

# Challenges for Scheduling Scientific Workflows on Cloud Functions

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# Outline

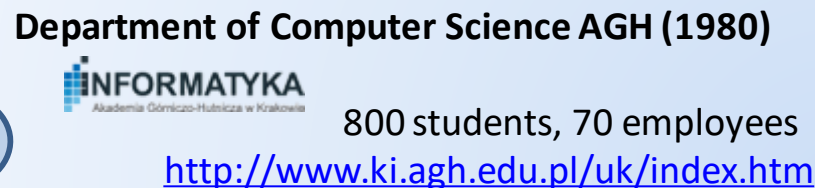
- Motivation: scientific workflows in clouds
- Experiments with HyperFlow
- Scheduling challenges
- Experiments with SDBWS algorithm
- Results on AWS Lambda
- Conclusions

# DICE Team

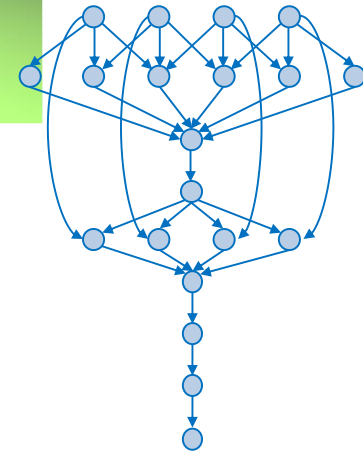
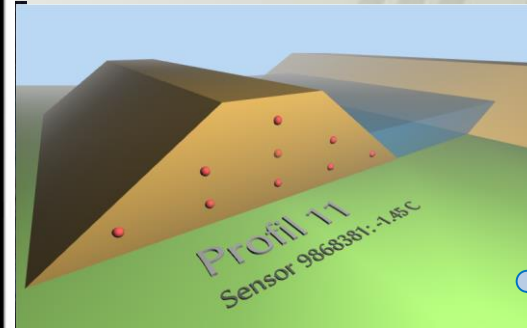
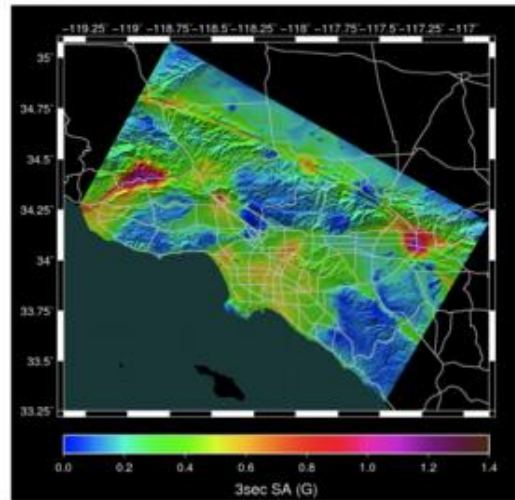
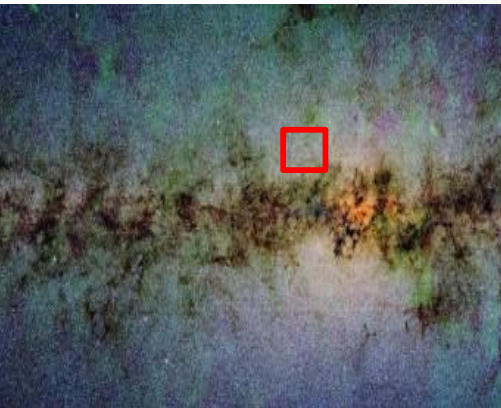
- Investigation of methods for building complex scientific collaborative applications
- Elaboration of environments and tools for e-Science
- Integration of large-scale distributed computing infrastructures
- Knowledge-based approach to services, components, and their semantic composition



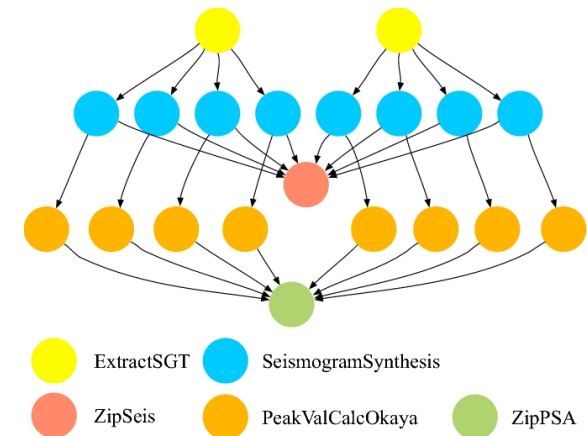
**Other 15  
faculties**



# 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)



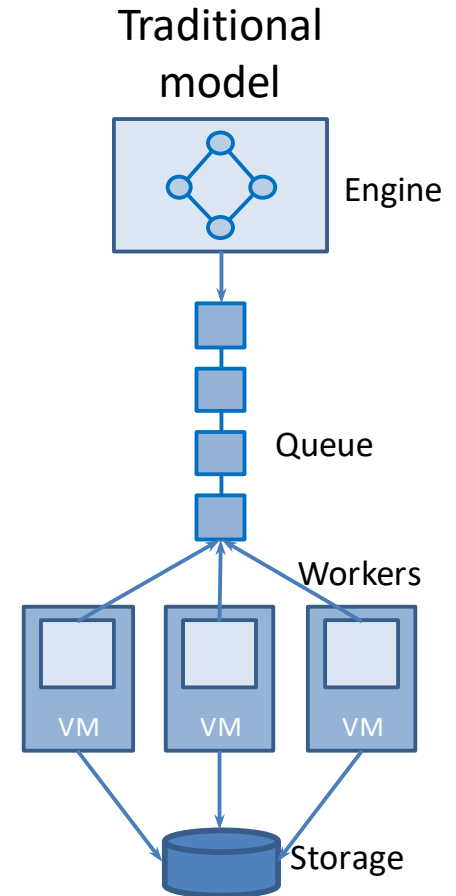
# Infrastructure – from clusters to clouds

- Traditional HPC clusters in computing centers
  - Job scheduling systems
  - Local storage
- Grids to Clouds
  - Infrastructure as a service
  - Globally distributed
  - Virtual machines (VMs)
  - On-demand
  - Cost in \$\$ per time unit



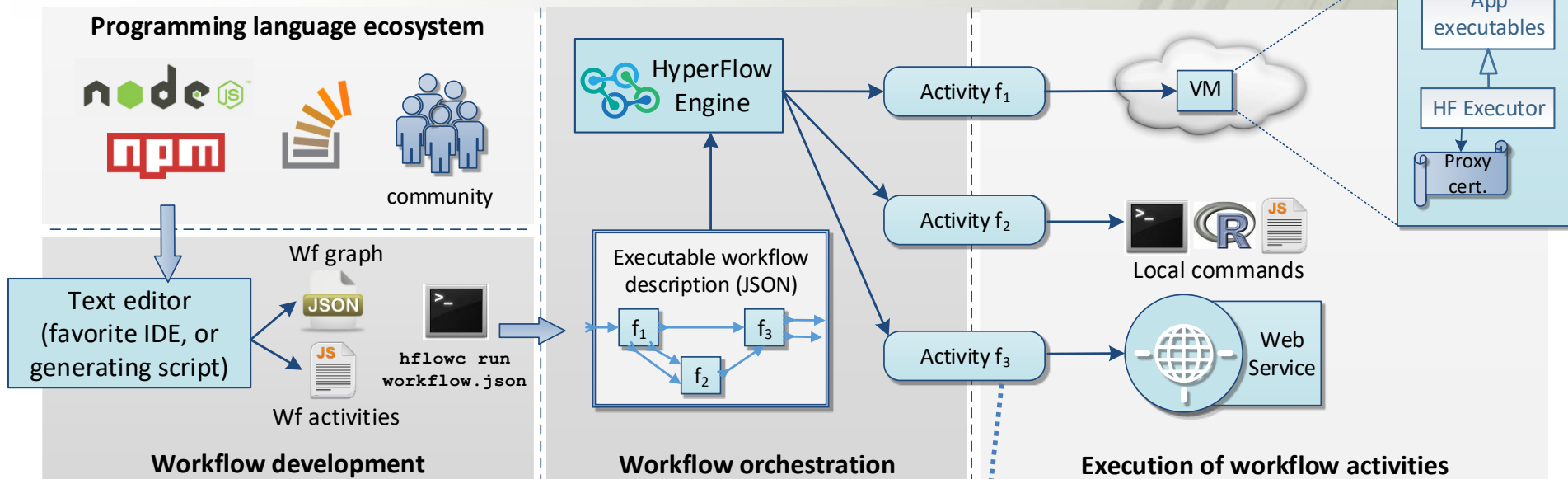
# Workflow execution model in (traditional) clouds

- 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)





## 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",
    "ins": [ "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

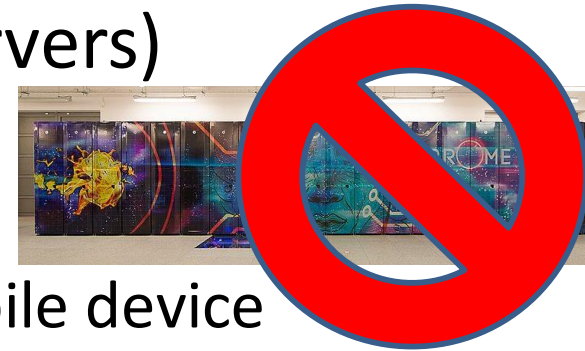
`hflowc run <workflow_dir>`

### <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

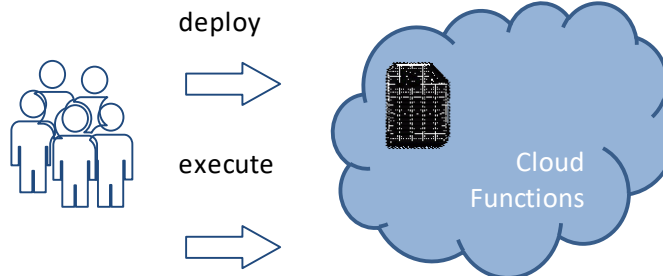
- Serverless – no traditional VMs (servers)
- Composing of applications from existing cloud services
  - Typical example: web browser or mobile device interacting directly with the cloud
- Examples of services:
  - Databases: Firebase, DynamoDB
  - Messaging: Google Pub/Sub
  - Notification: Amazon SNS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





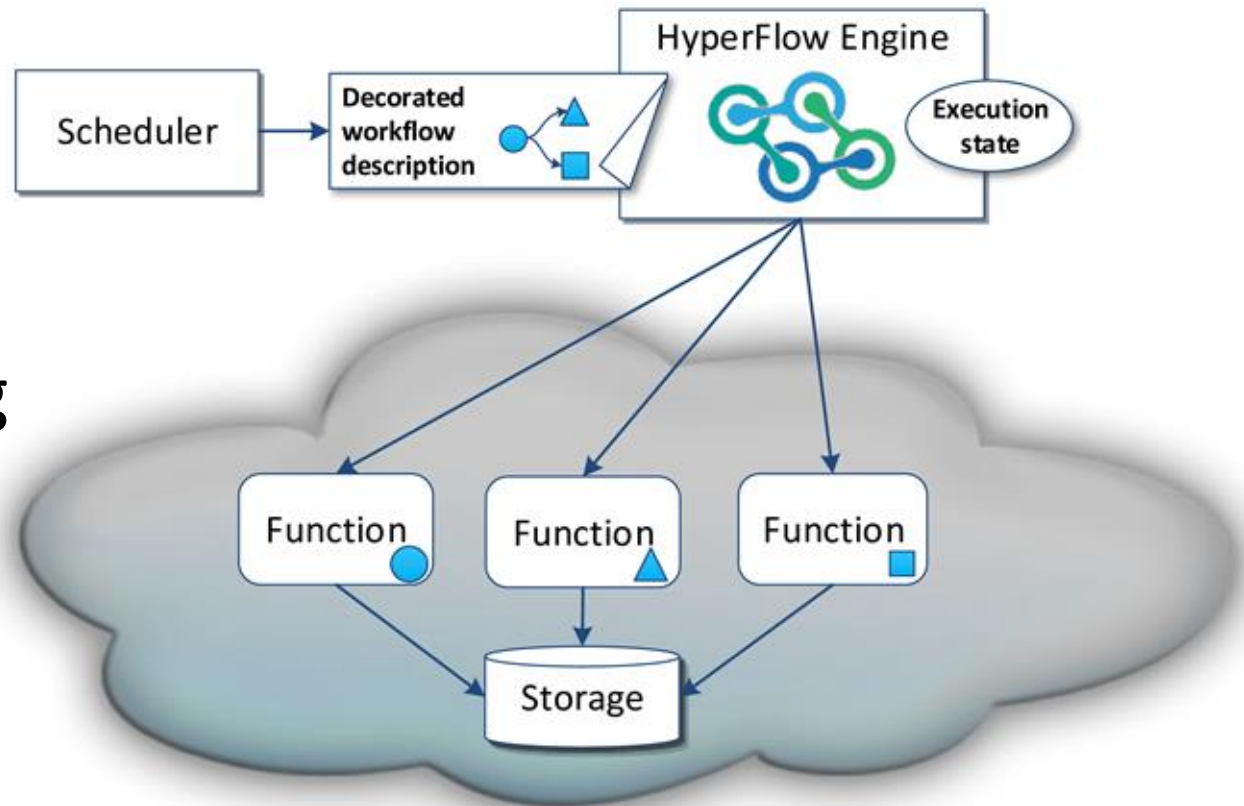
# Cloud Functions – good old RPC?

- 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
- Triggered by
  - Direct HTTP request
  - Change in cloud database
  - File upload
  - New item in the queue
  - Scheduled at specific time
- Developed in specific framework
  - Node.js, Java, Python
  - Custom code, libraries and binaries can be uploaded
- **Fine-grained pricing**
  - **Per 100ms \* GB (Lambda)**



# Execution model and earlier results

- HyperFlow on Serverless:
  - AWS, Google, IBM
- Benchmarking of cloud functions:
  - AWS, Google, Azure, IBM



- M. Malawski, A. Gajek, A. Zima, and K. Figiela. Serverless execution of scientific workflows: Experiments with hyperflow, aws lambda and google cloud functions, FGCS 2018
- K. Figiela, A. Gajek, A. Zima, B. Obrok, M. Malawski: "Performance Evaluation of Heterogeneous Cloud Functions", Concurrency and Computation Practice Experience, 2018 (accepted)
- <http://cloud-functions.icsr.agh.edu.pl/>

# 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?

# Serverless Deadline-Budget Workflow Scheduling

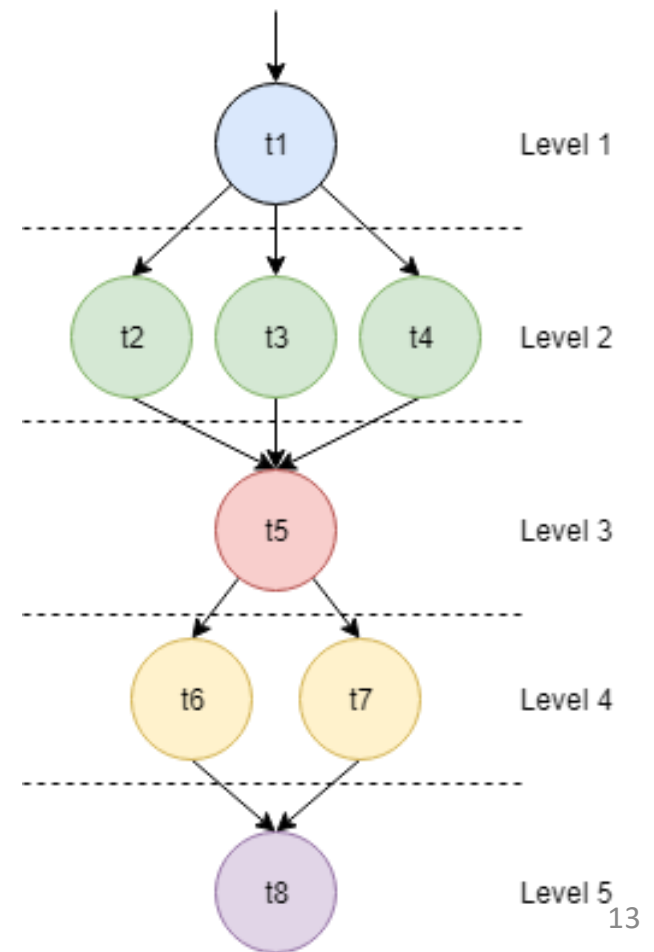
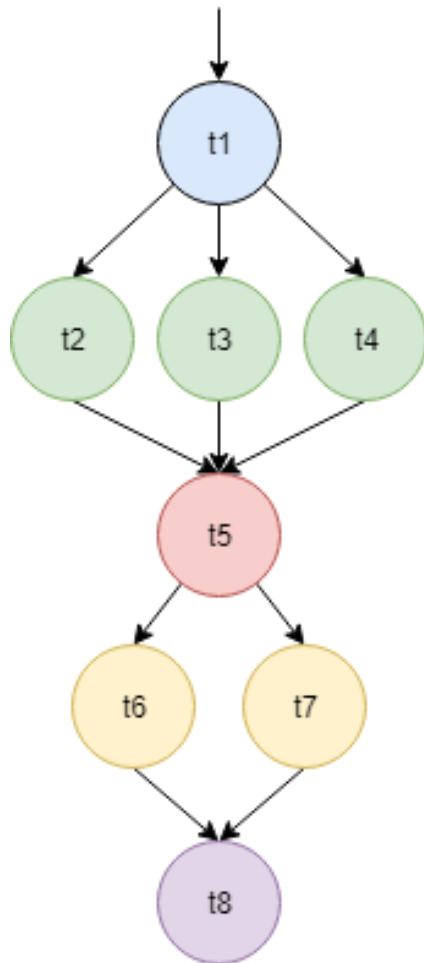
- Adaptation of existing DBWS heuristic for serverless model
  - Low complexity heuristic based on PEFT
  - Uses VM model with hourly billing
- List scheduling heuristic algorithms, two phases:
  - Task ranking / prioritization (not used here)
  - Resource selection
- Assumes the knowledge of task runtime estimates on each resource type
- Finds mapping between tasks and resources (cloud functions) to meet the deadline constraint and tries to meet the budget constraint

H. Arabnejad and J. G. Barbosa. List scheduling algorithm for heterogeneous systems by an optimistic cost table.

M. Ghasemzadeh, H. Arabnejad, and J. G. Barbosa. Deadline-budget constrained scheduling algorithm for scientific workflows in a cloud environment.

# Step 1: Levels

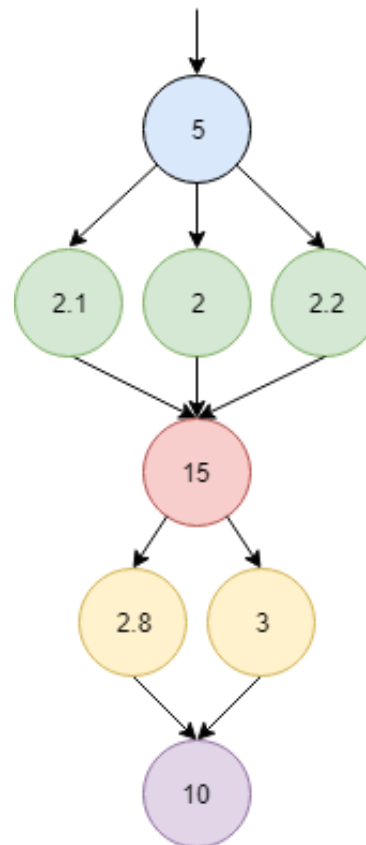
Divide DAG into levels



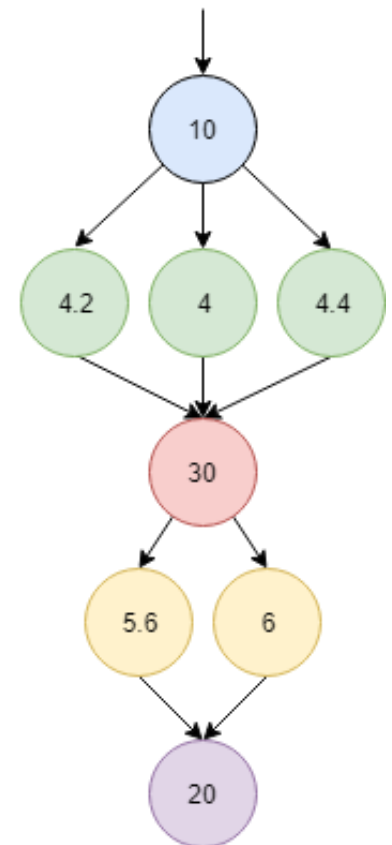
## Step 2: Task runtime estimates

- Prerequisite to scheduling
- Run the workflow on all resource types
- Homogenous execution:
  - Function 1 is faster
  - Function 2 is slower

Function Type 1

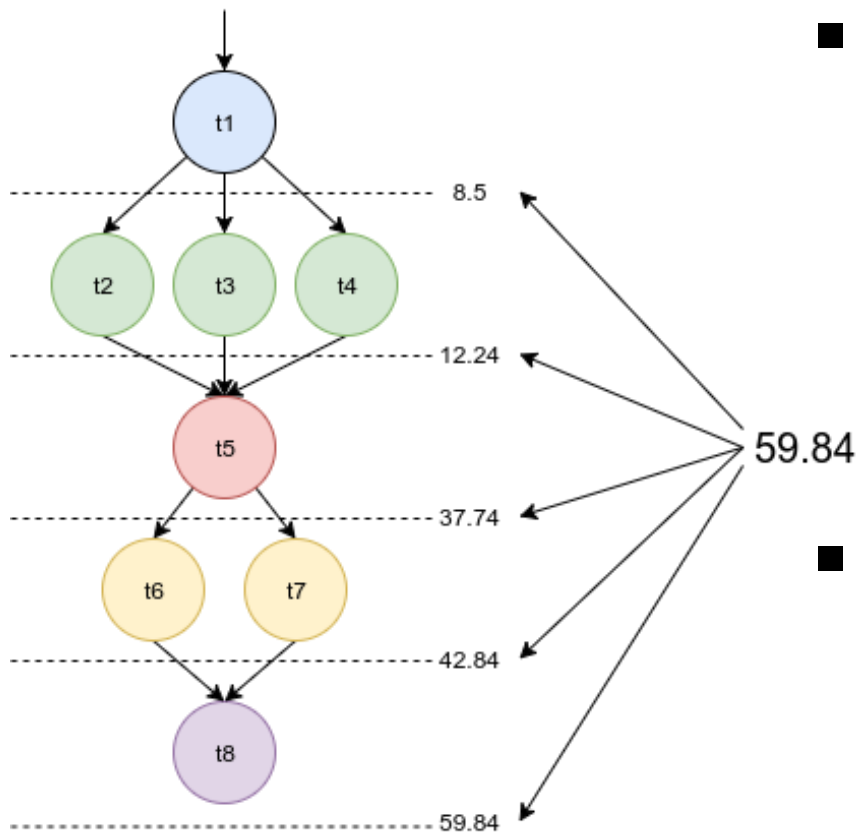


Function Type 2





# Levels and sub-deadlines



- For each workflow level compute the maximum execution time

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

- Divide the deadline into sub-deadlines proportionally 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 (1)

- Resource selection is based on the time and cost:

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

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

- $Time_Q$  – how far is task finish time on resource  $r$  from sub-deadline
- $Cost_Q$  – how cheaper it is from the most expensive resource

$$S_{DL}(t_{cur}) = \{Level_{DL}^j | l(t_i) == j\} \quad \xi = \begin{cases} 1 & \text{if } FT(t_{cur}, r) < S_{DL}(t_{cur}) \\ 0 & \text{otherwise} \end{cases}$$

## 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  $C_F$  is a trade-off factor:

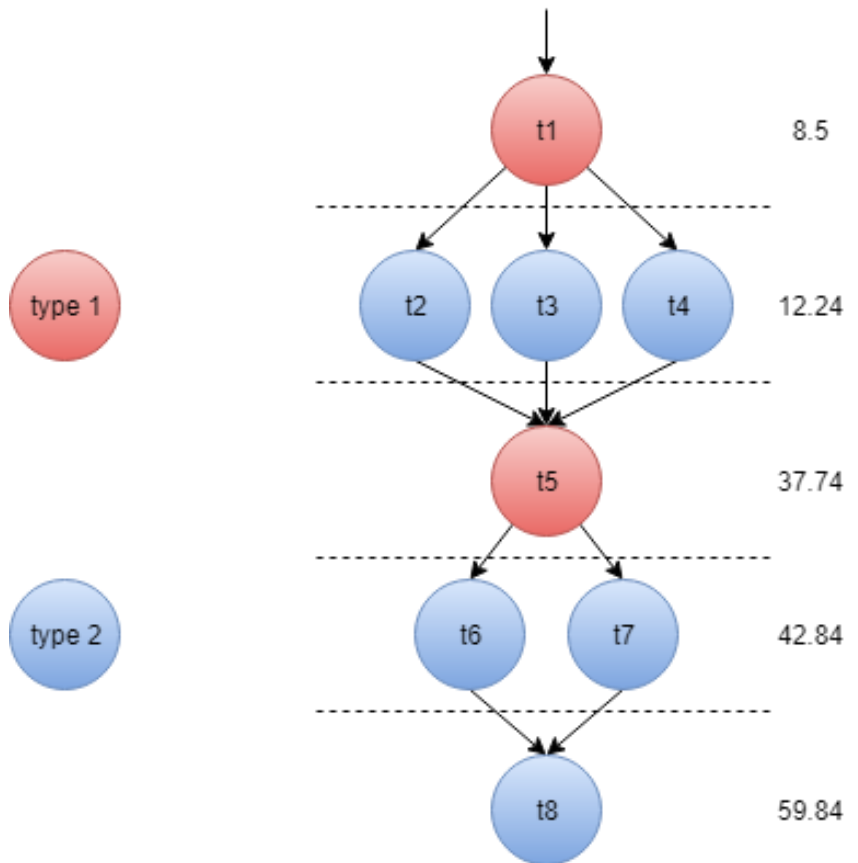
- $Cost_{low}$  – cost on cheapest resource
- $B_{user}$  – user's budget

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

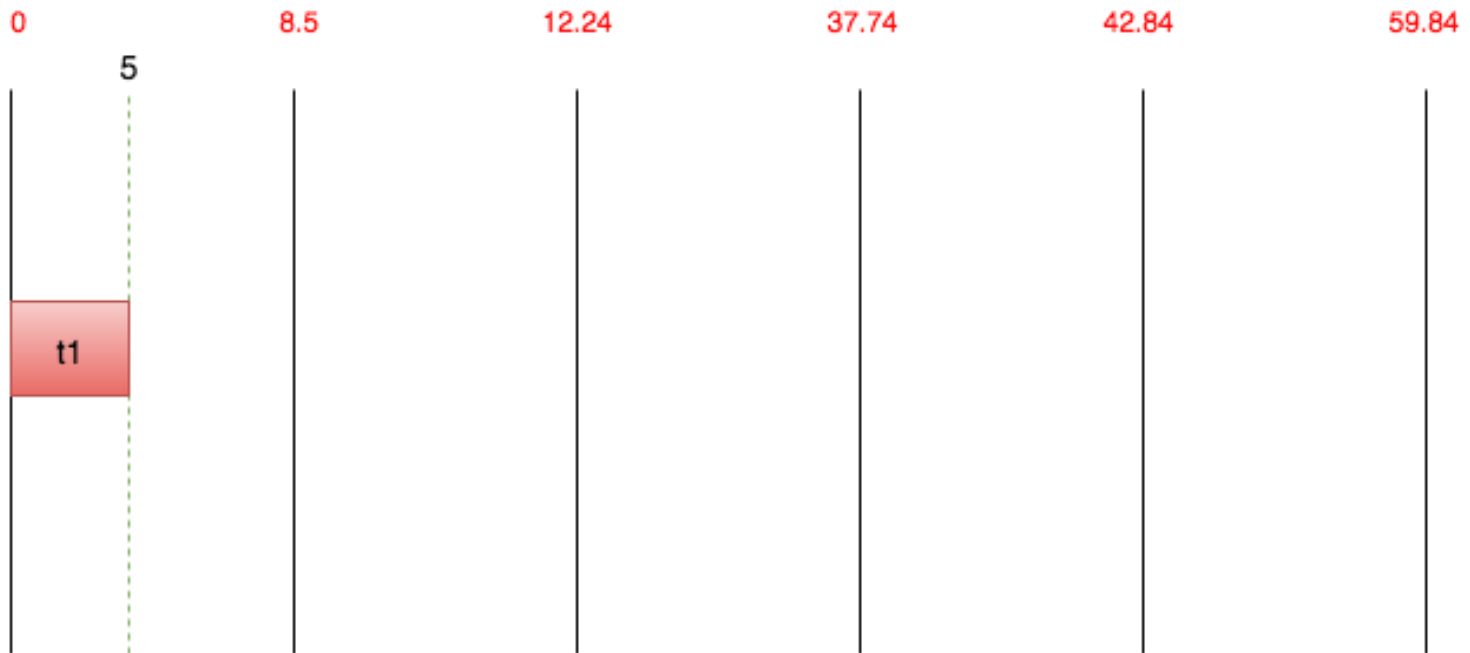
- It represents user preferences:
  - Lower value means we prefer to pay more for faster execution
  - Higher value means we prefer cheaper and slower solutions
- Idea:
  - To finish as early as possible, and
  - To find the cheapest resource

# Sub-deadlines and resource allocation

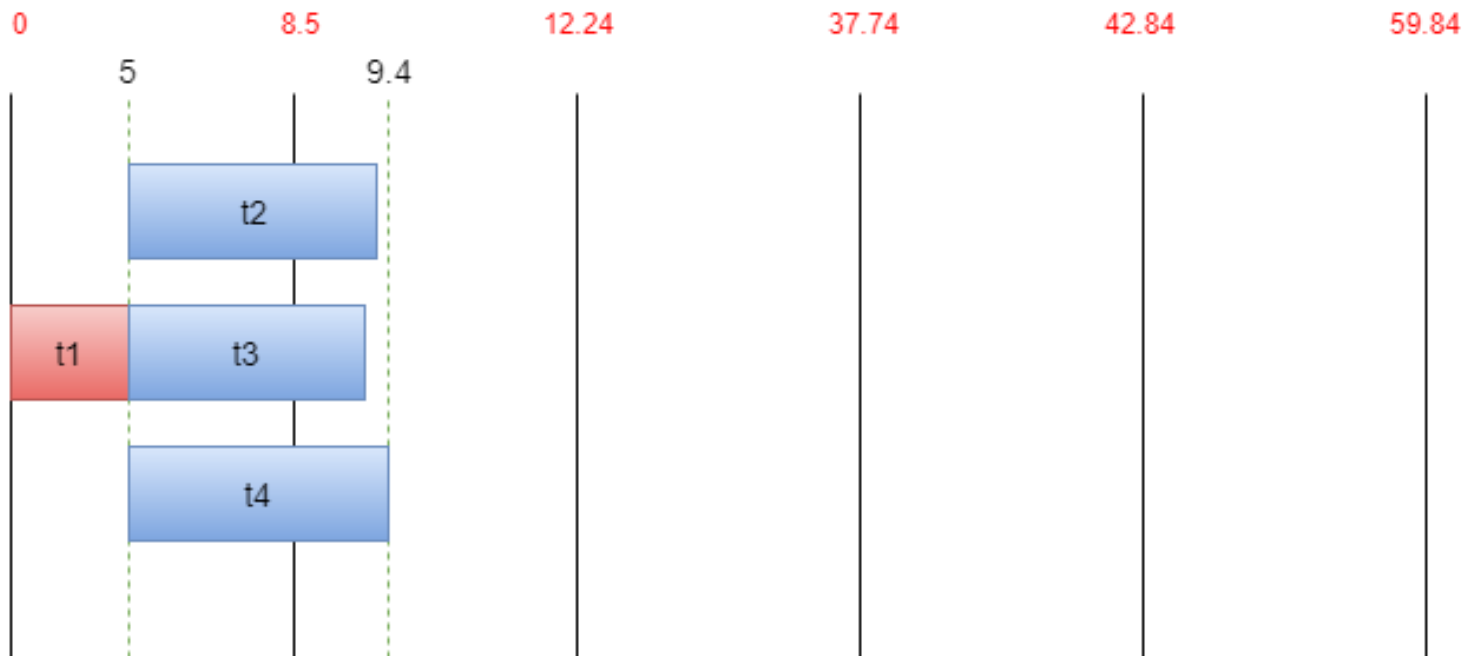
- Result:  
heterogeneous  
execution
- Resource  
performance:
  - Function 1 is faster
  - Function 2 is slower



# Schedule

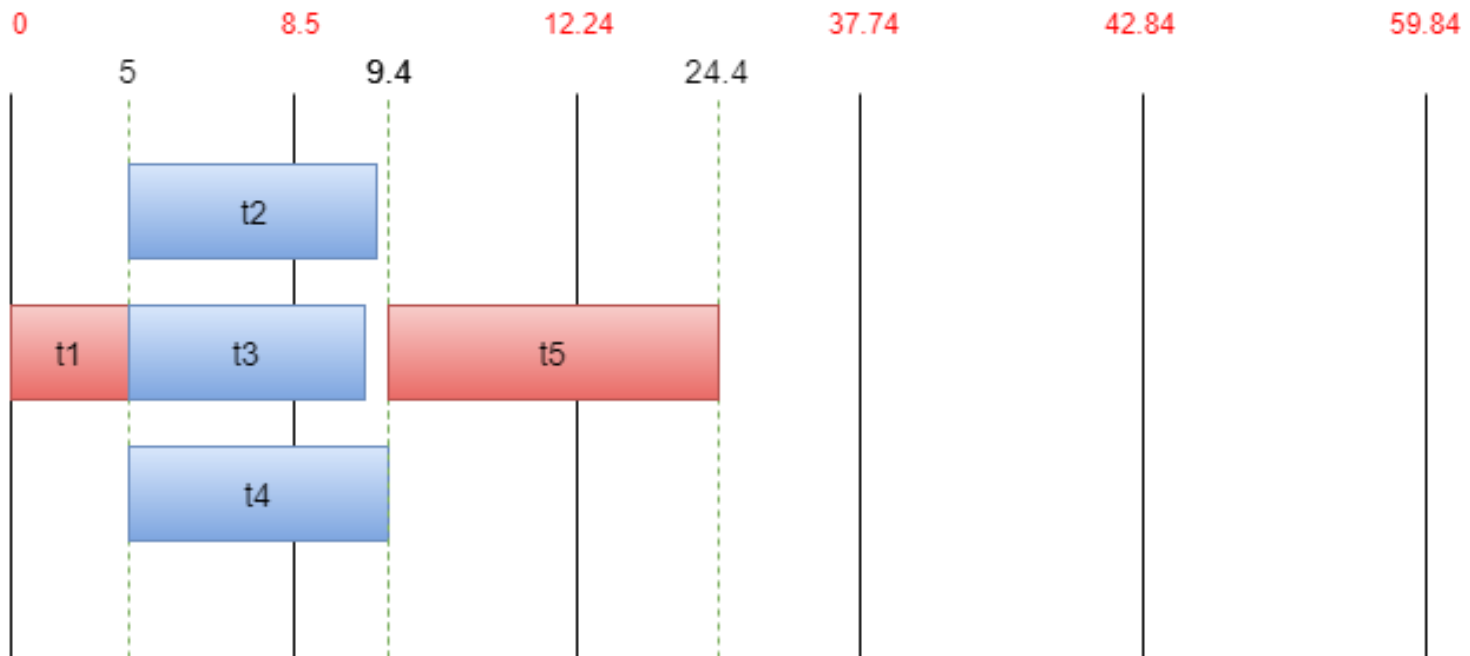


# Schedule

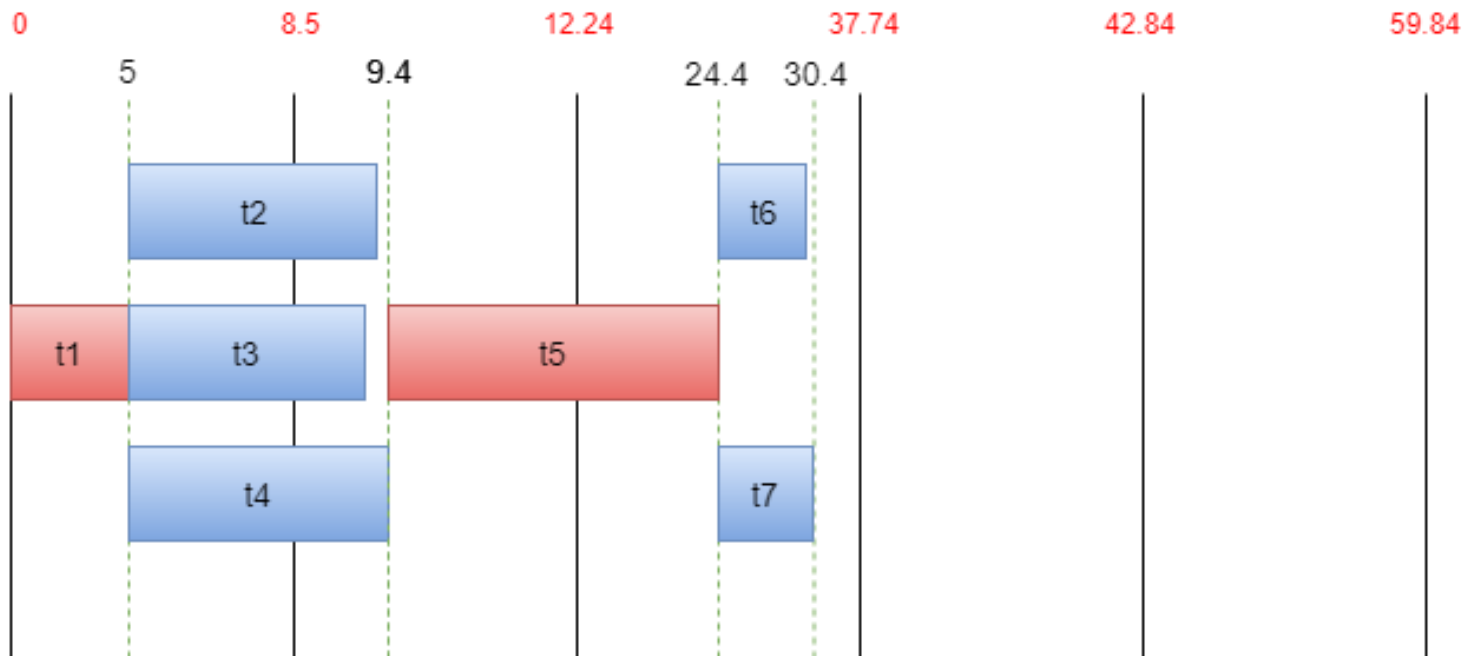




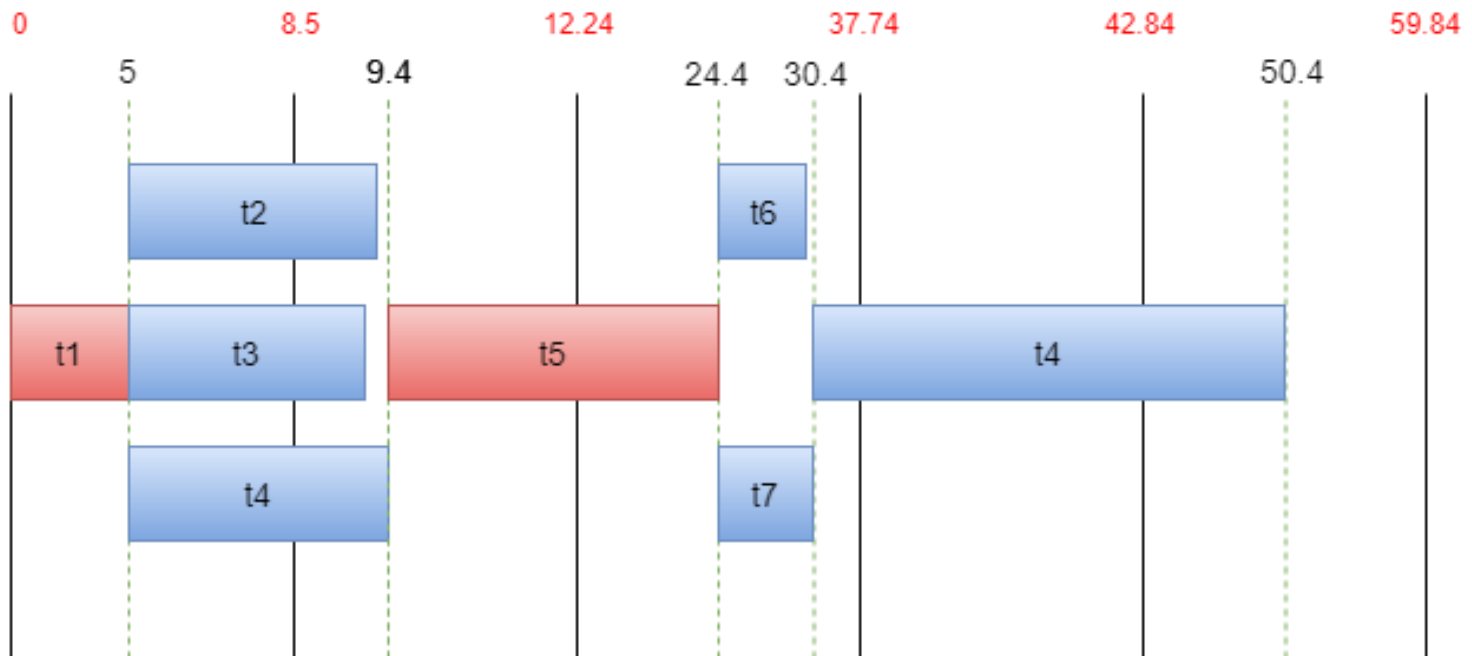
# Schedule



# Schedule

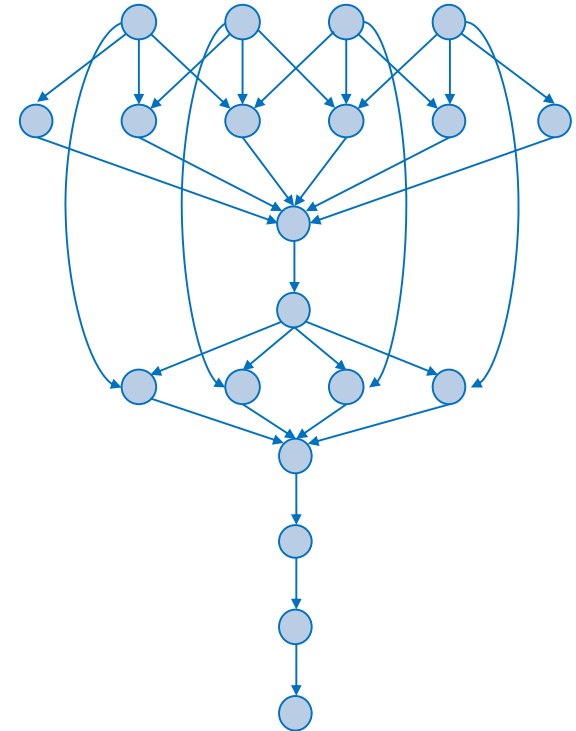


# Schedule

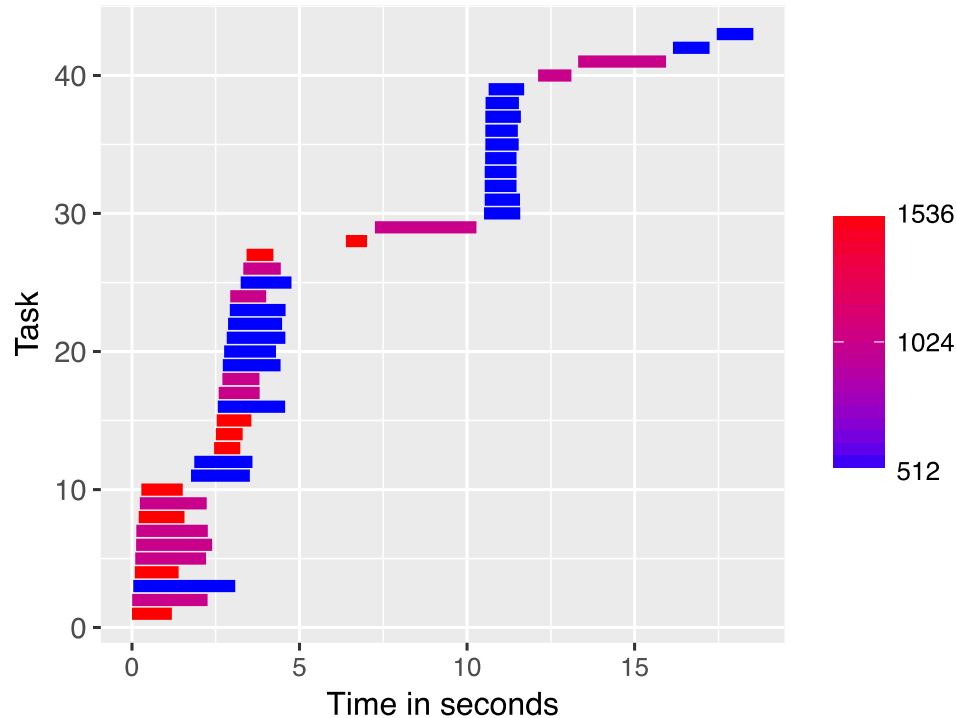


# Tests on AWS Lambda

- 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
- To take into account the delays of task execution, the makespan used to calculate the sub-deadlines includes all the overheads measured during runs on homogeneous resources.

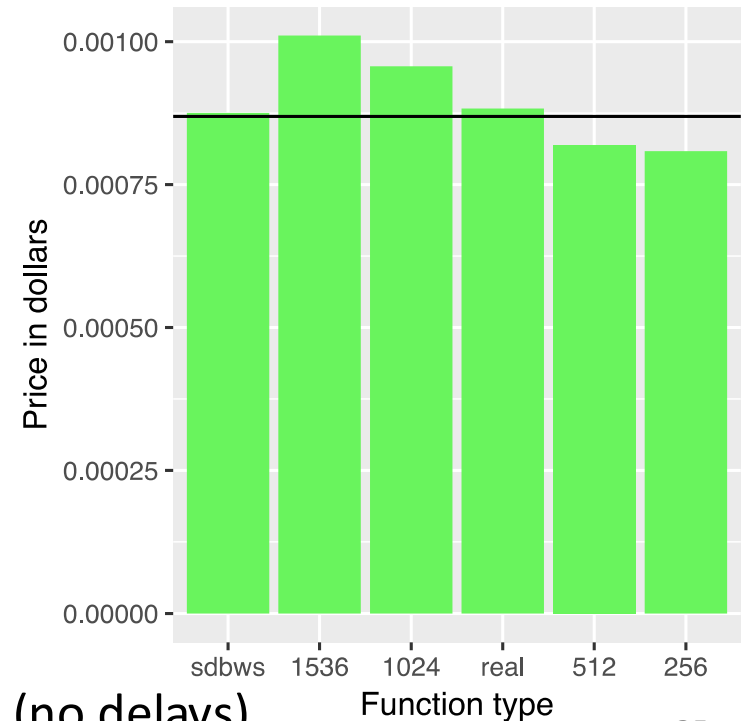
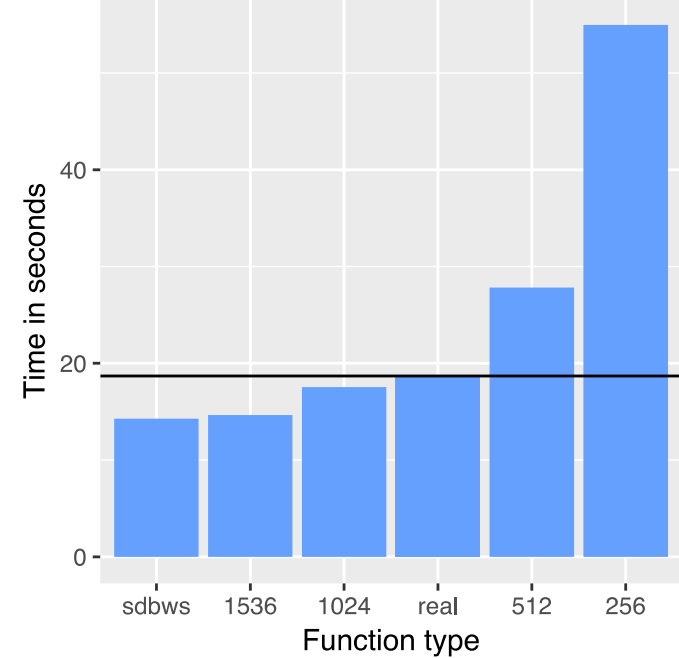


# Experiment 1

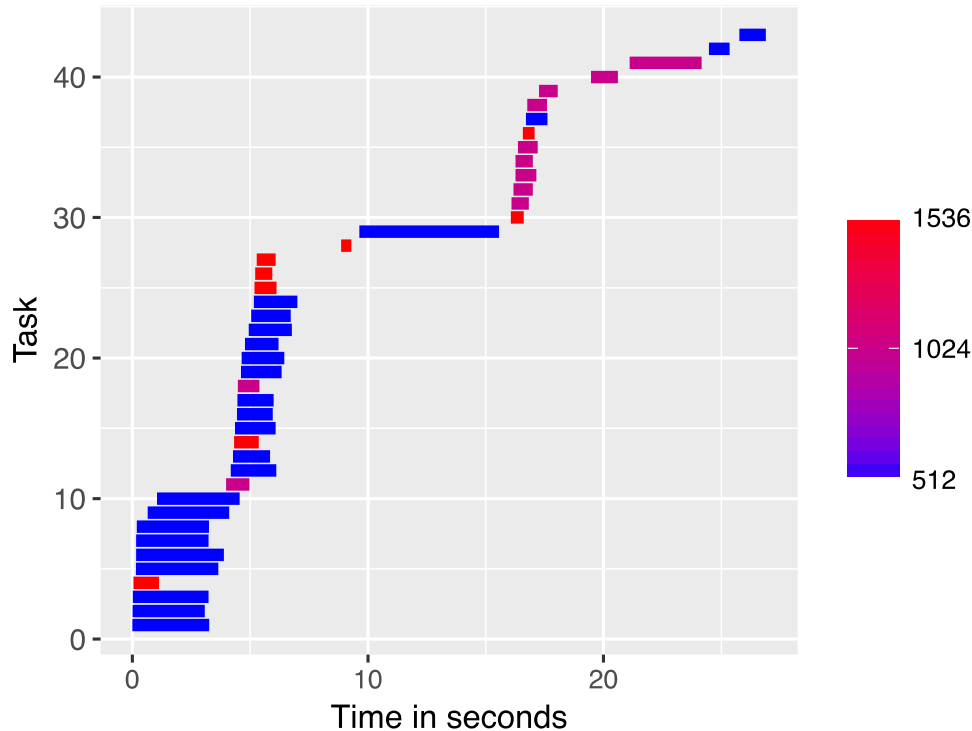


- Deadline: 18,6s (short)
  - Budget: \$0,00086 (small)
- result: faster resources selected

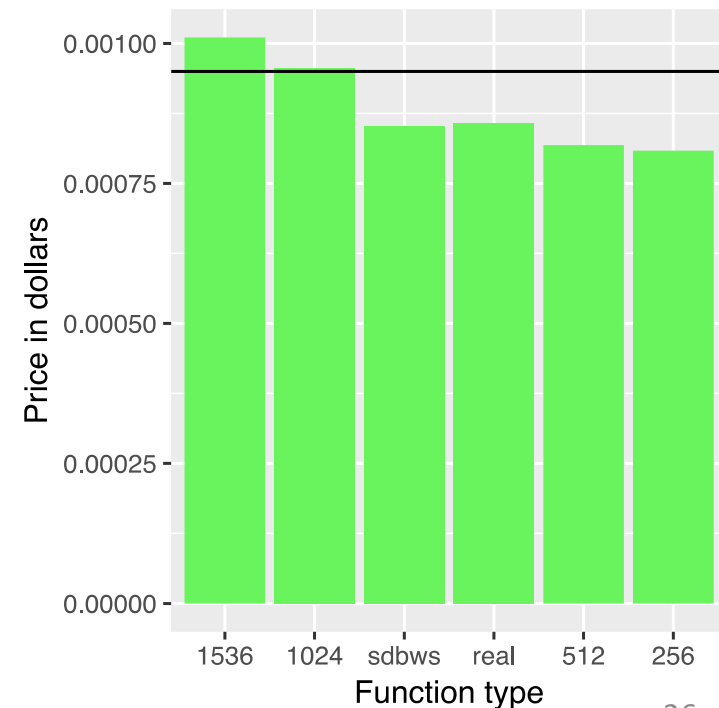
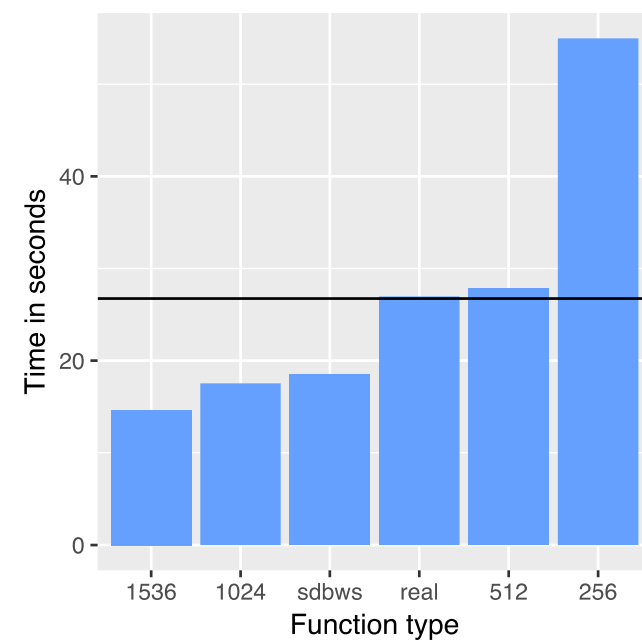
*real* – AWS Lambda execution, *sdbws* – ideal case (no delays)



# Experiment 2

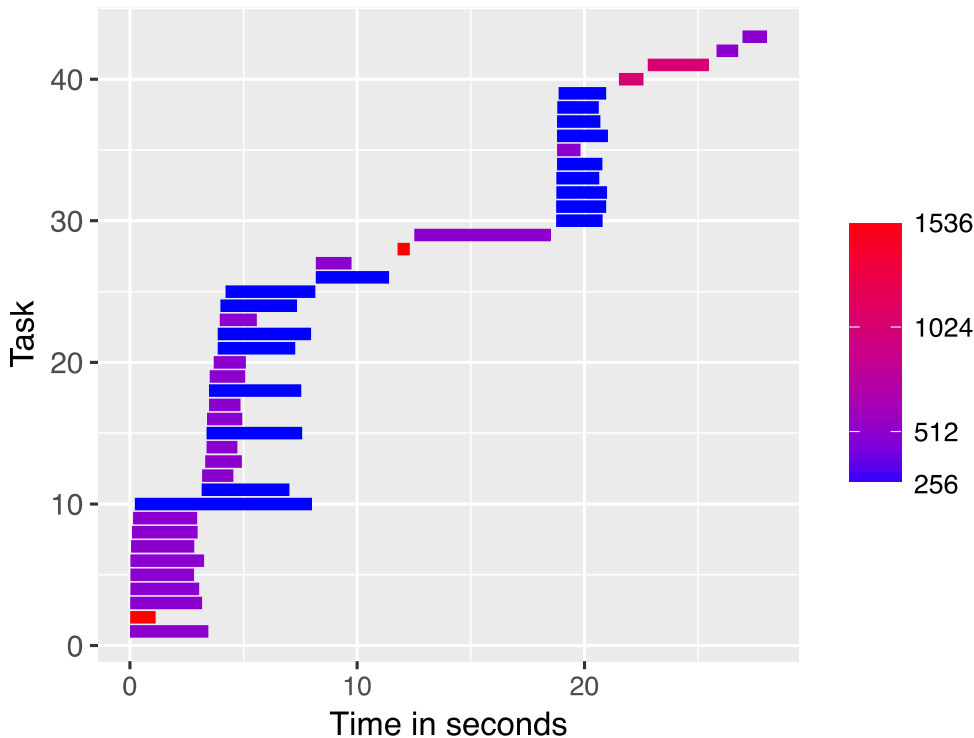


- Deadline: 26,7s (medium)
  - Budget: \$0,00094 (large)
- result: more slower resources selected

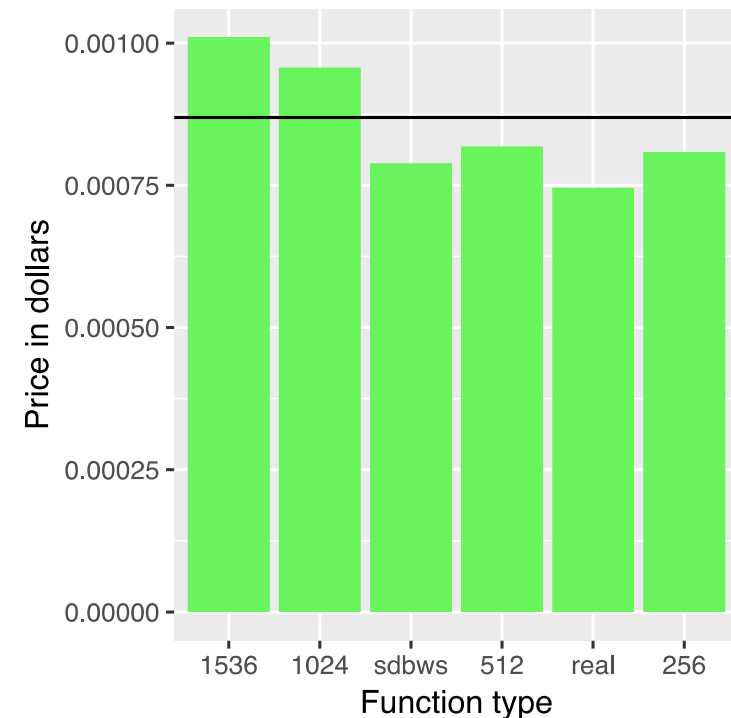
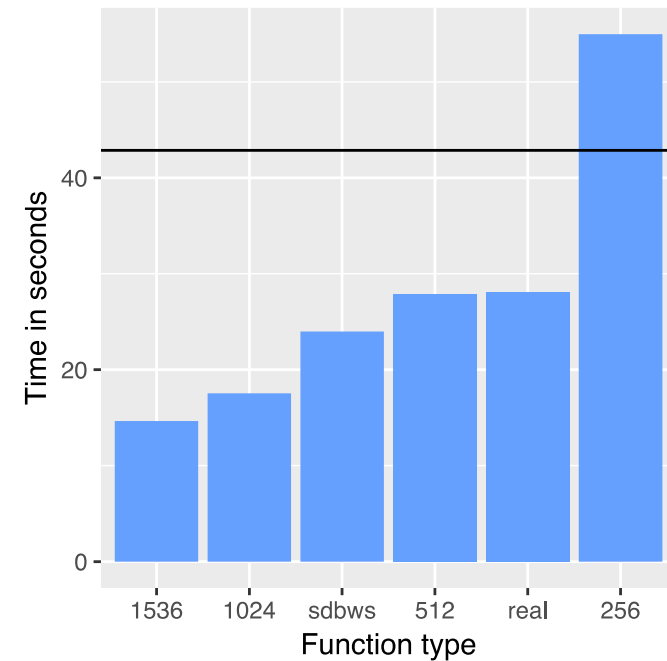




# Experiment 3



- Deadline: 42,8s (large)
  - Budget: \$0,00086 (small)
- result: slower resources selected

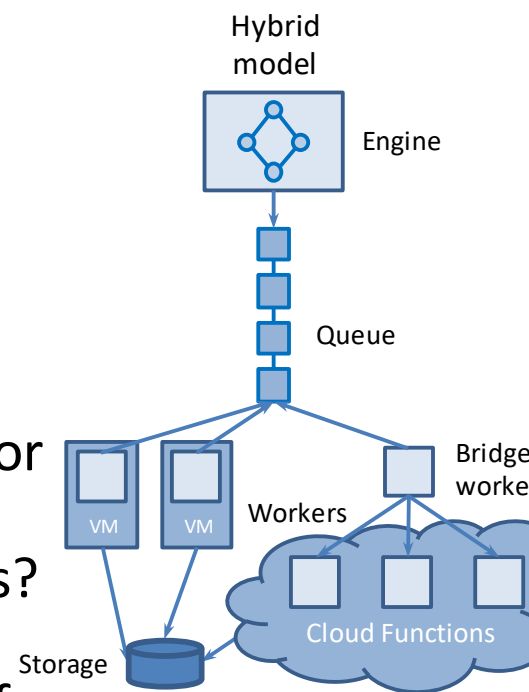


# Conclusions

- 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
- Experiments with SDBWS show that heterogeneous execution may have advantages, but more tests are needed
- Serverless provisioning model may change the game of resource management

# Future Work

- Evaluation of parallelism limits and influence of delays
- Combined FaaS-IaaS execution model
- 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!

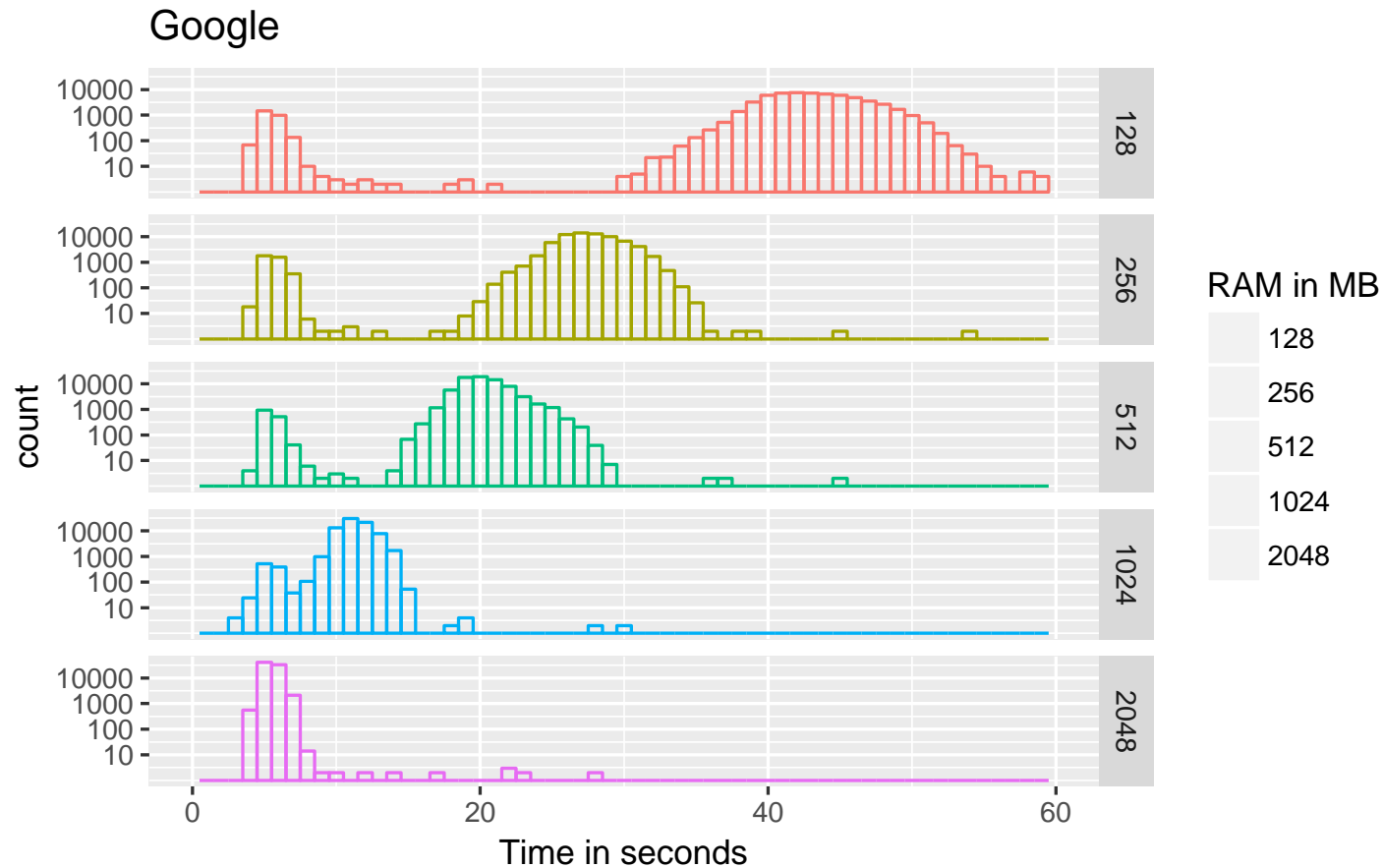
- DICE Team at AGH & Cyfronet
  - Marian Bubak, Piotr Nowakowski, Bartosz Baliś, Tomasz Gubała, Maciej Pawlik, Marek Kasztelnik, Bartosz Wilk, Jan Meizner
- Collaboration
  - USC/ISI:
    - Ewa Deelman & Pegasus Team
  - Notre Dame:
    - Jarek Nabrzyski
- Projects & Grants
  - National Science Center (PL)
  - ISMOP (PL)
- References:
  - HyperFlow:  
<https://github.com/dice-cyfronet/hyperflow/>
  - DICE Team:  
<http://dice.cyfronet.pl>



# Backup slides

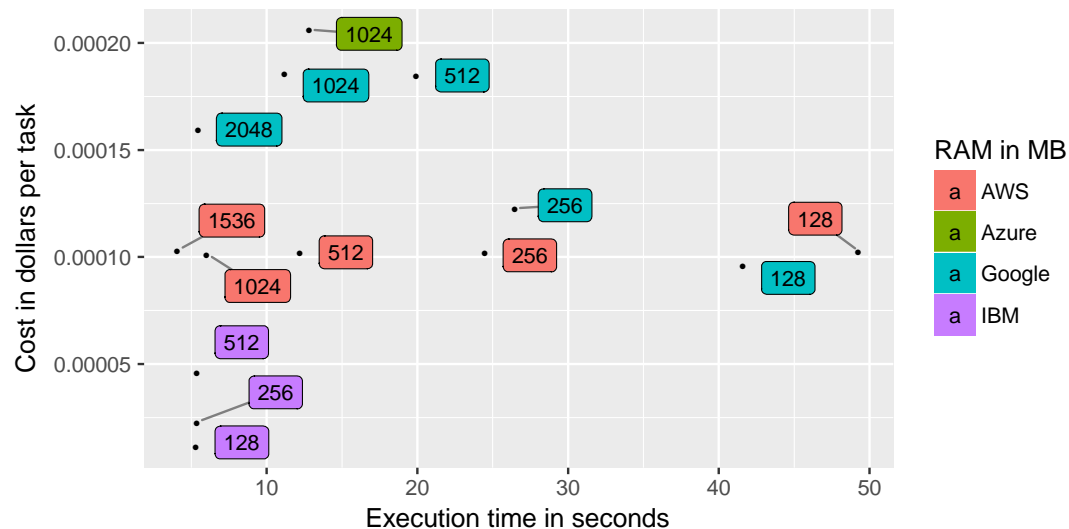
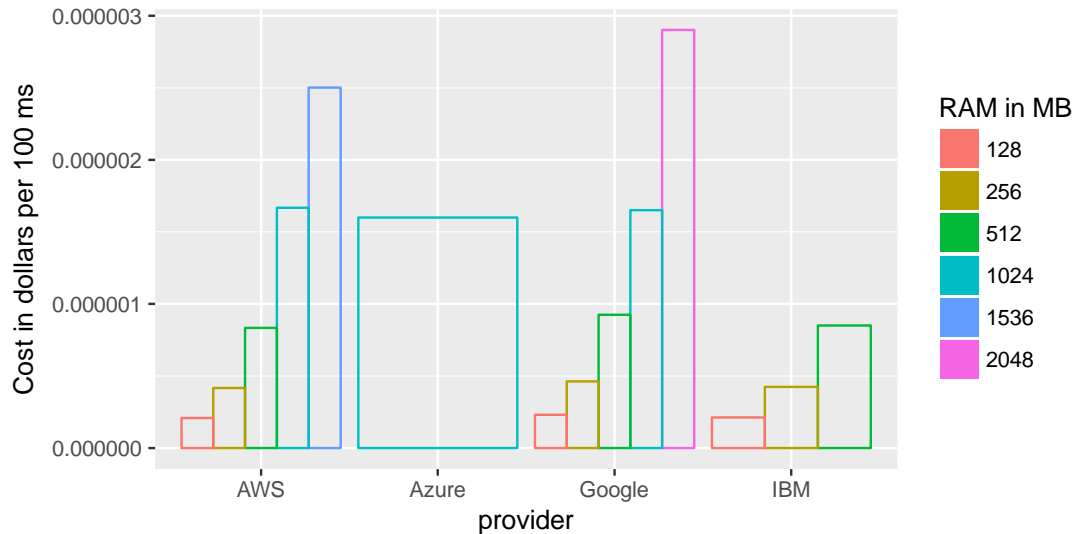
# Detailed Google Cloud Functions Performance Results

- 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