An Approach for Characterizing Workloads in Google Cloud to Derive Realistic Resource Utilization Models

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Contribution

--provide a reusable approach for characterizing the Cloud workload based on the patterns of both users and tasks.

--derive models which can be used by providers and other researchers to capture the behavior of Cloud environments

Introduction

--In this context, workload defined as the amount of work computed or processed within the Cloud datacenter that is mainly driven by two principal elements: tasks and users

   --task is defined as the basic unit of computation assigned or performed in the Cloud

   --user is defined as the actor responsible for creating and configuring the volume of tasks to be computed.

--The aim of this paper is to present a novel approach for characterizing Cloud datacenter workloads that creates a reusable generation model based on real operational data

   --analyzed the latest version of the Google Cloud tracelog

Dataset Overview

--the data used in this work was collected from the second version of the Google MapReduce Cloud tracelog that spans a period of approximately one month

--the log contains tens of millions of records for tasks, jobs, and server events

--it provides the normalized CPU, Memory, and disk utilization per task in a timestamp every 5 minutes

--The majority of analysis is focused on two data structures

--tasks events : provide information about the submission times and the link between users and tasks

--task resource usage :provide detailed information about the consumption of resources

--Data size : 250GB

Trace span	29 Days	**Num of servers**	12,532
Num of tasks	17,752,951	**Avg tasks / day**	612,170.72
Num of users	430	**Avg users / day**	153.20
Avg task length	61,575,043.48	**Avg tasks / user**	3,981.06

Dataset Overview—General Tracelog Statistical Analysis

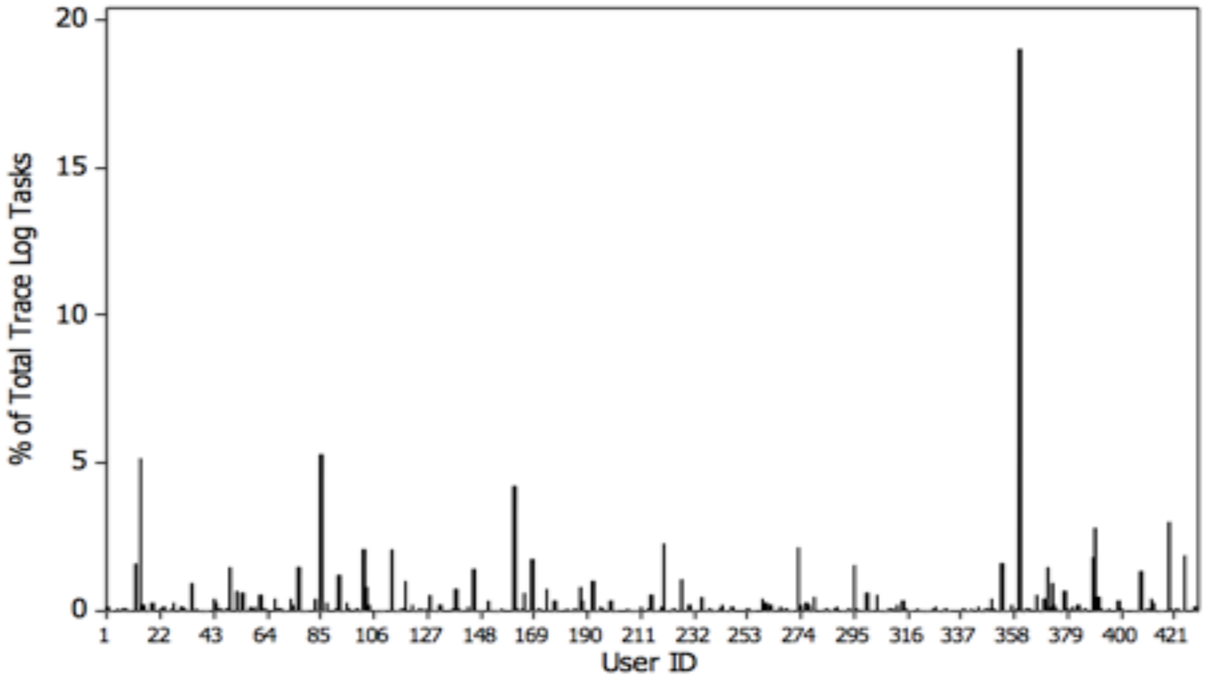

Figure 1. Distribution of Completed Tasks per User.

--A small portion of the users constitute a significant proportion of the submitted tasks, while the majority of users individually contribute less than 0.1 % of the total number

Dataset Overview—General Tracelog Statistical Analysis

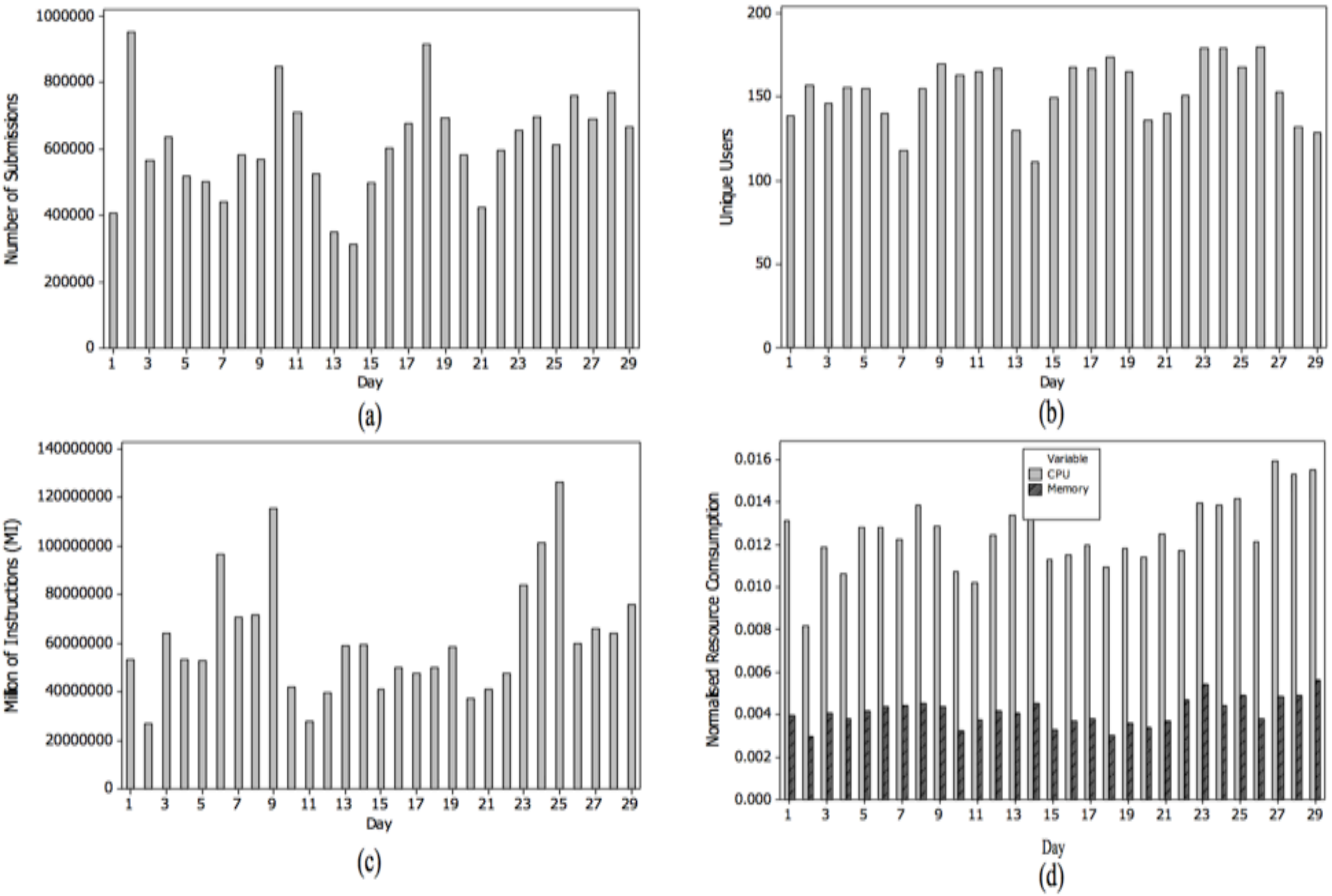

Figure 2. Statistical properties of (a) Completed-tasks, (b) Users, (c) Average task length, (d) Average resource consumption per task.

-- a loose correlation between the number of users and the number of tasks submitted per day at a coarse-grain analysis

-- resource utilization levels are very similar across all the analyzed days

- -- a strong correlation to the number of users, but a very loose one to the number of tasks and their average length

Conclusion:

-- resource consumption and task completion behavior is not homogenous across the observation period

--at such a high level of analysis, there appear to be loose correlations between tasks, users, task length and task resource consumption

-- coarse- grained analysis is insufficient

Model Description

-- proposed workload model comprises of the concepts of users and tasks and their relationship in matters of amount work and utilization of resources

--User has three important characteristic refer to as three dimensions

-- the submission rate (α) and the estimation ratios for CPU (β) and Memory (θ)

--Task

-- length (X), average resource utilization for CPU (γ) and Memory (π)

$$U = \{u_1, u_2, u_3, \ldots, u_i\} \quad (1)$$

$$T = \{t_1, t_2, t_3, \ldots, t_i\} \quad (2)$$

$$u_i = \{f(\alpha), f(\beta), f(\phi)\} \quad (3)$$

$$t_i = \{f(\chi), f(\gamma), f(\pi)\} \quad (4)$$

$$E(u_i) = u_i P(u_i) \quad (5)$$

$$E(t_i) = t_i (P(t_i) | P(u_j)) \quad (6)$$

Model Parameter

- -- characterize user and task behavior to derive the statistical parameters that define the workload model
  - -- determine the set of profiles U and T defined in Equations 1 and 2
  - -- derive the probabilistic functions for α, β, θ ,x, γ, π required in Equations 3 - 6

Model Parameter – Sampling Process

-- select a sample size of 24 hours from the overall tracelog population to attain the classification for tasks and users

-- The selection of the sample population was calculated by comparing the variance between the average task length and number of submitted tasks per day against the entire tracelog.

-- day 18 was selected as the sample population

-- Using k-means clustering to classify tasks and users based on to their respective dimensions

Model Parameter – Cluster Analysis

-- run the k-means clustering algorithm for k ranging from 1 to 10

-- K in user set is 6

-- K in task set is 3

TABLE II. PROPORTION OF ELEMENTS WITHIN CLUSTER FOR DAY 18.

Cluster	Pop %	Cluster	Pop %	Cluster	Pop %
u_1	0.68	u_4	77.40	t_1	1.84
u_2	0.68	u_5	15.75	t_2	72.56
u_3	2.74	u_6	2.74	t_3	25.60

Model Parameter – Cluster Analysis

-- To evaluate whether the derived user and task types are consistent across other periods of time in the same tracelog, the clustering process was repeated on another sample population

--Day 2 selected

-- it has the highest number of submissions and the number of users is lower than that of Day 18

-- is helpful to determine whether the variation of submissions and users can affect the number of clusters derived from the "average" day

--after run k from 1 to 10, k=6 and 3 also selected

Model Parameter – Cluster Analysis

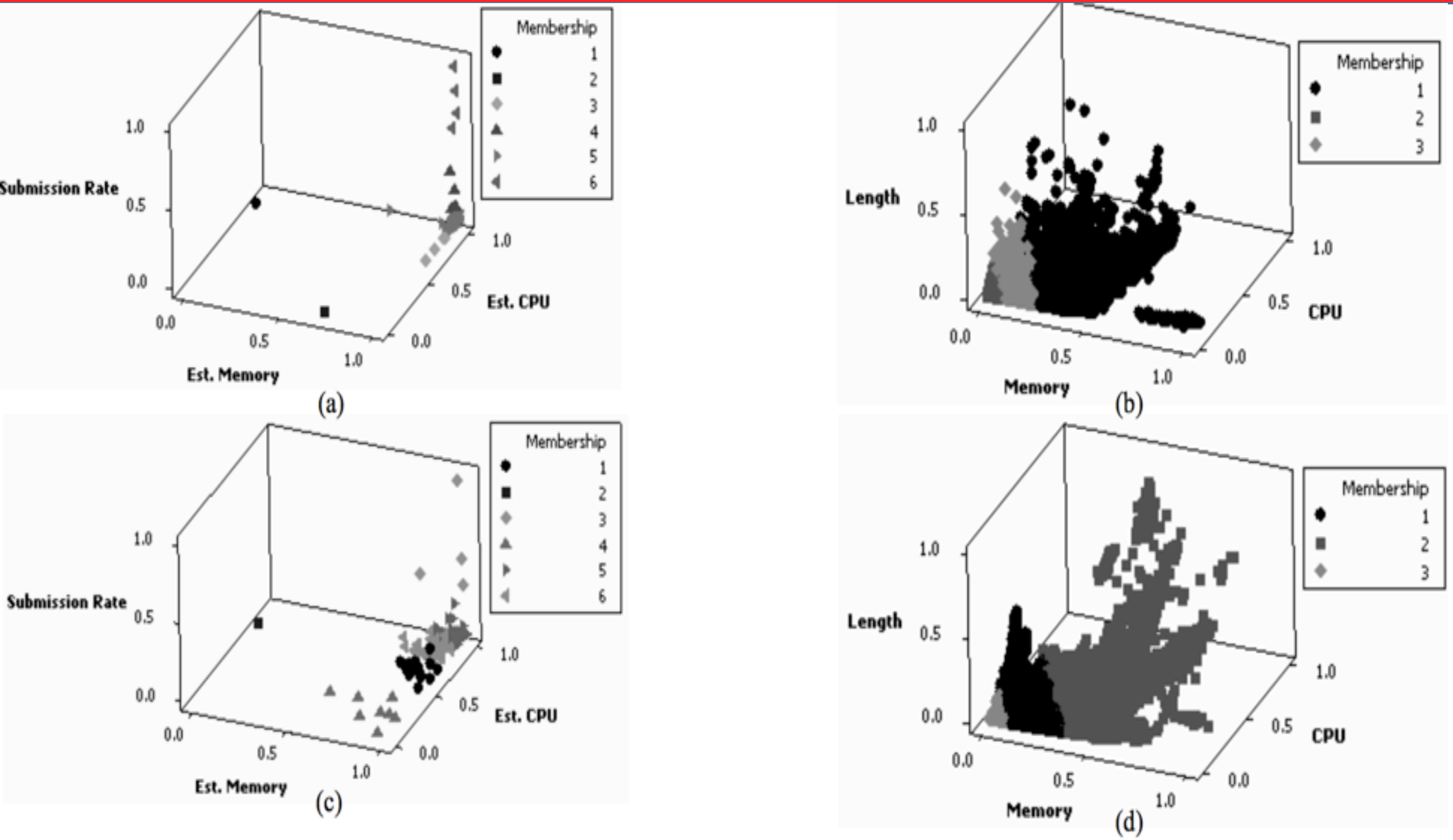

Figure 3. Clusterization results for (a) Users day 18, (b) Tasks day 18, (c) Users day 2 and (d) Tasks day 2.

--the general shape of the clusters for Day 2 are comparable to that of the cluster shapes for day 18 even though the workload for the two sampled days is different

Model Parameter – Cluster Analysis

TABLE III. CENTROID COMPARISON FOR USERS.

Day 2 Cluster	2	3	1	6	5	4
Sub Rate	0.0002	0.592	0.0152	0.0138	0.0124	0.0047
Est. CPU	0.7444	0.9089	0.6024	0.7978	0.948	0.1854
Est. Mem	0.0000	0.9624	0.9142	0.9057	0.9558	0.8557
Day 18 Cluster	**1**	**6**	**3**	**5**	**4**	**2**
Sub Rate	0.0003	0.7901	0.0027	0.0113	0.1801	0.0000
Est. CPU	0.8126	0.9838	0.7428	0.9718	0.9638	0.0000
Est. Mem	0.0000	0.9974	0.9947	0.9888	0.9922	0.7178
Euclidean Dist	**0.0682**	**0.2147**	**0.1623**	**0.1928**	**0.1723**	**0.2311**

TABLE IV. CENTROID COMPARISON FOR TASKS.

Day 2 Cluster	3	1	2
Length	0.0006	0.0244	0.075
CPU	0.0147	0.1041	0.2841
Memory	0.0115	0.0994	0.3849
Day 18 Cluster	**2**	**3**	**1**
Length	0.0007	0.0038	0.0107
CPU	0.0149	0.0810	0.2206
Memory	0.0089	0.0585	0.2556
Euclidean Dist	**0.0026**	**0.0512**	**0.1577**

--there is marginal difference of centroid values for tasks, which suggest a consistent resource utilization patterns during the two analyzed days

--User centroid dimensions experience a slightly increased discrepancy, especially for submission rate

--a larger number of submissions in day 2 being performed by a lower number of users in comparison to day 18

Model Parameter – Cluster Analysis

--Conclusion

- --tasks and users exhibit similar behavioral patterns across the two different observational periods
- --by comparing similar clusters it is possible to observe that although the patterns are close, they present differences evidently introduced by changes in the environment
- --cluster analysis depicts in general terms the individual user and tasks patterns but does not provide the fine-grained parameters required to characterize realistic utilization models

Model Parameter – Intra - Cluster Analysis

--studying the data distributions for each one of the cluster dimensions
   -- fitting the data from logs to specific distributions
   -- Regarding to the behavioral patterns there are two special cases: resource estimation and consumption
      -- resource consumption is how tasks consume resources
      -- resource estimation outline how users request resources
         --overestimation (OE) and underestimation (UE)

--For each parameter we evaluated several distributions including normal, lognormal, exponential, weibull, gamma, logistic, loglogistic, and extreme value among others

Model Parameter – Intra - Cluster Analysis

TABLE V. SET OF DATA DISTRIBUTIONS DERIVED FROM USER CLUSTERS.

		Day 2	Day 18
Cluster	***Dimension***	***Best Fit Distribution***	***Best Fit Distribution***
u_1	***Submission Rate*** ***CPU UE / OE*** ***Memory UE / OE***	-Lognormal -Gamma / General Extreme Value - Lognormal / General Extreme Value	-Uniform - Lognormal / General Extreme Value -Gamma / NA
u_2	***Submission Rate*** ***CPU UE / OE*** ***Memory UE / OE***	- Uniform -NA / Normal -Normal / NA	-Uniform -NA -NA
u_3	***Submission Rate*** ***CPU UE / OE*** ***Memory UE / OE***	- Uniform -Weibull / General Extreme Value -NA / General Extreme Value	-Uniform -Weibull / General Extreme Value -Gamma / General Extreme Value
u_4	***Submission Rate*** ***CPU UE / OE*** ***Memory UE / OE***	- Lognormal -Weibull / NA -NA / General Extreme Value	-Uniform - Lognormal / General Extreme Value - Lognormal / General Extreme Value
u_5	***Submission Rate*** ***CPU UE / OE*** ***Memory UE / OE***	- Lognormal -LogLogistic / General Extreme Value -NA / General Extreme Value	-Gamma - Lognormal / General Extreme Value - Lognormal / General Extreme Value
u_6	***Submission Rate*** ***CPU UE / OE*** ***Memory UE / OE***	-Weibull -Gamma / Normal -Loglogistic / General Extreme Value	-Uniform -Weibull / General Extreme Value - Lognormal / General Extreme Value

--General Extreme Value (GEV) distribution best fits CPU and Memory overestimations in both analyzed scenarios

-- indicates that users tend to highly overestimate both resources when tasks are submitted

--resource underestimations generally follow distributions such as Lognormal, Weibull, and Gamma

--indicates that when users underestimate they do it in small proportions especially for Memory

--(?)submission rates follow distributions such as Lognormal, Gamma, and Weibull.

--indicates that most of the users have low submission rates in comparison to very few users having high submission rates

Model Parameter – Intra - Cluster Analysis

TABLE VI. SET OF DATA DISTRIBUTIONS DERIVED FROM TASK CLUSTERS.

		Day 2		Day 18	
Cluster	***Dimension***	***Best Fit Distribution***	***P(0)***	***Best Fit Distribution***	***P(0)***
t_1	***Length*** ***CPU*** ***Memory***	-Lognormal -Normal -Lognormal	-NA -16% -22%	-Loglogistic -Lognormal -Loglogistic	-NA -20% -37%
t_2	***Length*** ***CPU*** ***Memory***	-Lognormal -Weibull -Normal	-NA -18% -22%	-Lognormal -Lognormal -Loglogistic	-NA -13% -30%
t_3	***Length*** ***CPU*** ***Memory***	-Lognormal -Lognormal -Lognormal	-NA -41% -60%	-Lognormal -Lognormal -Loglogistic	-NA -13% -30%

--the length generally follows a lognormal distribution

--indicate that even within the clusters most of the tasks have a short length

--CPU and Memory consumption follow lognormal, loglogistic, and Weibull distributions

--indicate a high proportion of tasks consume resources at lower rates

Model Evaluation

--performed simulation experiments and contrasted the results against the production data from Google traces

-- include

--Workload Generator

--Simulation Environment

--Result Analysis

Model Evaluation--Workload Generator

--input of the model : parameters for users and tasks

--output of the model : a set of instructions to be executed by the simulator to mimic the operational environment behavior

--integrated by 5 modules: User Profiles, Task Profiles, User Generator, Task Generator, and Workload Coordinator

$$U = \{u_1, u_2, u_3, \ldots, u_i\} \tag{1}$$

$$T = \{t_1, t_2, t_3, \ldots, t_i\} \tag{2}$$

$$u_i = \{f(\alpha), f(\beta), f(\phi)\} \tag{3}$$

$$t_i = \{f(\chi), f(\gamma), f(\pi)\} \tag{4}$$

$$E(u_i) = u_i P(u_i) \tag{5}$$

$$E(t_i) = t_i (P(t_i) | P(u_j)) \tag{6}$$

--User Profiles, Task Profiles behavior outlined through the intra-cluster analysis

--using the statistical parameters derived for day 2

--User Generator correspond to equation (5)

--Task Generator correspond to equation (6)

Model Evaluation—Simulation Environment

--simulated a datacenter composed by 12,583 servers based on the capacities described in the Google tracelog
--the simulation time is set up to emulate 29 days and contains 153 users per day

Model Evaluation—Result Analysis

-- compare the proportions of users, tasks and the task per users classified by cluster membership

-- the discrepancies in most of the cases lie between the error margins of +/- 5%

-- in Fig. 5(b) for t2,t3 and where the differences have been measured as 6% and 8% respectively

-- this seems to have a negligible impact in the distribution of tasks per user where the differences are no greater than +/- 0.6% as shown in Fig. 5(c)

--u5 selected to compare the 3 dimension of user behavior pattern

--t3 selected to compare the 3 dimension of task behavior pattern

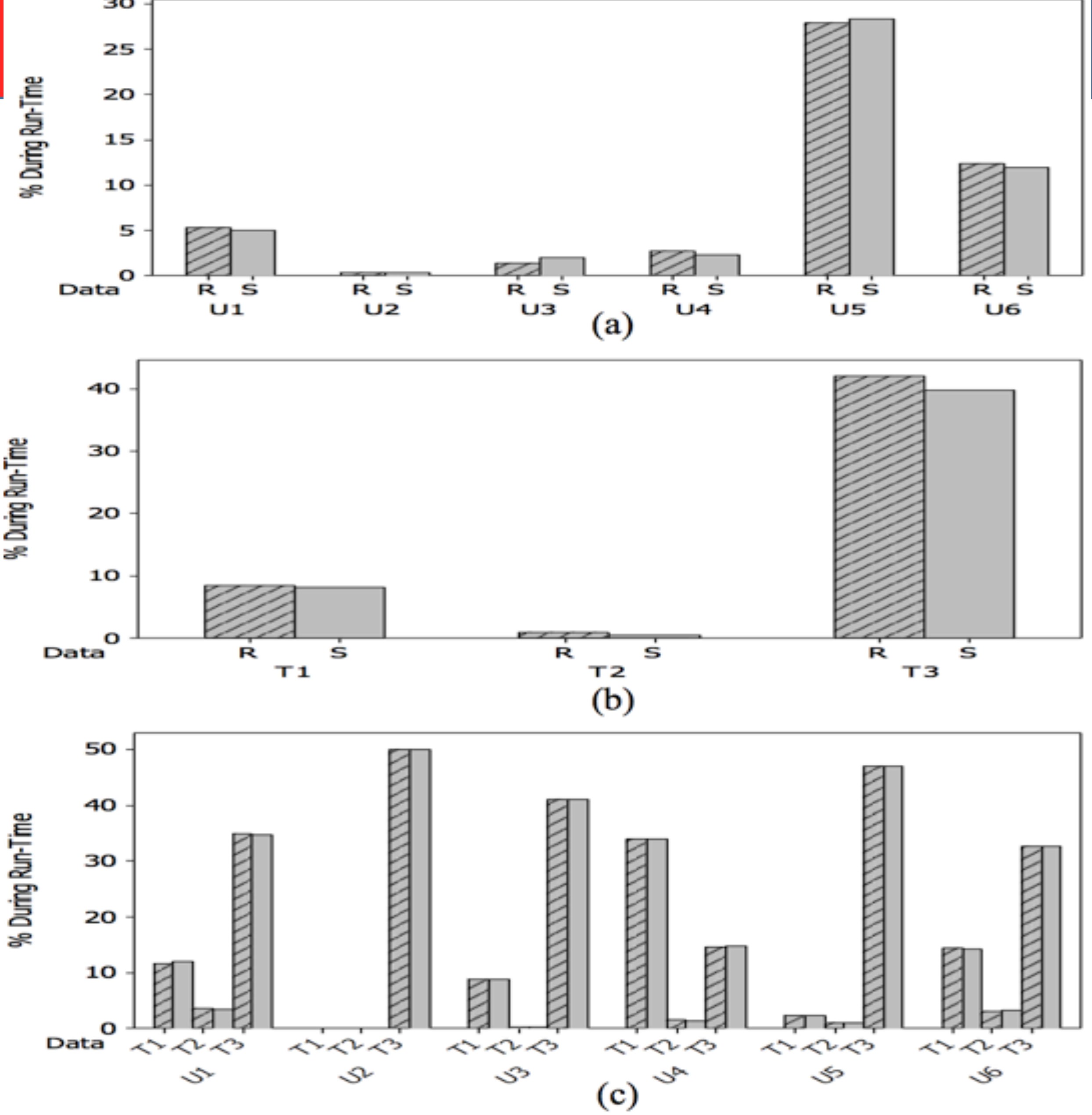

Figure 5. Comparisons of the proportions between logged data and the outcome from the simulation. (a) Proportions of user per cluster membership, (b) Proportions of task per cluster membership, and (c) illustrates the comparison of task per user.

Model Evaluation—Result Analysis

--compare user pattern

--the distributions for the user dimensions during the simulation match closely the patterns observed from the logged data

--the percentage of error was calculated as 1.68%, 2.0%, and 1.03% for submission rate, CPU and Memory estimation ratio respectively

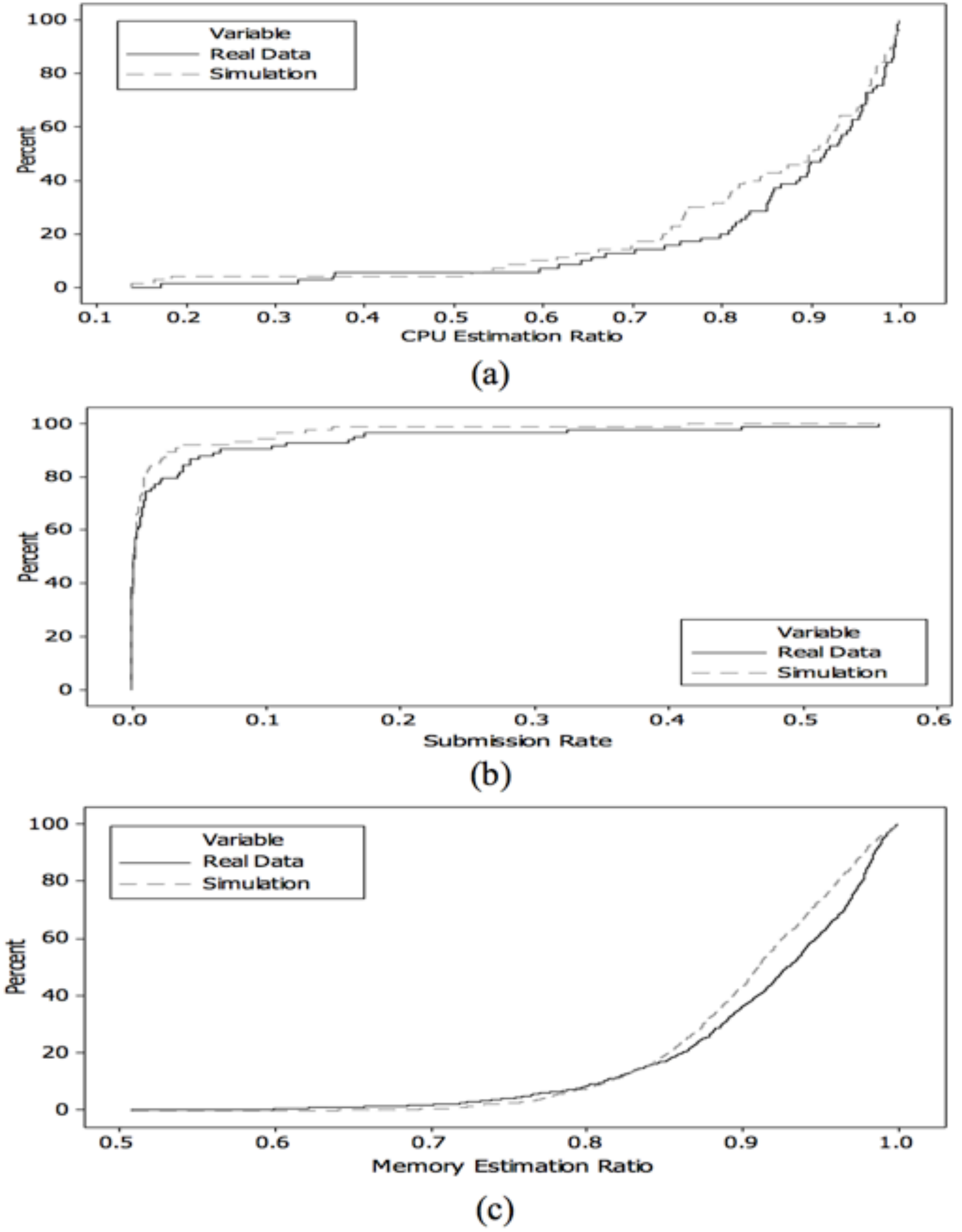

Figure 6. Comparison of user patterns between real and simulated data for $\boldsymbol{u}_5$ (a) estimation ratio for CPU, (b) submission rates, and (c) estimation ratio for Memory requests.

Model Evaluation—Result Analysis

TABLE VII. EVALUATION OF THE ACCURACY OF USER PATTERNS.

	Cluster	Real	Simulation	%Error
Submission Rate	u_1	5.248	5.107	2.69
	u_2	0.006	0.006	0.00
	u_3	1.543	1.336	13.42
	u_4	6.171	6.318	2.38
	u_5	6.648	6.760	1.68
	u_6	5.600	5.943	6.13
CPU Estimation	u_1	0.648	0.622	3.99
	u_2	0.423	0.412	2.48
	u_3	0.848	0.863	1.74
	u_4	0.848	0.863	1.74
	u_5	0.092	0.090	2.00
	u_6	0.585	0.580	0.85
Memory Estimation	u_1	0.906	0.901	0.54
	u_2	1.148	1.146	0.17
	u_3	0.968	0.963	0.54
	u_4	0.488	0.461	5.59
	u_5	0.941	0.931	1.03
	u_6	0.889	0.894	0.60

--compare accuracy for all the user clusters

--the percentage of error is considerably low for CPU and Memory estimation, calculated on average as 2.14% and 1.41% respectively

--in the case of submission rate with an average of 4.38%,u3 introduces a moderately high error value

--because just 4 user in u3 cluster

-- after try normal distribution, average error is 3.15%

Model Evaluation—Result Analysis

--The percentage of error was determined as 0.19%, 0.55%, and 2.5% for task length, CPU and Memory consumption respectively

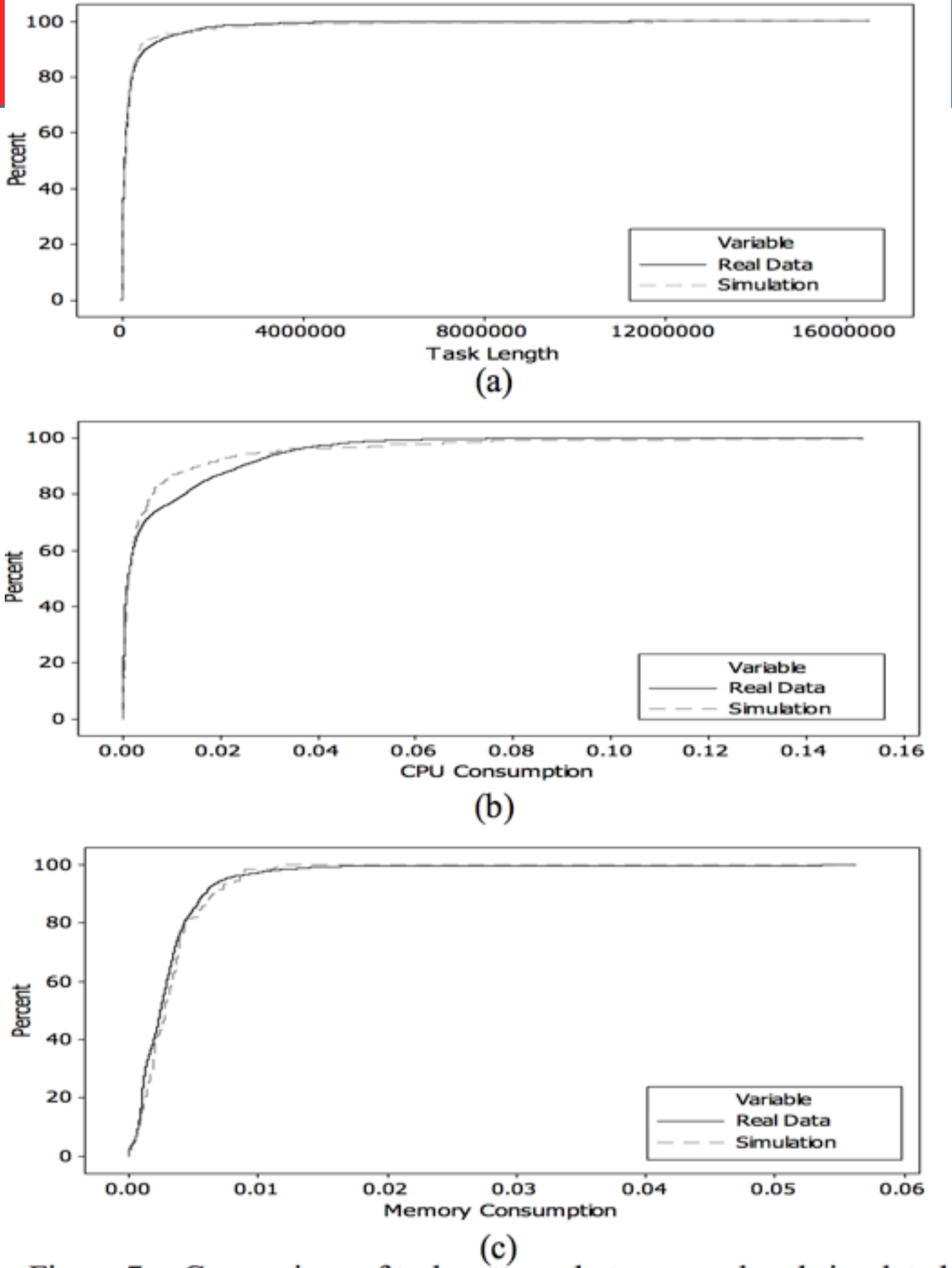

Figure 7. Comparison of task patterns between real and simulated data for t_3 (a) task length, (b) CPU consumption, and (c) Memory consumption.

Model Evaluation—Result Analysis

TABLE VIII. EVALUATION OF THE ACCURACY OF TASK PATTERNS.

	Cluster	Real	Simulation	%Error
Length	t_1	11.07	11.1	0.27
	t_2	16.57	16.53	0.24
	t_3	15.46	15.43	0.19
CPU Utilization	t_1	0.029	0.036	24.66
	t_2	0.071	0.065	7.70
	t_3	6.56	6.596	0.55
Memory Utilization	t_1	4.294	4.294	0.00
	t_2	0.046	0.050	7.50
	t_3	6.196	6.041	2.50

--the average percentage of error for length and Memory usage is 0.24% and 3.33% respectively

--for CPU usage the average error percentage is approximately 10.97% caused by a very highly-inaccurate simulated CPU usage pattern in t1

--change a new distribution function, t1 error is 0.95%

Model Applicability

--a model to reduce the energy waste by exploiting the workload heterogeneity that exists in Cloud environments is proposed

--The core idea is to co-allocate different types of workloads based on the level of interference that they create to reduce the resultant overhead and consequently to improve the energy-efficiency of the datacenter

-- The approach classifies the incoming workloads based on their resource usage patterns, pre-selects the hosting servers based on resources constraints, and makes the final allocation decision based on the current servers' performance interference level