Università
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Understanding and Comparing Unsuccessful Executions in Large Datacenters

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Abstract

The project aims at comparing two different traces coming from large datacenters, focusing in particular on unsuccessful executions of jobs and tasks submitted by users. The objective of this project is to compare the resource waste caused by unsuccessful executions, their impact on application performance, and their root causes. We will show the strong negative impact on CPU and RAM usage and on task slowdown. We will analyze patterns of unsuccessful jobs and tasks, particularly focusing on their interdependency. Moreover, we will uncover their root causes by inspecting key workload and system attributes such asmachine locality and concurrency level.

Advisor
Prof. Walter Binder
Assistant
Dr. Andrea Rosá

Advisor's approval (Prof. Walter Binder): Date:

Introduction (including Motivation)

State of the Art

- Introduce Ros'a 2015 DSN paper on analysis
- Describe Google Borg clusters
- Describe Traces contents
- Differences between 2011 and 2019 traces

Project requirements and analysis

(describe our objective with this analysis in detail)

Analysis methodology

Technical overview of traces' file format and schema

Overview on challenging aspects of analysis (data size, schema, avaliable computation resources)

Introduction on apache spark

General workflow description of apache spark workflow

The Google 2019 Borg cluster traces analysis were conducted by using Apache Spark and its Python 3 API (pyspark). Spark was used to execute a series of queries to perform various sums and aggregations over the entire dataset provided by Google.

In general, each query follows a general Map-Reduce template, where traces are first read, parsed, filtered by performing selections, projections and computing new derived fields. Then, the trace records are often grouped by one of their fields, clustering related data toghether before a reduce or fold operation is applied to each grouping.

Most input data is in JSONL format and adheres to a schema Google profided in the form of a protobuffer specification[1].

On of the main quirks in the traces is that fields that have a "zero" value (i.e. a value like 0 or the empty string) are often omitted in the JSON object records. When reading the traces in Apache Spark is therefore necessary to check for this possibility and populate those zero fields when omitted.

Most queries use only two or three fields in each trace records, while the original records often are made of a couple of dozen fields. In order to save memory during the query, a projection is often applied to the data by the means of a .map() operation over the entire trace set, performed using Spark's RDD API.

Another operation that is often necessary to perform prior to the Map-Reduce core of each query is a record filtering process, which is often motivated by the presence of incomplete data (i.e. records which contain fields whose values is unknown). This filtering is performed using the .filter() operation of Spark's RDD API.

The core of each query is often a groupBy followed by a map() operation on the aggregated data. The groupby groups the set of all records into several subsets of records each having something in common. Then, each of this small clusters is reduced with a .map() operation to a single record. The motivation behind this computation is often to analyze a time series of several different traces of programs. This is implemented by groupBy()-ing records by program id, and then map()-ing each program trace set by sorting by time the traces and computing the desired property in the form of a record.

Sometimes intermediate results are saved in Spark's parquet format in order to compute and save intermediate results beforehand.

General Query script design

Ad-Hoc presentation of some analysis scripts (w diagrams)

[1] Google 2019 Borg traces Protobuffer specification on Github

Analysis (w observations)

machine_configs

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	8729	1.639218%
1.000000	0.500000	124234	23.329891%
0.591797	0.333496	103013	19.344801%
0.259277	0.166748	78078	14.662260%
0.708984	0.333496	55801	10.478864%
0.386719	0.333496	36237	6.804943%
0.958984	0.500000	31151	5.849843%
0.708984	0.666992	29594	5.557454%
0.386719	0.166748	27011	5.072393%
1.000000	1.000000	12286	2.307187%
0.591797	0.166748	9902	1.859496%
1.000000	0.250000	7550	1.417814%
0.958984	1.000000	3552	0.667030%
0.259277	0.333496	3024	0.567877%
0.591797	0.666992	1000	0.187790%
0.259277	0.083374	634	0.119059%
0.958984	0.250000	600	0.112674%
0.500000	0.062500	54	0.010141%
0.500000	0.250000	34	0.006385%
0.479492	0.250000	12	0.002253%
0.708984	0.250000	6	0.001127%
0.591797	0.250000	4	0.000751%
0.708984	0.500000	2	0.000376%
0.479492	0.500000	2	0.000376%

(a) All clusters

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	1377	1.623170%
0.591797	0.333496	29487	34.758469%
1.000000	0.500000	13440	15.842705%
0.708984	0.333496	12495	14.728764%
0.386719	0.333496	9057	10.676144%
0.386719	0.166748	5265	6.206238%
0.708984	0.666992	4608	5.431784%
1.000000	1.000000	4446	5.240823%
0.591797	0.166748	2484	2.928071%
0.958984	0.500000	1143	1.347337%
0.958984	1.000000	654	0.770917%
1.000000	0.250000	366	0.431431%
0.479492	0.250000	6	0.007073%
0.708984	0.250000	6	0.007073%

(b) A cluster

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	134	0.264812%
0.591797	0.333496	16184	31.982926%
1.000000	0.500000	9790	19.347061%
0.708984	0.333496	8448	16.694992%
0.958984	0.500000	5502	10.873088%
0.708984	0.666992	3832	7.572823%
1.000000	1.000000	2214	4.375321%
0.591797	0.166748	2152	4.252796%
0.386719	0.333496	816	1.612584%
0.958984	1.000000	618	1.221296%
0.591797	0.666992	500	0.988103%
0.386719	0.166748	412	0.814197%

(c) Cluster B

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	1466	2.274208%
0.259277	0.166748	15754	24.439204%
0.386719	0.333496	11104	17.225652%
0.591797	0.333496	10404	16.139741%
0.958984	0.500000	6634	10.291334%
1.000000	0.500000	5654	8.771059%
0.386719	0.166748	3580	5.553660%
0.708984	0.666992	2900	4.498774%
1.000000	1.000000	2736	4.244361%
1.000000	0.250000	2132	3.307375%
0.958984	1.000000	766	1.188297%
0.708984	0.333496	620	0.961807%
0.958984	0.250000	600	0.930781%
0.591797	0.166748	112	0.173746%

(d) Cluster C

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	498	0.794309%
0.591797	0.333496	28394	45.288376%
0.386719	0.333496	8402	13.401174%
0.259277	0.166748	8020	12.791885%
0.386719	0.166748	5806	9.260559%
0.708984	0.666992	4380	6.986092%
0.708984	0.333496	3924	6.258772%
0.591797	0.166748	2548	4.064055%
0.259277	0.333496	426	0.679469%
1.000000	0.500000	292	0.465739%
0.591797	0.250000	4	0.006380%
0.708984	0.500000	2	0.003190%

(e) Cluster D

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	536	0.671915%
0.259277	0.166748	38452	48.202377%
0.708984	0.333496	11786	14.774608%
0.958984	0.500000	8646	10.838389%
0.708984	0.666992	7606	9.534674%
1.000000	0.500000	5586	7.002457%
0.386719	0.166748	4470	5.603470%
0.259277	0.333496	1268	1.589530%
0.259277	0.083374	634	0.794765%
0.591797	0.333496	324	0.406158%
1.000000	0.250000	268	0.335957%
1.000000	1.000000	138	0.172993%
0.500000	0.062500	54	0.067693%
0.500000	0.250000	4	0.005014%

(f) Cluster E

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	1432	2.299958%
1.000000	0.500000	41340	66.396839%
0.708984	0.333496	6878	11.046866%
0.591797	0.333496	5564	8.936430%
0.958984	0.500000	2172	3.488484%
0.386719	0.166748	1544	2.479843%
0.708984	0.666992	1244	1.998008%
1.000000	0.250000	792	1.272044%
0.958984	1.000000	536	0.860878%
0.386719	0.333496	398	0.639234%
1.000000	1.000000	344	0.552504%
0.500000	0.250000	18	0.028910%

(g) Cluster F

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	1566	2.261568%
0.259277	0.166748	15852	22.892958%
1.000000	0.500000	11808	17.052741%
0.708984	0.333496	7968	11.507134%
0.591797	0.333496	7830	11.307839%
0.386719	0.166748	4690	6.773150%
0.708984	0.666992	4258	6.149269%
0.958984	0.500000	4196	6.059731%
0.386719	0.333496	3864	5.580267%
0.591797	0.166748	2606	3.763503%
1.000000	0.250000	2100	3.032754%
0.259277	0.333496	1330	1.920744%
0.958984	1.000000	778	1.123563%
1.000000	1.000000	378	0.545896%
0.500000	0.250000	12	0.017330%
0.479492	0.250000	6	0.008665%
0.479492	0.500000	2	0.002888%

(h) Cluster G

CPU (NCU)	RAM (NMU)	Machine count	% Machines
Unknown	Unknown	1720	2.933251%
1.000000	0.500000	36324	61.946178%
0.591797	0.333496	4826	8.230158%
0.708984	0.333496	3682	6.279205%
0.958984	0.500000	2858	4.873973%
0.386719	0.333496	2596	4.427163%
1.000000	1.000000	2030	3.461919%
1.000000	0.250000	1892	3.226577%
0.386719	0.166748	1244	2.121491%
0.708984	0.666992	766	1.306320%
0.591797	0.666992	500	0.852689%
0.958984	1.000000	200	0.341076%

(i) Cluster H

Figure 1. Overwiew of machine configurations in terms of CPU and RAM resources for each cluster

Observations:

- machine configurations are definitely more varied than the ones in the 2011 traces
- some clusters have more machine variability

machine_time_waste

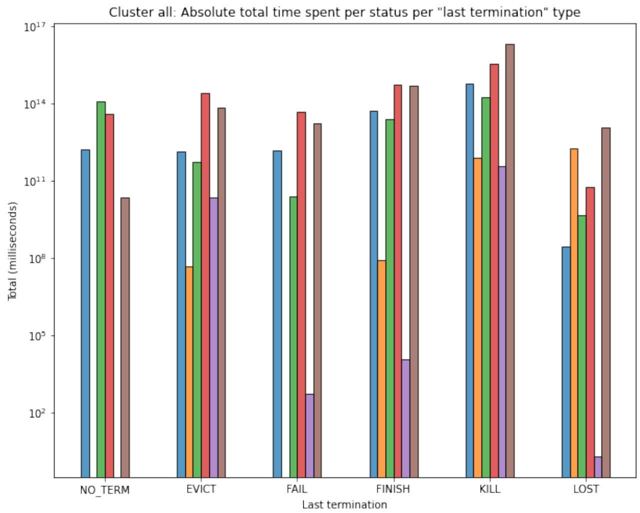
Observations:

task_slowdown

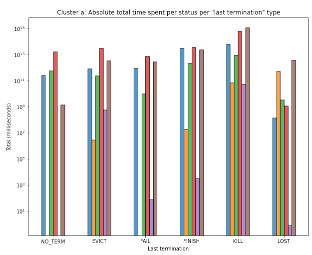
spatial_resource_waste

Color	Execution phase
Blue	Queued
Orange	Ended
Green	Ready
Red	Running
Violet	Evicted
Brown	Unknown

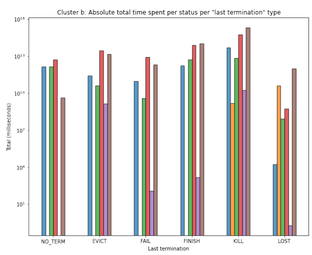
(a) Execution state legend for the graphs



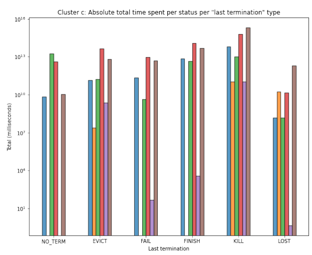
(b) All clusters



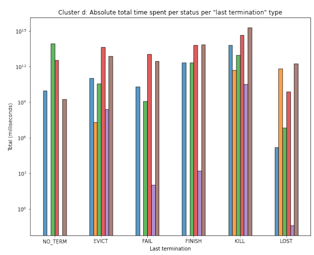
(c) Cluster A



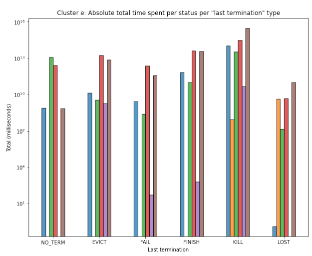
(d) Cluster B



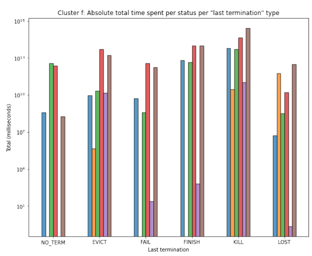
(e) Cluster C



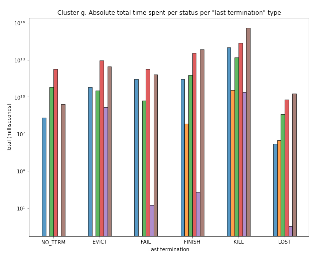
(f) Cluster D



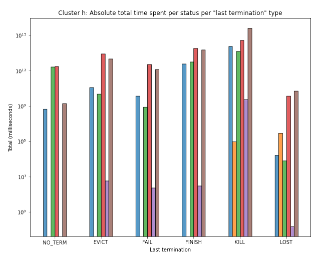
(g) Cluster E



(h) Cluster F



(i) Cluster G

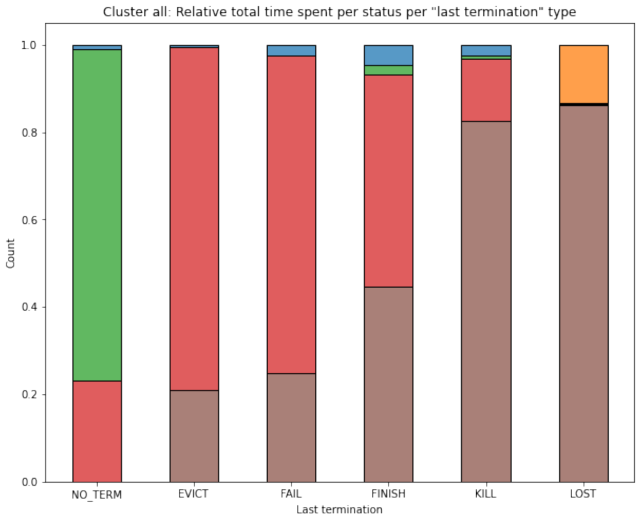


(j) Cluster H

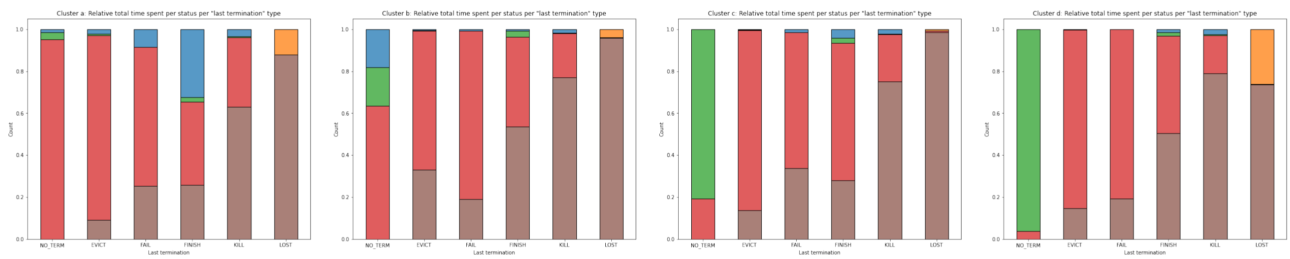
Figure 2. Total task time (in milliseconds) spent in each execution phase w.r.t. task termination.

Color	Execution phase
Blue	Queued
Orange	Ended
Green	Ready
Red	Running
Violet	Evicted
Brown	Unknown

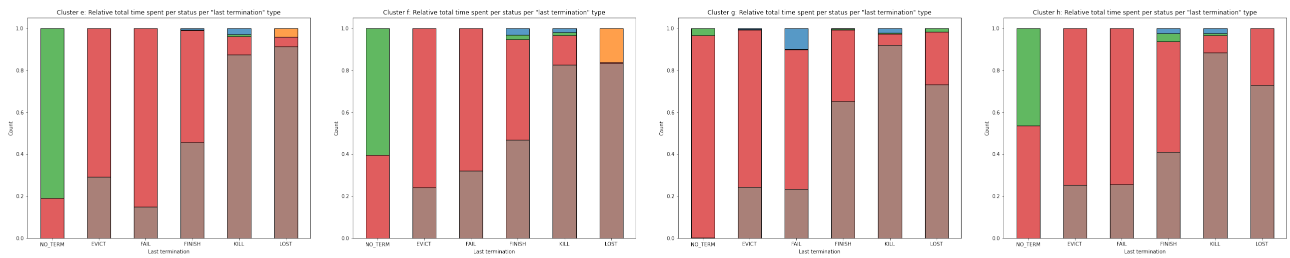
(a) Execution state legend for the graphs



(b) All clusters



(c) Cluster A **(d)** Cluster B **(e)** Cluster C **(f)** Cluster D



(g) Cluster E **(h)** Cluster F **(i)** Cluster G **(j)** Cluster H

Figure 3. Relative task time (in milliseconds) spent in each execution phase w.r.t. task termination.

figure_7

figure_8

figure_9

table_iii, table_iv, figure_v

Potential causes of unsuccesful executions

Implementation issues – Analysis limitations

Discussion on unknown fields

Limitation on computation resources required for the analysis

Other limitations . . .

Conclusions and future work or possible developments

Some examples

Figure 1 shows how to insert figures in the document.

Figure 4. Caption of the figure

Table 1 shows how to insert tables in the document.

Table 1. Caption of the table

Col 1	**Col 2**	**Col 3**	**Col 4**
1	2	3	Goofy
4	5	6	Mickey