Overhead-Aware-Best-Fit(OABF) Resource Allocation Algorithm for Minimizing VM Launching Overhead

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Presenter: Hao Wu

Work supported by the U.S. Department of Energy under contract No. DE-ACO2-07CH11359

And by joint CRADA FRA 2014-0002 / KISTI-C14014 between KISTI and Fermilab

And supported in part by NSF under grant number CAREER 0746643 and CNS 1018731







Outline

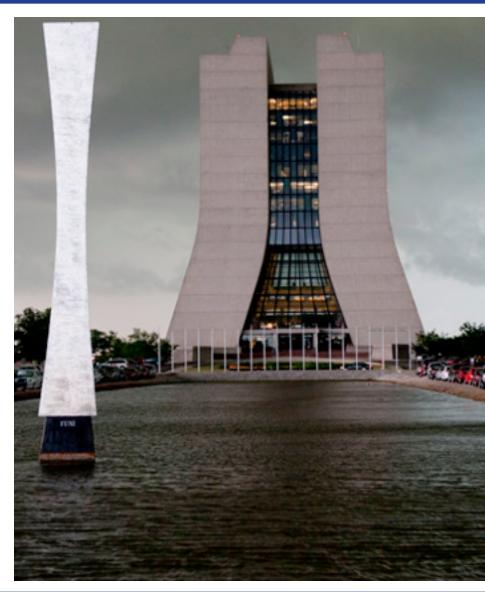
- *≻***Introduction**
 - FermiCloud
- Cloud Bursting Implementation
 - vcluster
- ➤VM Launching Overhead Reference Model Training
 - VM Launching Overhead Reference Model
- **➢Overhead-Aware-Best-Fit (OABF) Algorithm**
- **>**Evaluation
- **≻**Conclusion





Fermi National Accelerator Laboratory:

☐ Lead United States particle physics laboratory







- ☐ Lead United States particle physics laboratory
- □ Data center for:





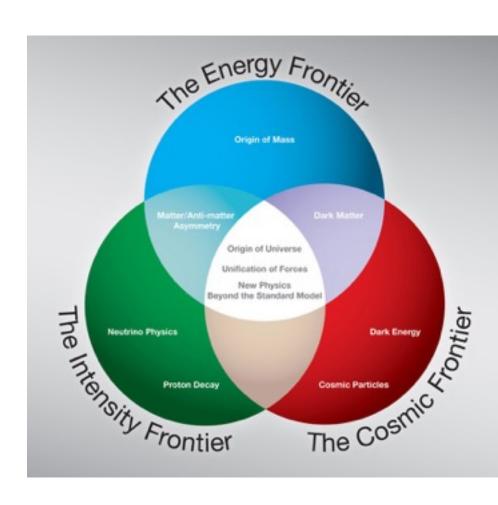


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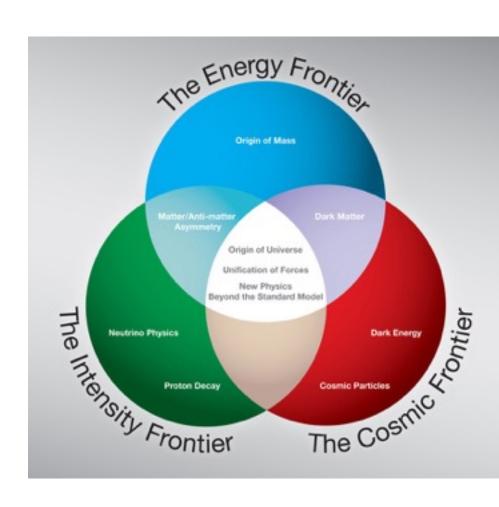
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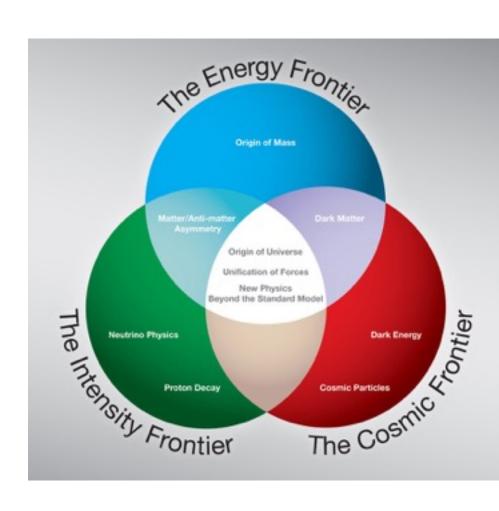
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 - Energy Frontier (CDF, D0, CMS)





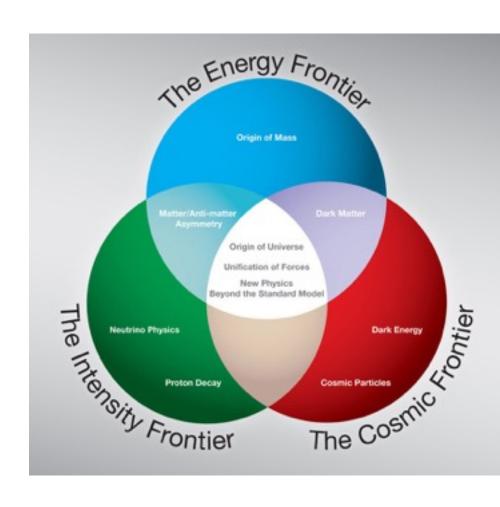


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 - Energy Frontier (CDF, D0, CMS)
 - Cosmic Frontier (DES, LSST, Darkside, etc.)
 - Intensity Frontier (LBNE, Mu2e, MINOS, etc.)





Introduction: FermiCloud

- FermiCloud Project was established in 2009 with the goal of developing and establishing Scientific Cloud capabilities for the Fermilab Scientific Program.
- FermiCloud Infrastructure as a Service (laaS) running since 2010.
- FermiCloud Project now focusing on On-demand Services for Scientific Users (PaaS, SaaS).
- The FermiCloud project is a program of work that is split over several overlapping phases.
 - Each phase builds on the capabilities delivered as part of the previous phases.





Introduction: KISTI

Korea Institute of Science and Technology Information:

- ■Provision of World-Class Infrastructure for Global Collaboration
- ☐ Leading Nation-wide Super Computing Infrastructure
- ☐ Leading Nation-wide Scientific laaS Infrastructure







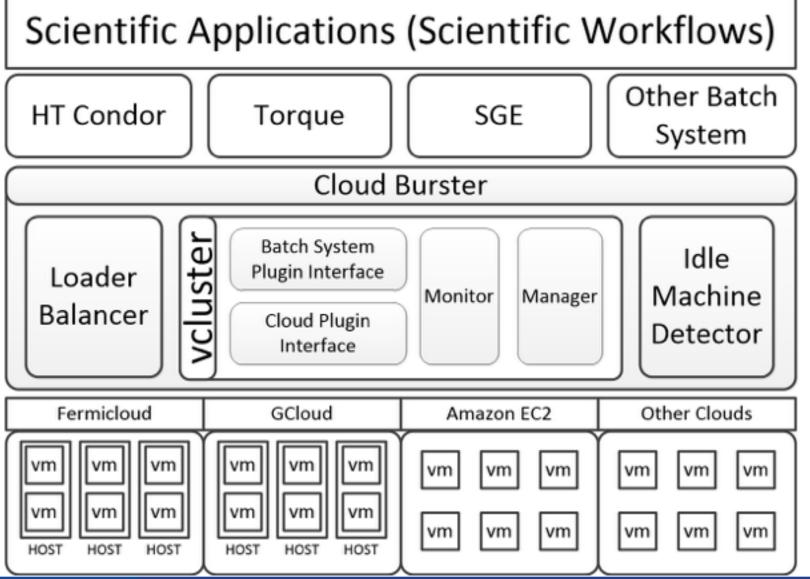


Introduction: Collaboration on Cloud Computing

- ◆Fermilab and KISTI both support global physics collaborations, (CMS, CDF, STAR, ALICE, etc.)
- ◆IIT has joint activities on cloud computing with Fermilab
- ◆These experiments identify cloud computing as key technology for ✓Data preservation
 - ✓Burst capacity
 - ✓ Software distribution
- ◆Global collaborations will not converge on single cloud solution.
- ◆Three key components for success:
 - √ Federation—Group of users run transparently on many resources
 - ✓ Interoperability—Find common method that works on all resources
 - √Throughput—Data flow to and from resources across WAN.
- ◆Goal is to enable real scientific stakeholders to get their computing done.



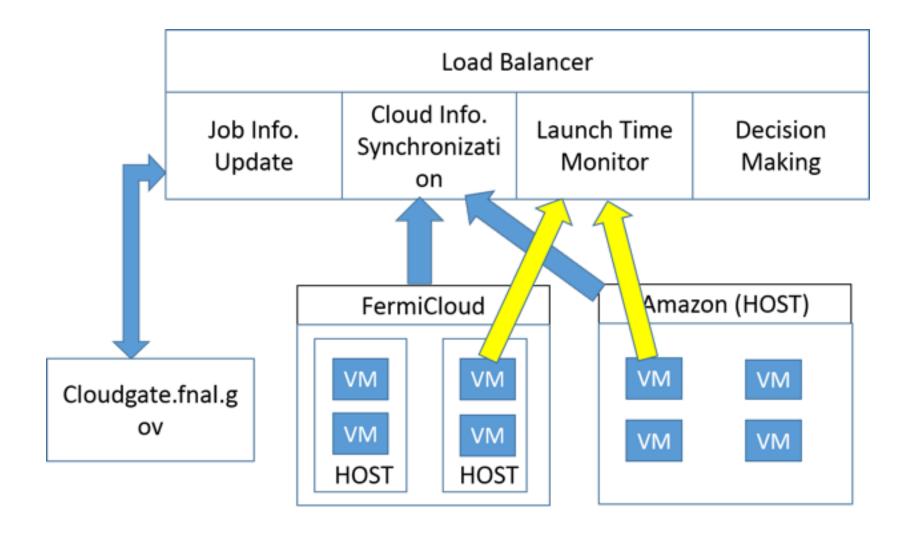
Cloud Bursting Implementation: vcluster







Design of the Load Balancer











□Load Balancing





- □ Load Balancing
 - When to burst





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 - When to burst
 - Where to burst





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 - What to burst





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- ☐ Impact of VM Launching Overhead





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 - Over Provisioning!

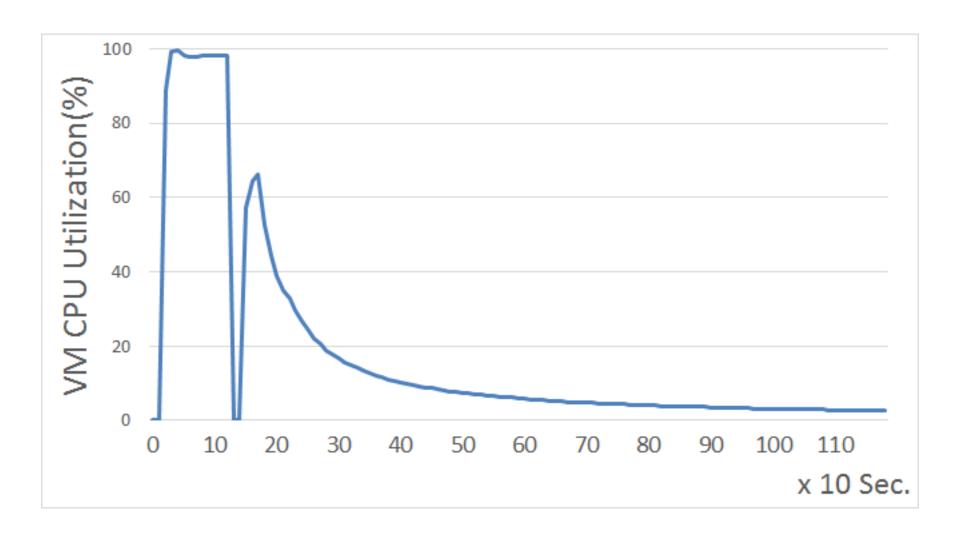




- □ Load Balancing
 - When to burst
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- ■Impact of VM Launching Overhead
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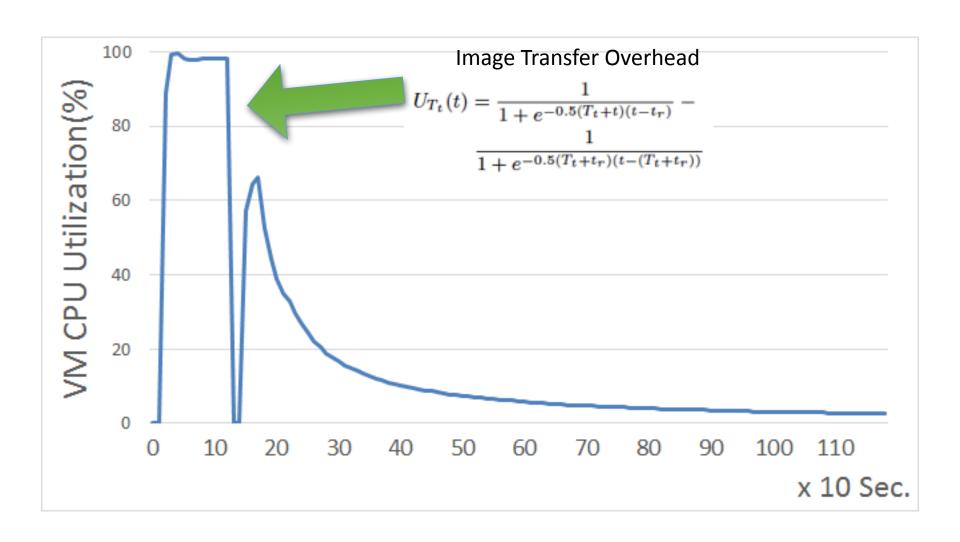
To minimize the VM launching overhead!





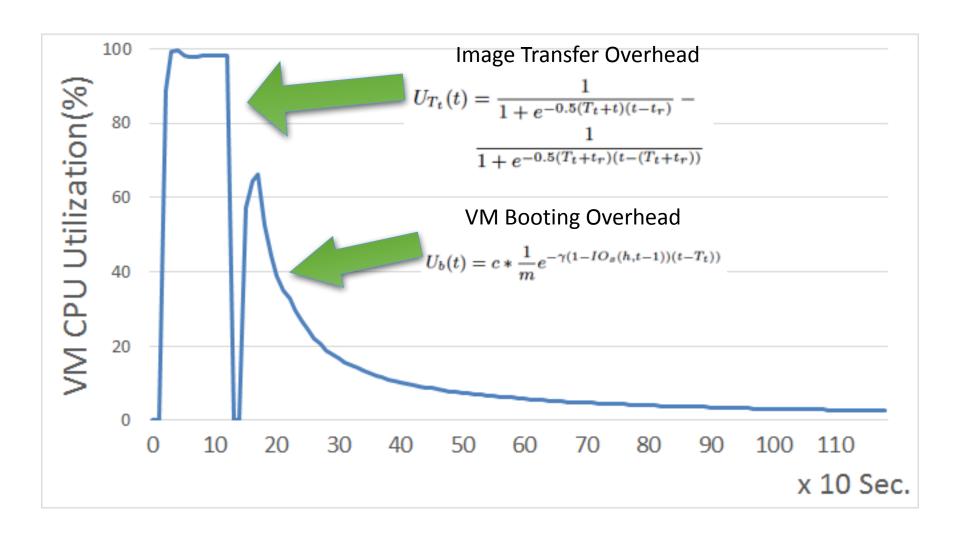






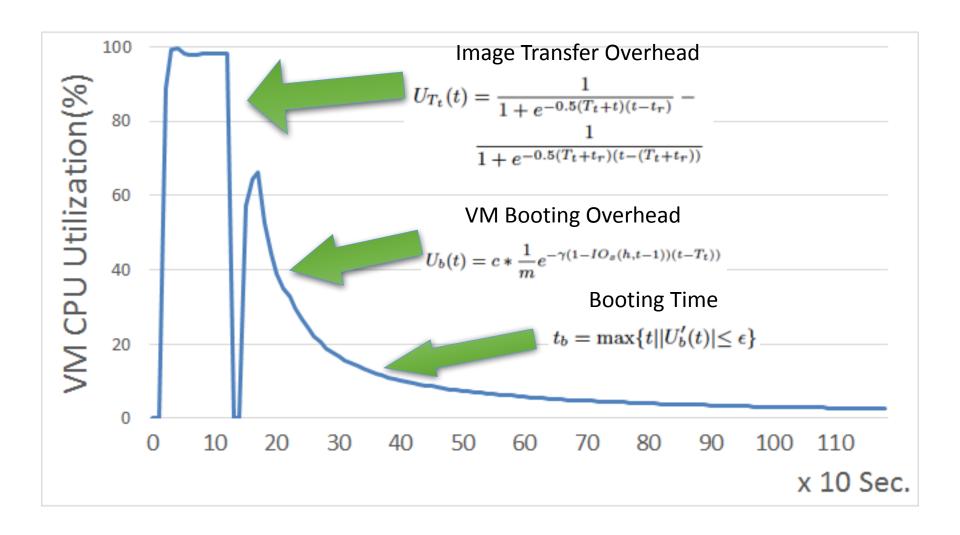
















VM Launching Overhead Model Training

- ■Prediction Accuracy Evaluation
- ■Mean Absolute Scaled Error:

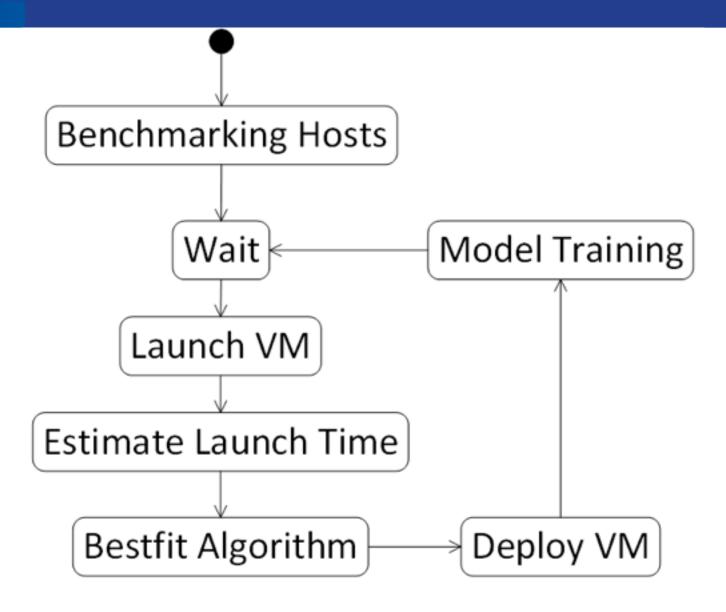
$$MASE = mean(|q_t|)$$

$$q_t = \frac{e_t}{\frac{1}{n-1} \sum_{i=2}^{n} |Y_i - Y_{i-1}|}$$





Resource Allocation Automation Workflow











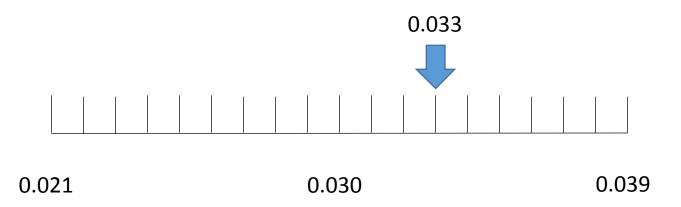


Assume the calibrated error from last round training is 0.032





Assume the calibrated error from last round training is 0.032 Step1: Round the error to 0.030



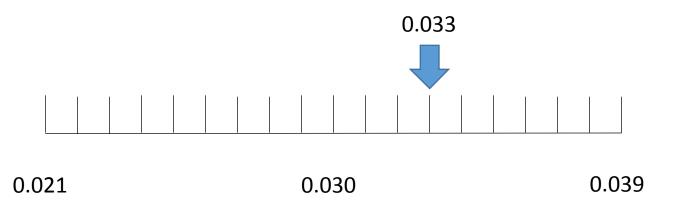




Assume the calibrated error from last round training is 0.032

Step1: Round the error to 0.030

Step2: Calculate the precision of the error: 0.001





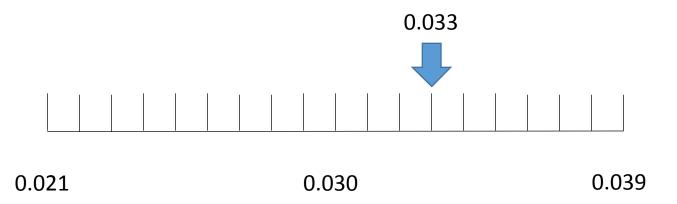


Assume the calibrated error from last round training is 0.032

Step1: Round the error to 0.030

Step2: Calculate the precision of the error: 0.001

Step3: Calculate MASE for each error within range 0.021 - 0.039







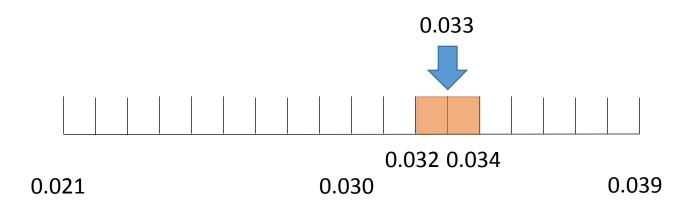
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Step4: Choose the new error with minimal MASE: 0.033







Assume the calibrated error from last round training is 0.032

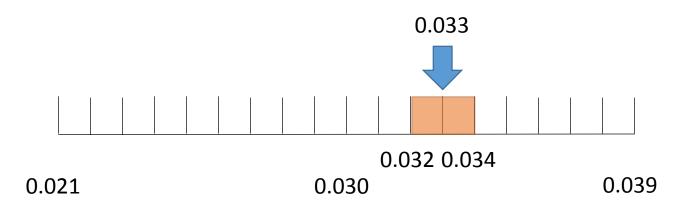
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Termination Condition:







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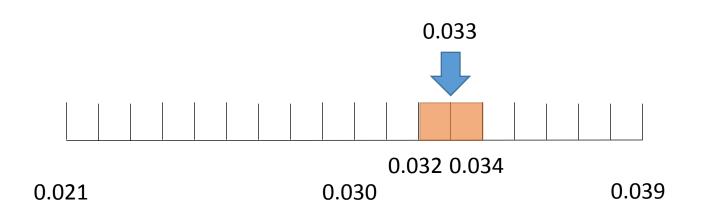
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1: Error is smaller than threshold







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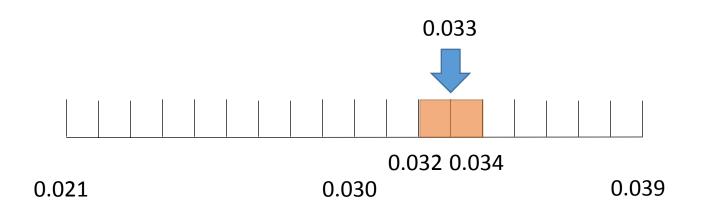
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Termination Condition:

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2: Training round is smaller than threshold







Assume the calibrated error from last round training is 0.032

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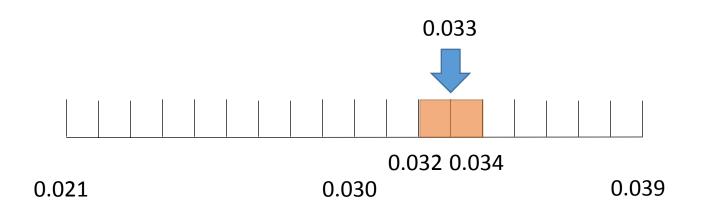
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Overhead-Aware-Best-Fit (OABF) Algorithm

Algorithm 2: overhead-aware-best-fit Algorithm Input : Empty Virtual Machine $v = \{t_r, h, t_w\}$, Host set $H = \{h_1, \ldots, h_n\}$, VM waiting queue $Q = \{v_1^q, \dots, v_m^q\}$ Output: Virtual Machine $v = \{t_r, h, t_w\}$ with host and waiting time information 1 $v.h \leftarrow \text{null}; v.t_w \leftarrow 0; h' \leftarrow null$ 2 $t'_w \leftarrow 0$; $t_b \leftarrow \infty$; $t'_r \leftarrow v.t_r$ 3 for $i \leftarrow 1$ to n do $v.t_r \leftarrow t'_r$ $t_p \leftarrow \text{calculatePredictLaunchTime}(h_i, v)$ if $t_p \leq t_b$ then $t_b \leftarrow t_p$; $h' \leftarrow h_i$ for $j \leftarrow 1$ to m do if v_i^q is deployed on h_i then 10 $t_t \leftarrow v_i^q$'s predicted image transfer time 11 if $t_t + v_j^q . t_r + v_j^q . t_w \ge v . t_r$ then 12 $v.t_r \leftarrow t_t + v_j^q.t_r + v_j^q.t_w$ $t_p \leftarrow \text{calculatePredictLaunchTime}(h_i, v)$ if $t_p + t_t + v_j^q.t_r + v_j^q.t_w - v.t_r \leq t_b$ then 13 14 15 $t_b \leftarrow t_p; h' \leftarrow h_i$ $t'_w \leftarrow t_t + v_j^q.t_r + v_j^q.t_w - v.t_r$ 16 17 18 end19 end20 end 21 23 $v.t_r \leftarrow t'_r$; $v.h \leftarrow h'$; $v.t_w \leftarrow t'_m$ 24 return v

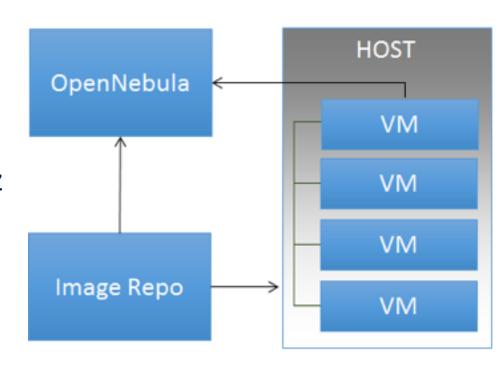




Evaluation: Environment

System Configuration:

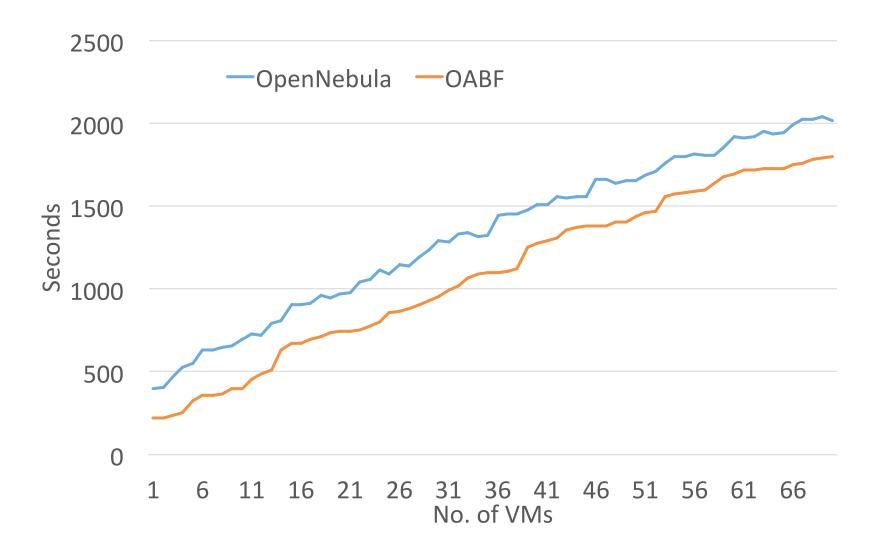
- Front-end: 16-core
 Intel(R)Xeon(R) CPU E5640 @
 2.67GHz, 48GB memory.
- 15 VM hosts: 8-core Intel(R) Xeon(R) CPU X5355 @ 2.66GHz and 16GB memory
- Cloud Platform: OpenNebula







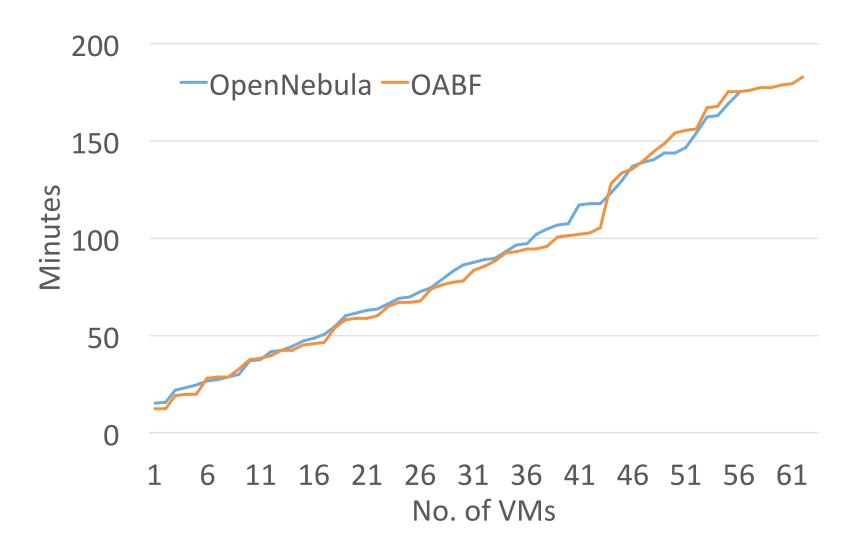
Evaluation: Small Image (2.6GB QCOW2)







Evaluation: Large Image (16GB RAW)







Conclusion

- Present a mechanism to automatically train the VM launching overhead reference model that we previously developed.
- Based on the virtual machine launching overhead reference model, we have developed in this paper an overhead-aware-best-t resource allocation algorithm to help the cloud reduce the average VM launching time.
- Presented an implementation of the developed OABF algorithm on FermiCloud
- For relatively small VM images commonly used in FermiCloud, OABF provides significant improvement in launch time.





Thanks!

Questions?





