Log Parsing Evaluation in the Era of Modern Software Systems

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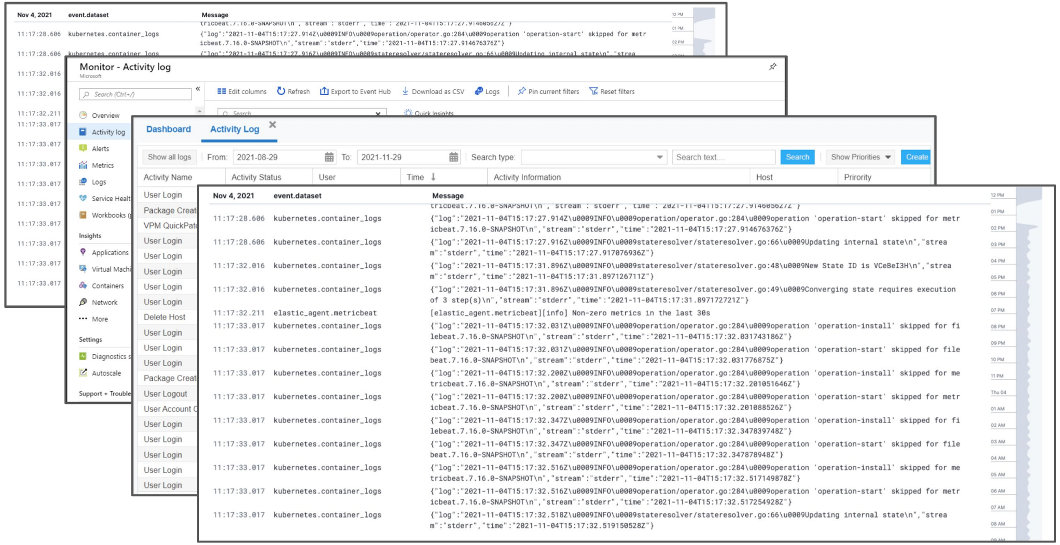
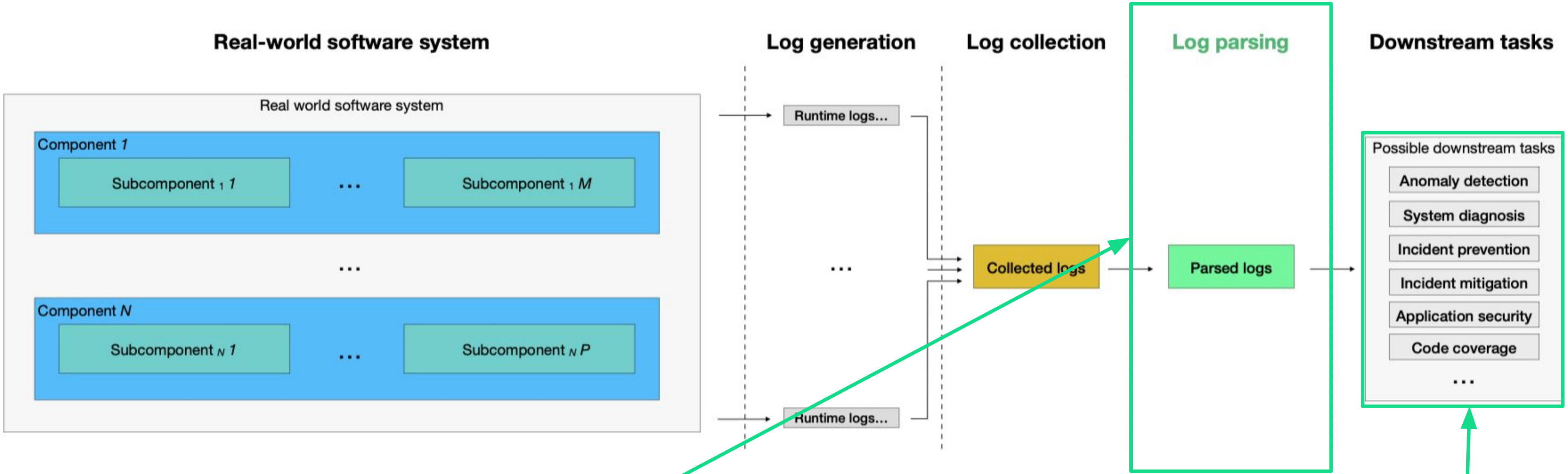
Logs in Modern Organizations



- TBs of logs daily
- Thousands of machines & different software
- High complexity

Logs, Downstream Tasks, Log Parsing



Log parsing is a critical step

The Good

- Many log parsing solutions exist, with various algorithmic approaches (ML, heuristics, etc.)
- 70% average accuracy for SOTA log parsers; even 99% accuracy

The Bad

The performance of these solutions may have been inflated
(20% instead of 70%)

The Ugly

Log parsing in real-world scenarios has received too little attention:
disconnect between research and industry (5% on industry logs)

Main Contributions

What is the performance of log parsing?

Rethinking evaluation methodology

Our tool: `logchimera`

How can we connect industry log parsing and academia?

Log Parsing Example

Runtime log

```
Input size for job job_1445062781478_0011 = 1256521728. Number of splits = 10
```

Parsed log

Template	`Input size for job <*> = <*>. Number of splits = <*>`
Variables	`["job_1445062781478_0011", "1256521728", "10"]`

Evaluating Log Parsing Performance: Goal

- Performance on publicly available data
- Performance on publicly available data that resemble industry
- Performance on industry data

- Reproducing claimed results
- Scrutinizing results (which led to rethinking metrics)

Evaluating Log Parsing Performance: How

- 11 log datasets
- 14 methods
- Reproducing claimed results (70% accuracy)
- Scrutinizing previous evaluation & rethinking metrics (20% accuracy)

- Next up, two tables, measurements averaged over 10 runs
- Metrics used: *edit-distance* and *log template accuracy*
- For consistency with further experiments, we highlight results for AEL, Drain, and IPLoM

Evaluating Log Parsing Performance: Results

Dataset	AEL	Drain	IPLoM	LenMa	LFA	LKE	LogC
Apache	10.426	10.426	10.442	13.760	10.576	14.872	16.
Com							
Ind							

Dataset	AEL	Drain	IPLoM	LenMa	LFA	LKE								Spell
Apache	**0.694**	**0.694**	**0.694**	0.000	0.688	0.000								**0.694**
BGL	0.341	0.341	0.292	0.082	0.230	0.057								0.196
HDFS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.435**	0.000	0.000	0.000
HealthApp	0.164	0.238	0.158	0.136	0.149	0.133	0.138	0.220	0.126	0.166	**0.341**	0.041	0.322	0.152
HPC	0.644	0.620	0.638	0.632	0.609	0.360	0.632	0.632	0.509	0.632	**0.827**	0.226	0.661	0.530
Mac	0.172	0.224	0.041	0.132	0.101	0.172	0.162	0.228	0.118	0.042	**0.274**	0.163	0.148	0.032
OpenStack	0.018	0.018	0.000	0.018	0.008	0.010	0.010	0.010	0.010	0.000	**0.359**	0.018	0.119	0.000
Spark	0.194	0.194	0.192	0.004	0.190	0.001	0.006	0.038	0.000	0.208	0.204	0.004	**0.543**	0.192
Windows	0.154	0.159	0.001	0.154	0.142	0.148	0.153	0.156	0.150	0.006	**0.387**	0.151	0.140	0.004
Combined Dataset	0.267	0.258	0.214	0.140	0.180	0.140	0.128	0.258	0.092	0.180	**0.323**	0.067	0.280	0.186
Industry Dataset	0.054	**0.056**	0.041	0.001	0.022	0.001	0.002	0.054	0.000	0.048	0.050	0.002	0.034	0.041

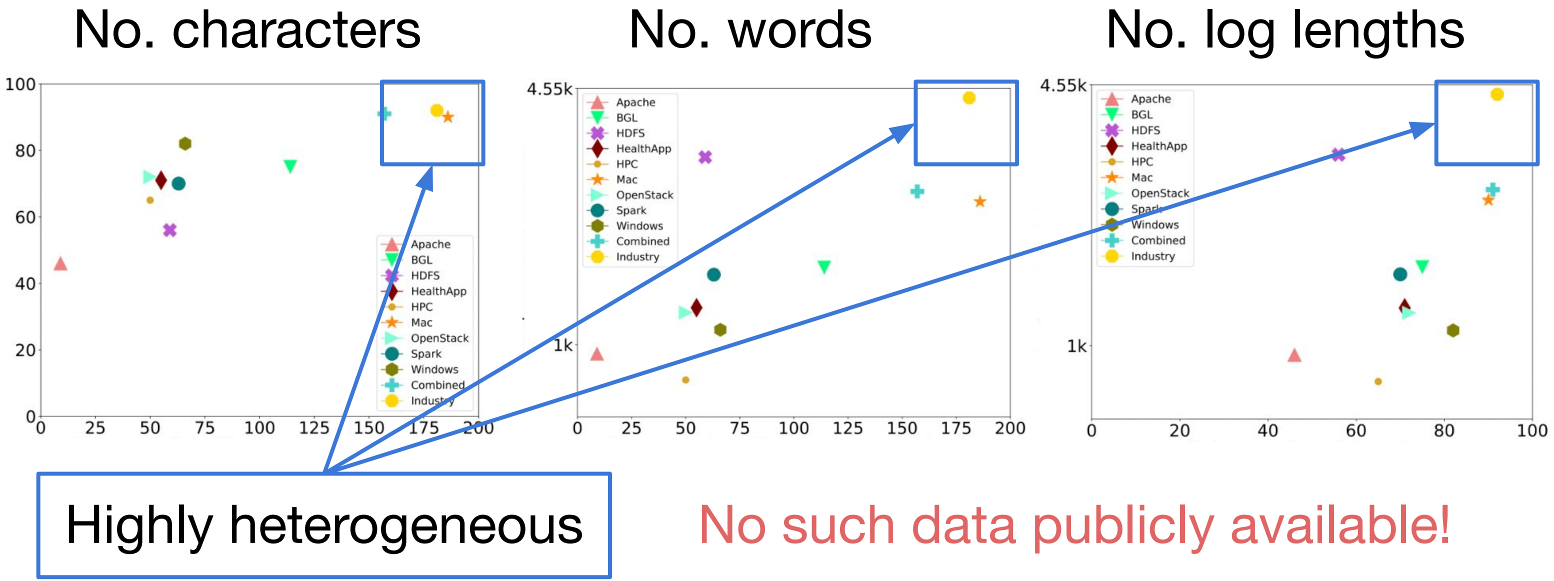
Public data: poor results
20% accuracy

Even worse, 5% accuracy on industry data

Why?

Industry Data Characteristics

- Industry data is significantly more heterogeneous

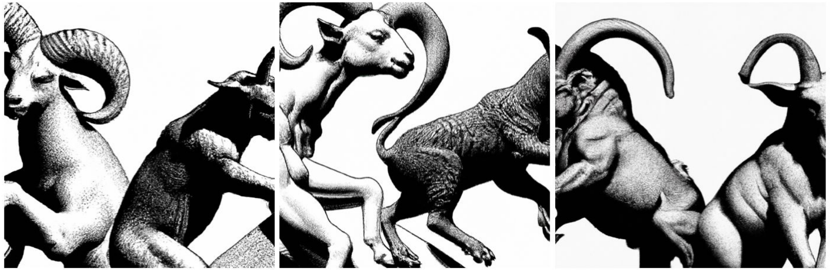


Connecting Industry Log Parsing to Academia

- We propose a tool: `logchimera`

logchimera

`logchimera` was born out of a research innitiative (Log Parsing Evaluation in the Era of Modern Software Systems), as a consequence of a general lack of access to heterogeneous log data typically found in industry. With `logchimera` you can generate and evaluate log parsing on heterogeneous industry-like data from publicly available logs. The name of the tool is inspired by the mythological creature *chimera*, which symbolizes a fusion or combination of different elements; and in this case, it reflects heterogeneity by enabling bringing together diverse formats from various logs to resemble industry-like contexts.



release v0.1.0

Access to industry-like logs

How?

Estimating log heterogeneity

- No established way to estimate *H*
- We chose a proxy metric for heterogeneity (*H*)

No	**Metric**	σ^2
1	No. unique words	0.278
2	No. unique characters	0.159
3	No. unique log lengths	0.331

$$H = 0.4 * \mathtt{nuw}\% + 0.2 * \mathtt{nuc}\% + 0.4 * \mathtt{nuldl}\%$$

- Next, we considered *Mixing* and *Fuzzing*

Logchimera Experiments: *Mixing*

Steps
1. labeling*
2. pre-processing
3. statistical analysis
4. weighing function
5. log replacement
6. consistency check

**optional*

More details in the paper.

```
mod_jk child workerEnv in error state 6
mod_jk child workerEnv in error state 7
mod_jk child workerEnv in error state 8
...
```

Initial dataset

```
mod_jk child workerEnv in error state 6
setting hostname to "authorMacBook-Pro.loc"
mod_jk child workerEnv in error state 8
...
```

Mixed dataset

(25% max)

Logchimera Experiments: *Mixing*

What is the performance when mixing?

Performance drops consistently as logs are mixed

H level	Dataset	AEL	Drain	IPLoM
0.219	Apache init	0.694/10.426	0.694/10.426	0.694/10.442
0.530	Apache (5)	0.653/15.925	0.653/15.923	0.653/15.369
0.640	Apache (10)	0.618/19.596	0.618/19.602	0.618/19.414
0.737	Apache (15)	0.586/23.468	0.586/23.495	0.586/22.809
0.816	Apache (20)	0.552/27.504	0.552/27.547	0.552/26.877
0.886	Apache (25)	0.514/32.265	0.514/32.135	0.514/31.34
0.259	HPC init	0.644/1.405	0.620/2.015	0.638/2.323
0.524	HPC (5)	0.605/6.510	0.581/7.081	0.599/7.257
0.661	HPC (10)	0.566/11.734	0.542/12.272	0.560/12.301
0.735	HPC (15)	0.525/16.720	0.501/17.300	0.519/17.124
0.817	HPC (20)	0.486/22.040	0.462/22.566	0.480/21.809
0.881	HPC (25)	0.447/27.875	0.423/28.234	0.441/27.349
0.608	BGL init	0.341/5.014	0.341/4.930	0.292/6.882
0.756	BGL (5)	0.321/11.004	0.321/10.940	0.273/12.665
0.833	BGL (10)	0.303/15.623	0.303/15.495	0.254/16.325
0.908	BGL (15)	0.285/20.665	0.285/20.639	0.251/20.970
0.949	BGL (20)	0.265/25.665	0.265/25.771	0.216/25.926
0.868	Mac init	0.172/19.534	0.224/19.882	0.041/20.928
0.901	Mac (5)	0.169/25.184	0.217/25.518	0.041/26.410
0.919	Mac (8)	0.169/28.507	0.217/28.838	0.041/29.730
0.830	Combined Dataset	0.267/13.612	0.258/17.302	0.214/14.094
1	Industry Dataset	0.054/21.959	0.056/27.201	0.041/24.122

Logchimera Experiments: *Mixing*

What is the performance when mixing?

Performance drops consistently as logs are mixed

Increased log complexity

H level	Dataset	AEL	Drain	IPLoM
0.219	Apache init	0.694/10.426	0.694/10.426	0.694/10.442
0.530	Apache (5)	0.653/15.925	0.653/15.923	0.653/15.369
0.640	Apache (10)	0.618/19.596	0.618/19.602	0.618/19.414
0.737	Apache (15)	0.586/23.468	0.586/23.495	0.586/22.809
0.816	Apache (20)	0.552/27.504	0.552/27.547	0.552/26.877
0.886	Apache (25)	0.514/32.265	0.514/32.135	0.514/31.34
0.259	HPC init	0.644/1.405	0.620/2.015	0.638/2.323
0.524	HPC (5)	0.605/6.510	0.581/7.081	0.599/7.257
0.661	HPC (10)	0.566/11.734	0.542/12.272	0.560/12.301
0.735	HPC (15)	0.525/16.720	0.501/17.300	0.519/17.124
0.817	HPC (20)	0.486/22.040	0.462/22.566	0.480/21.809
0.881	HPC (25)	0.447/27.875	0.423/28.234	0.441/27.349
0.608	BGL init	0.341/5.014	0.341/4.930	0.292/6.882
0.756	BGL (5)	0.321/11.004	0.321/10.940	0.273/12.665
0.833	BGL (10)	0.303/15.623	0.303/15.495	0.254/16.325
0.908	BGL (15)	0.285/20.665	0.285/20.639	0.251/20.970
0.949	BGL (20)	0.265/25.665	0.265/25.771	0.216/25.926
0.868	Mac init	0.172/19.534	0.224/19.882	0.041/20.928
0.901	Mac (5)	0.169/25.184	0.217/25.518	0.041/26.410
0.919	Mac (8)	0.169/28.507	0.217/28.838	0.041/29.730
0.830	Combined Dataset	0.267/13.612	0.258/17.302	0.214/14.094
1	Industry Dataset	0.054/21.959	0.056/27.201	0.041/24.122

Logchimera Experiments: *Fuzzing*

```
mod_jk child workerEnv in error state 6
mod_jk child workerEnv in error state 7
mod_jk child workerEnv in error state 8
…
```

Initial dataset

```
mod_jk child workerEnv in error state 6
mod_jk child workerEnv in error state 0xE0074
mod_jk child workerEnv in error state 8
…
```

Fuzzed dataset

Steps
1. labeling*
2. pre-processing
3. candidate discovery
4. variable replacement
5. consistency check

**optional*

More details in the paper.

Logchimera Experiments: *Fuzzing*

What is the performance when fuzzing?

H level	Dataset	AEL	Drain	IPLoM	LFA	LogMine
0.219	Apache init	0.694	0.694	0.694	0.688/10.576	0.694/10.426
0.886	Apache (25)	0.514/32.265	0.514/32.135	0.514/31.34	0.509/20.243	0.515/32.016
1	Apache (25) fuzzed	0.078/77.541	0.118/76.820	0.059/45.555	0.231/38.866	0.060/82.104
0.259	HPC init	0.644/1.405	0.620/2.015	0.638/2.323	0.609/3.182	0.632/3.218
0.881	HPC (25)	0.447/27.875	0.423/28.234	0.441/27.349	0.296/17.434	0.436/30.290
0.954	HPC (25) fuzzed	0.242/97.492	0.260/93.240	0.219/45.718	0.141/42.085	0.236/100.324
0.608	BGL init	0.341/5.014	0.341/4.930	0.292/6.882	0.230/12.524	0.220/18.598
0.949	BGL (20)	0.265/25.665	0.265/25.771	0.216/25.926	0.150/22.355	0.104/33.728
1	BGL (20) fuzzed	0.143/95.117	0.143/96.156	0.073/62.862	0.077/46.389	0.016/79.8035
0.868	Mac init	0.172/19.534	0.224/19.882	0.041/20.928	0.101/41.804	0.228/17.048
0.919	Mac (8)	0.169/28.508	0.217/28.838	0.041/29.73	0.098/51.167	0.224/25.933
1	Mac (8) fuzzed	0.018/135.994	0.011/116.706	0.001/112.063	0.013/79.454	0.022/207.376
0.830	Combined Dataset	0.267/13.612	0.258/17.302	0.214/14.094	0.180/24.144	0.258/15.858
1	Industry Dataset	0.054/21.959	0.056/27.201	0.041/24.122	0.022/41.960	0.054/23.506

Performance drops consistently with fuzzing

Similar performance to industry

Logchimera Experiments: Labels vs No Labels

Does fuzzing & mixing work without labels?

Dataset	H level gdth	H level parsed
Apache parsed (25) fuzzed	1	0.960
HPC parsed (25) fuzzed	0.954	0.938
BGL parsed (20) fuzzed	1	1
Mac parsed (8) fuzzed	1	0.906

Similar to industry, even without labels

Conclusion

- Log parsing is a critical process in automated log analysis
- Often times log parsing performance is misleading (70% instead of 20%)
- We rethink the evaluation methodology with an emphasis on industry: focus on log heterogeneity
- We propose `logchimera`, a tool to generate industry-like logs
- Open sourced (QR) at https://github.com/spetrescu/logchimera
- Rich potential for future research

Thanks!