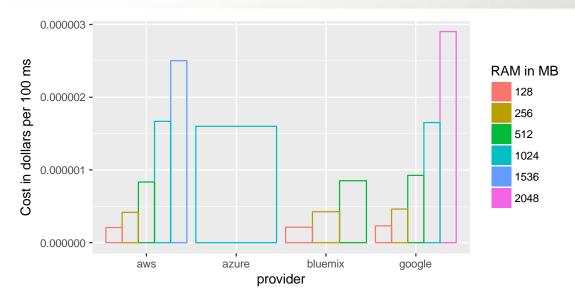
# Detailed Google Cloud Functions Preformance Results

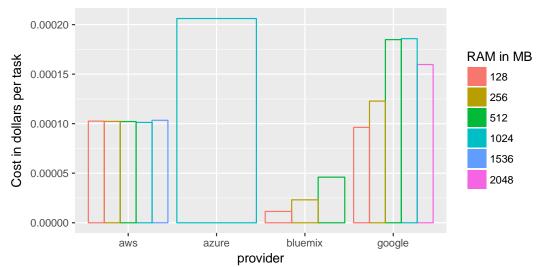
- Functions
   often run
   much
   faster than
   expected
- How often? About 5% times.





## Cost analysis





- List price vs.price/performance
- Different models:
  - AWS proportional
  - IBM invariant
  - Google: mixed
- For Azure we assume 1024 MB



#### References

- [1] H. Arabnejad and J. G. Barbosa. List scheduling algorithm for heterogeneous systems by an optimistic cost table.
- [2] M. Ghasemzadeh, H. Arabnejad, and J. G. Barbosa. Deadline-budget constrained scheduling algorithm for scientific workflows in a cloud environment.
- [3] A. Ilyushkin, B. Ghit, and D. Epema. Scheduling workloads of workflows with unknown task runtimes.
- [4] M. Malawski, K. Figiela, M. Bubak, E. Deelman, and J. Nabrzyski. Scheduling multilevel deadline-constrained scientific workflows on clouds based on cost optimization.
- [5] M. Malawski, K. Figiela, A. Gajek, and A. Zima. Benchmarking heterogeneous cloud functions.
- [6] M. Malawski, K. Figiela, and J. Nabrzyski. Cost minimization for computational applications on hybrid cloud infrastructures.
- [7] M. Malawski, A. Gajek, A. Zima, and K. Figiela. Serverless execution of scientific workflows: Experiments with hyperflow, aws lambda and google cloud functions.
- [8] M. Malawski, G. Juve, E. Deelman, and J. Nabrzyski. Algorithms for cost- and deadline-constrained provisioning for scientific workflow ensembles in iaas clouds.
- [9] B. Baliś. Hyperflow: A model of computation, programming approach and enactment engine for complex distributed workflows