## **BLARE:**EXPLOITING STRUCTURE IN REGULAR EXPRESSION QUERIES

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## INTRODUCTION

Analyzing large volume of log data is crucial for large-scale system management
① Security, ② Customer Support, ③ Understanding system usage

Log analysis extract structured information from, schema-less, semi-structured logs

 O Unsuitable for relational DBMS

o Done in ad-hoc data science approach



Higher-level language (e.g., Python)

## INTRODUCTION

- Identify the frequency and pattern of VMs' redeployment due to resizing within clusters in US-East-X region.
  - o Obtain the relevant logs
  - Inspect sample logs to construct appropriate regular expression (regex)
     replacing VM (VmId=([a-z0-9\-]+), VmName=us-east-X-([a-z0-9]+)-vm
  - o Extract the VM IDs using the regex
  - o Deeper analysis of the specific VMs





## PRIOR WORKS

- State-of-art regex evaluation under the hood
- Existing state-of-art regex libraries in several analytics and RDBMSs
  - o Google's **RE2** is used in spam filtering, Google Sheets, MS Azure Data Explorer, etc.





- o PCRE2 is widely used in intrusion detection, packet filtering, and spam filtering
- o MySQL uses ICU Regex for Unicode regex support
- C++ version Lucene and C++ standard library uses **Boost Regex**



### REGEX EVAL BASICS

• NFA

• Each character requires O(m) memory lookups, where m = # states in automata

- DFA
  - Special case of NFA when input can transit to only one state
  - o O(1) lookup per character, but larger state graph compared to NFA
- Existing Optimization Example Prefix literal
  - o Prefiltering some irrelevant inputs Read on \"(.+)\" failed: (.+)

#### OBSERVATION:

Regex engines use DFAs/NFAs and need to do bookkeeping. Expensive even for the simplest task of string matching.

## REGEX CHARACTERISTICS

- 14.5 million public notebooks on GitHub authored between 2017-2020
   35% out of 200,000 unique regexes contain at least 1 literal
- Our collected workloads

		SQL Server	Azure Data Explorer	US-Accident
# literal per regex	mean	3.2	1.4	1.8
	median	3	1	2
Mean # char in literal		39.9	12.2	5.1

#### OBSERVATION:

Most regexes contain literal components;

Regexes used in log analysis contain long literals and simple regex components.

## INSIGHT

Move string matching related computation outside regex engine
 Gap between evaluating string matching using a regex library vs string matching in code is ~3x



### BLARE: OUR CONTRIBUTIONS A FRAMEWORK FOR REGEX EVALUATION

#### Framework Design

 Implemented as a module on top of a regex engine that is used as a "blackbox"

- o (R1) engine-agnostic
- o (R3) no prior statistics needed
- o (R4) no specialized SW & HW dependence

• BLARE uses lightweight mechanisms to identify whether our new evaluation strategy is better than running the entire regex as-is on the regex engine

o (R2) no large regressions

#### Framework Performance

• We implement BLARE on 4 regex engines (RE2, PCRE2, ICU Regex, Boost Regex)

o 1.6x to 168x improvement over two production workloads and an open-source workload



## REGEX DECOMPOSITION

- Split regex R to (prefix S suffix) where prefix and suffix are strings of literals
- R = replacing VM (VmId=([a-z0-9\-]+), VmName=us-east-X-([a-z0-9]+)-vm
  Prefix Regex Suffix
- We call 3-way-split of the regex
   X-way-split: split a regex to a maximum of X literal-regex alternating components
- Recursively continue decomposing the regex gives us the **multi-way-split**.

• F	R = replacing VM (	(VmId=([a-z0-9\-]+),	VmName=us-east-X-	([a-z0-9]	+) -∨m
	LiteralO	Regex0	Literal1	Regex1	Literal2

## WHAT SPLITTING STRATEGY IS BEST?

• Cost Model (k: number of literals)

$$\mathsf{SMCost}(r,k) = |\ell| + \sum_{i=1}^{k} f \cdot (c \cdot (1 - \sigma_i) \cdot \prod_{j=1}^{i-1} \sigma_j + i \cdot \prod_{j=1}^{i} \sigma_j \cdot \mathsf{lsize}) + \underbrace{2 \cdot \sigma \cdot \sum_{i=1}^{k-1} |\ell'_i|}_{\mathsf{substring extraction cost}} + \underbrace{\Theta(r) \cdot \sum_{i=1}^{k-1} |\ell'_i| \cdot \sigma}_{\mathsf{running on engine}}$$

- 1. The more we decompose a regex, the higher the string-matching cost
- 2. The lower the selectivity's of the string literals, the lesser the advantage of doing regex decomposition + higher the substring extraction cost
- 3. If string literals are selective, we often get to ignore the log line at early stage

OBSERVATION: k=2 (3-Way-Split) is most beneficial in majority of the time.

## WHAT SPLITTING STRATEGY IS BEST?

Regeves			Run Time (s)		
	<i>k</i> = 1	k = 2	k = 4	k = 6	<i>k</i> > 6
A	2.03	1.99	2.27	2.21	2.22
В	2.03	1.99	2.27	2.21	2.22
C	2.10	2.04	2.30	2.24	2.25
D	2.00	1.94	2.22	2.16	2.20
E	1.84	1.80	2.05	2.00	2.00
F	2.09	2.03	2.32	2.24	2.26
G	2.08	2.02	2.31	2.24	2.26
Н	2.40	1.99	2.18	2.08	1.99

• Experimental Verification

NOTE: regex-specific best strategy may still vary depending on engine & selectivity.

## BLARE ARCHITECTURE

- Splitter
  - Construct different regex decompositions of interest
- Learner
  - Use a learning component to identify which split is likely to give the best performance.
- Split-Matcher
  - Execute the best strategy identified for the regex



## LEARNING

- Learn to choose strategy *on the fly*. No prior statistics needed
- Multi-Armed Bandit (MAB)
  - o 3 arms: 3-Way-Split, Multi-Way-Split, Direct
  - o Thompson Sampling addressing the exploration-exploitation dilemma
  - o Ensemble Method dealing with noisy measured data



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## DESIGN CONSIDERATIONS

#### Extensibility & Simplicity

- Implement BLARE as a layer on top, calling underlying regex engine
- Easy to adopt, benefit from advancement of underlying engine
- Easily extended by adding arm(s)
- Small codebase (<1000 LOC) aids explainability

#### Minimize Learning Overhead

- Since learning is an overhead (proportional in the number of strategies), we deliberately keep the number of modes in BLARE to be small.
- Early stopping in MAB
- Thresholding number of log fed to learner

#### Prefix and Suffix Sizes

• Since selectivity is most important, and it is not directly connected to the length of the literal, we do not discard short prefix/suffix

#### Experiment Setup

- We use 4 SOTA regex libraries: RE2, PCRE2, Boost Regex, and ICU Regex.
- All experiments on a machine running Intel Xeon@2.8GHz, 256 GB RAM.
- Sample size for learning is max {0.001% of the log, 200 lines}

#### Query Result Reporting

- Regex matching is performed 10 times and we record the trimmed mean.
- We store the extracted content of the <u>first match</u> result in a local variable. *Workloads*
- 132 regexes used for SQL Server log analysis over 100M+ log lines
- 18 regexes used for log analysis over 890M+ log lines sourced from Kusto
- Open-source datasets on traffic accident in US with 2.8M+ log lines and 4 relevant regex

#### - OVERALL PERFORMANCE

• Speedup obtained from BLARE w.r.t. running the workload on the underlying engine

	SQL Server	Azure Data Explorer	US-Accident
Google RE2	3.7x	3.3x	1.6x
PCRE2	3.2x	3.1x	168.3x
ICU Regex	1.6x		61.7x
Boost Regex	7.9x	4.9x	3.4x

- Nearly every query experienced a performance improvement across all the engines
- For queries that did not, the gap to the best strategy was < 2%

#### - LEARNING OVERHEAD

• Mean % of time spent in learning in BLARE

	SQL Server	Azure Data Explorer	US-Accident
BLARE-RE2	5.1%	6.7%	16.5%
BLARE-PCRE2	9.1%		23.8%
BLARE-ICU Regex		8.1%	28.1%
BLARE-Boost Regex	10.7%	6.1%	27.4%

- Note: US-Accident is consistently higher because the log size is small, lower threshold number of logs for learning takes a larger proportion compared to other workloads
- The cost of learning is **justified** by the overall gains made by BLARE

- SPLITTING STRATEGIES
- Overall performance and distribution of per-regex running time for BLARE vs.
   3-Way-Split vs. Multi-Way-Split
- Using Google-RE2 on SQL Server



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- Overall performance and distribution of per-regex running time for BLARE vs.
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- Using Google-RE2 on SQL Server



- OTHER QUERIES
- Overall performance in terms of workload running time in seconds for 3 types of queries.
- Using Google-RE2 on SQL Server

		Running Time (s)	
	FirstMatch	CountAllMatches	LongestMatch
Google RE2	1105.7	1148.7	1128.5
BLARE - RE2	301.0	299.8	306.1
Improvement	3.67x	3.83x	3.68x

### EXPERIMENTAL EVALUATION - EXTENSIBILITY



- Add an additional Reversed 3-Way-Split arm
  - Instead of doing string containment checks left to right, we can also add another strategy that does right to left
- Overall performance and distribution of per-regex running time for BLARE vs. 3-Way-Split vs. Multi-Way-Split vs. Reversed 3-Way-Split
- Using Google-RE2 on SqlServer

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   3-Way-Split vs. Multi-Way-Split vs. Reversed 3-Way-Split
- Using Google-RE2 on SQL Server



### CONCLUSION

- We presented BLARE, a framework for faster regex evaluation for large volume log analysis.
- BLARE is engine-agnostic, does not make any assumptions on the hardware, statistics, etc.
- Experimental evaluation demonstrates speedups ranging from 1.6x to 168x over real-world datasets and workloads.
- Code: <u>github.com/mush-zhang/Blare</u>
- Future work:
  - Incorporate indexing, light-weight statistics collection, add more evaluation operators and build a regex query optimizer.

### SUMMARY

#### BLARE ARCHITECTURE

#### Regex r Log L Output r(L) 6 (sample) mode 2 (4) Split-Matcher Splitter Learner regex splits regex splits BLARE 3 5 **Underlying Regex Engine**

(R.1) BLARE is <u>engine-</u> agnostic

<u>7</u>7 ?

**BLARE PROPERTIES** 



(R.2) BLARE is <u>extensible</u> with no long-term dependency on specialized hardware or software.



(R.3) BLARE introduces no large regressions for any specific query in the workload (R.4) BLARE requires <u>no prior</u> <u>statistics or catalogs</u> about the workloads