Contributions to Large-Scale Data Processing Systems

PhD Defense

Matthieu Caneill

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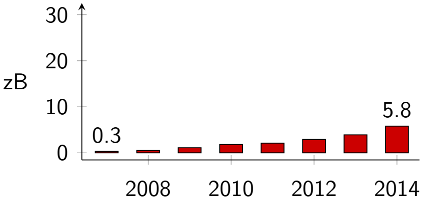
Daniel Hagimont
INP Toulouse
ENSEEIHT

Jean-Marc Menaud
IMT Atlantique

Sihem Amer-Yahia
CNRS / Université Grenoble Alpes

Noël De Palma
Université Grenoble Alpes

Worldwide data production



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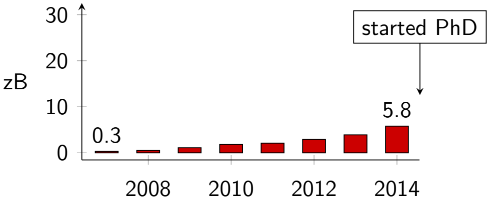

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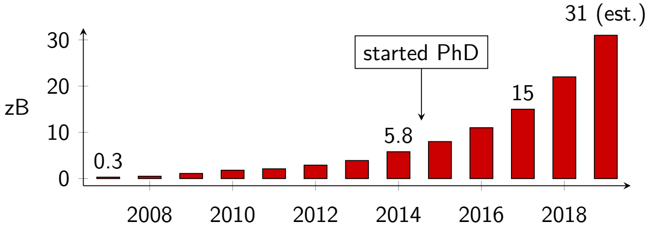

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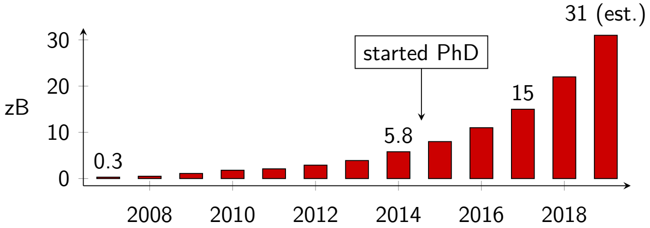

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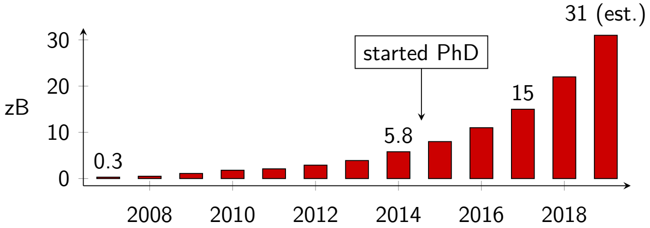

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(1 zetabyte is 2 billion times my hard drive)

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- Data processing in reasonable time

Motivation

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Problems

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- . . . and reasonable price

How to design. . .

- An industrial system to handle monitoring data and make predictions about future failures?

Research questions

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- An algorithm to improve locality in distributed streaming engines?

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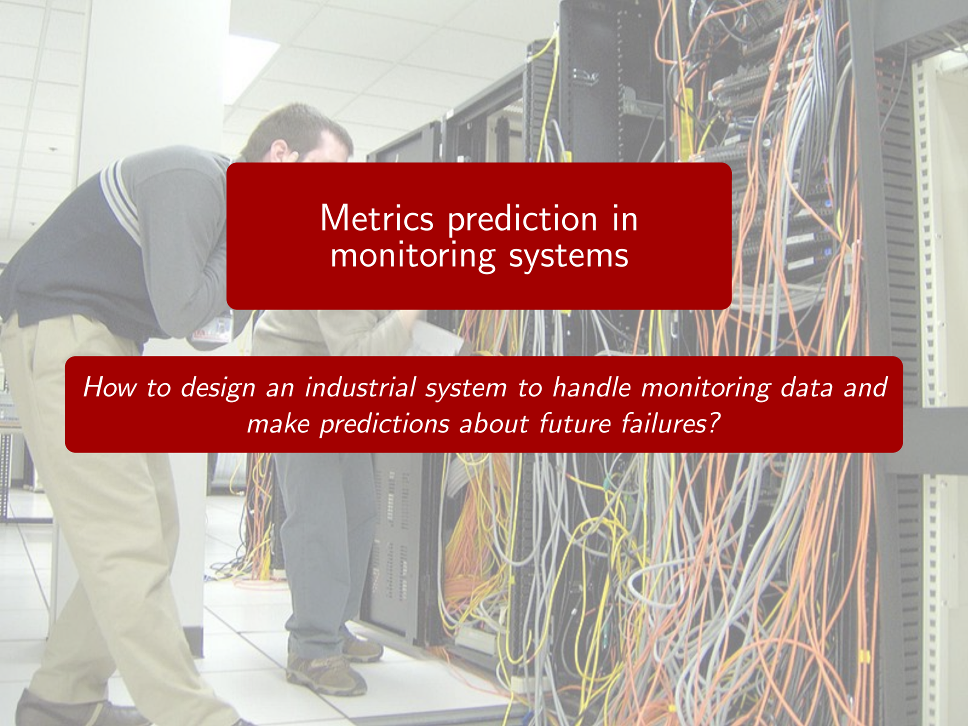
- An industrial system to handle monitoring data and make predictions about future failures?
- An algorithm to improve locality in distributed streaming engines?
- A framework to compose data processing algorithms in a descriptive fashion, while reasoning on high level abstractions?

Structure of this presentation

1. Online metrics prediction in monitoring systems
2. Locality data routing
3. λ-blocks
4. Conclusion



Metrics prediction in monitoring systems

How to design an industrial system to handle monitoring data and make predictions about future failures?

Actors and roles of Smart Support Center

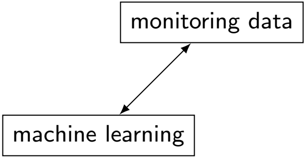
- **Coservit**: Monitoring services
- **HP**: Cloud computing, hardware
- **LIG – AMA**: Machine learning
- **LIG – ERODS**: Cloud computing, systems

Scope of Smart Support Center

monitoring data

- Monitoring insights

Scope of Smart Support Center



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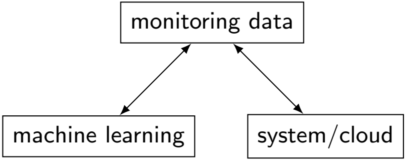

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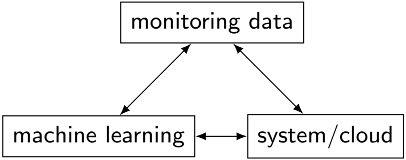

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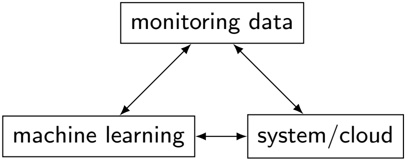

- Monitoring insights
- Failure prediction
- Infrastructure scaling
- More server uptime

Challenges

- Scale monitoring infrastructure (from 1 to N nodes)

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Metrics

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- CPU load, memory, service status
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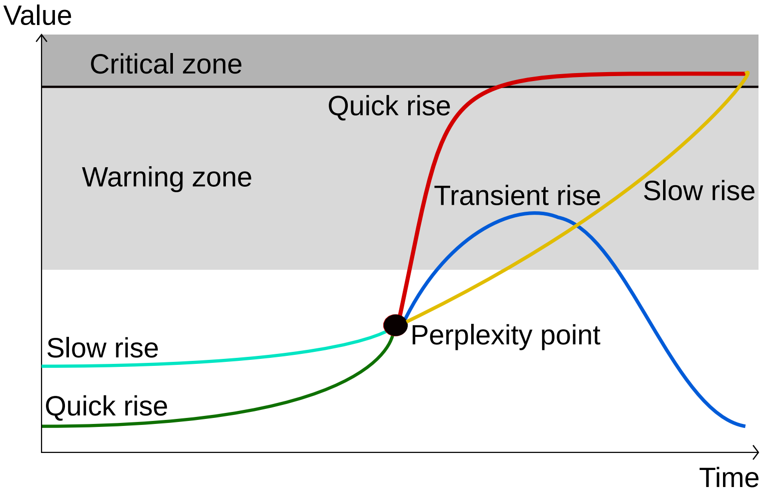
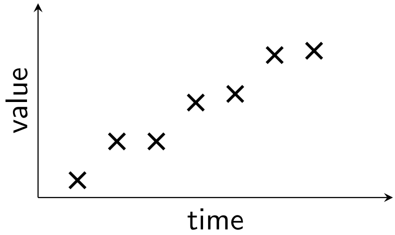
- Computed as time-series
- Associated to thresholds: warning and critical

Metrics behaviour: 6 scenarios



Linear regression



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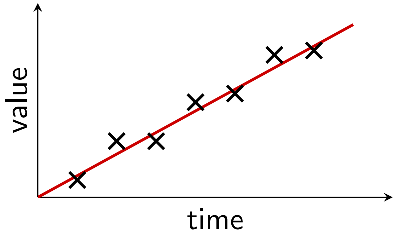

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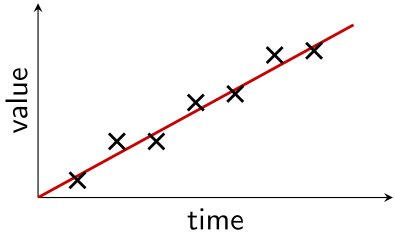

- Ability to identify local trends (few hours)

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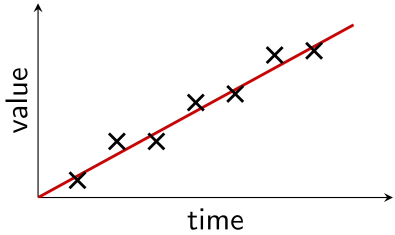

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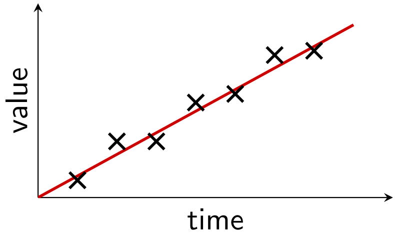

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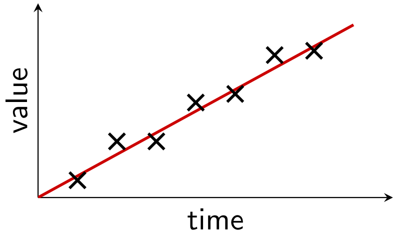

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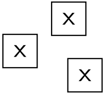
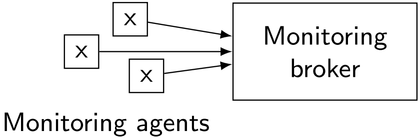
- Library: MLlib (part of Apache Spark)

System architecture



Monitoring agents

System architecture



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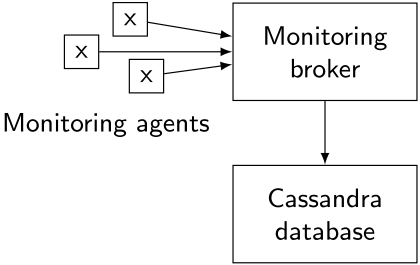

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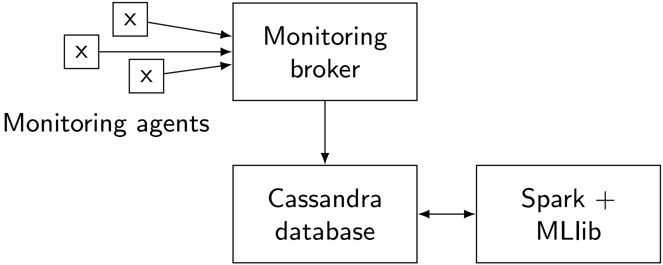

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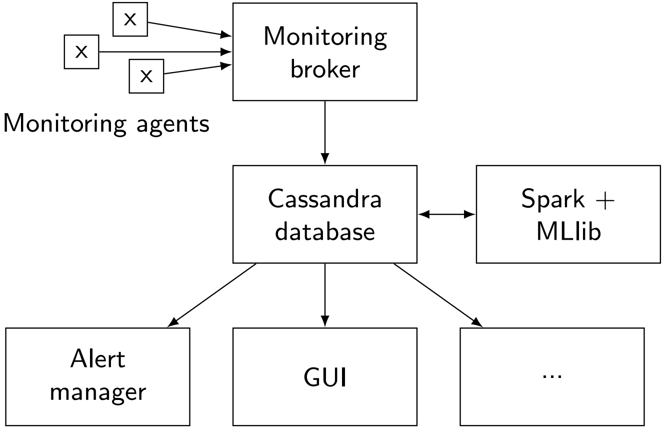

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- Scalable: up to a few servers (150 CPU cores) to handle Coservit's load

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- End-to-end fault tolerance: metrics can never be lost
- Performances: "fast" to compute metrics predictions

Evaluation

Setup

- Hardware: 4 servers (16–28 cores, 128–256 GB RAM)
- Dataset: Replay on production data recorded at Coservit
- 424 206 metrics, 1.5 billion data points monitored on 25 070 servers

Evaluation

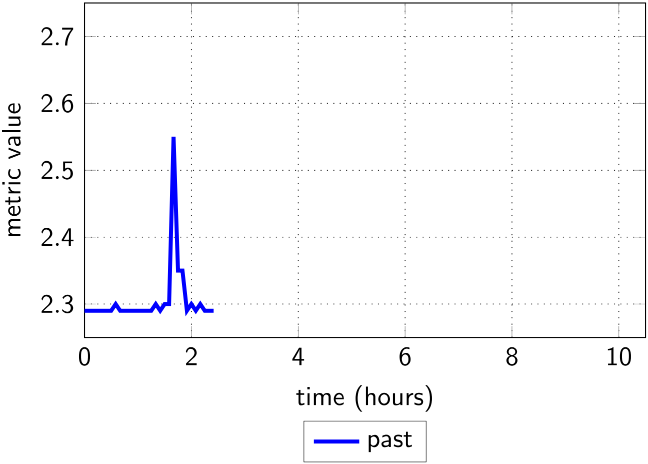
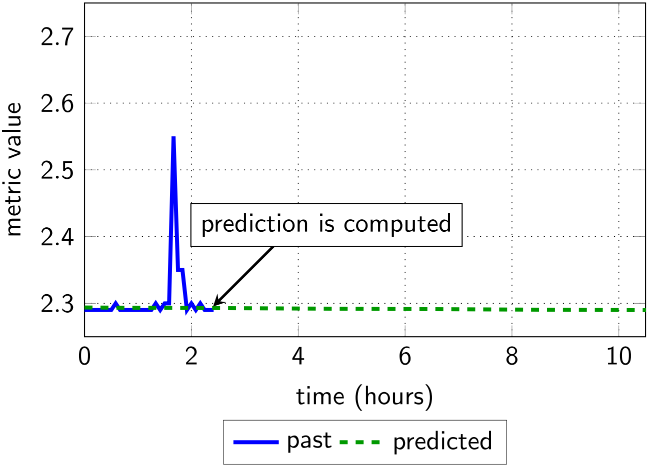


Figure: swap memory

Evaluation



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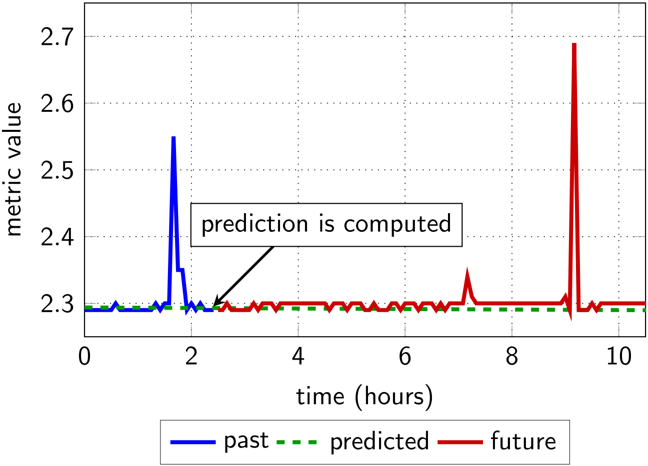

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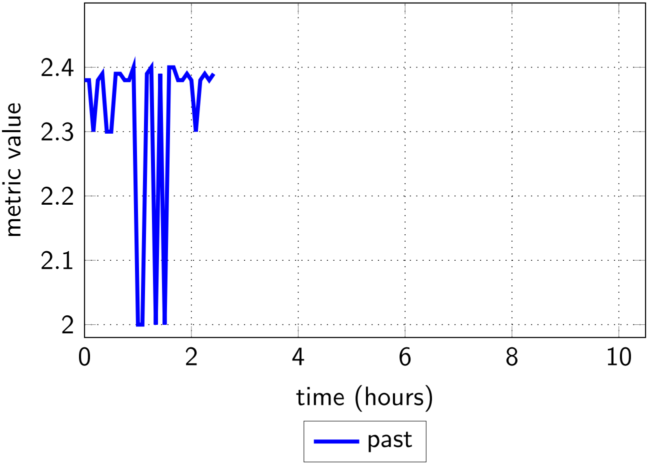

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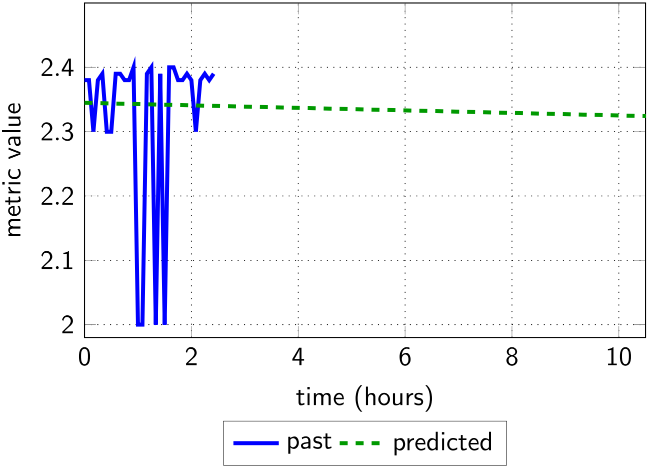

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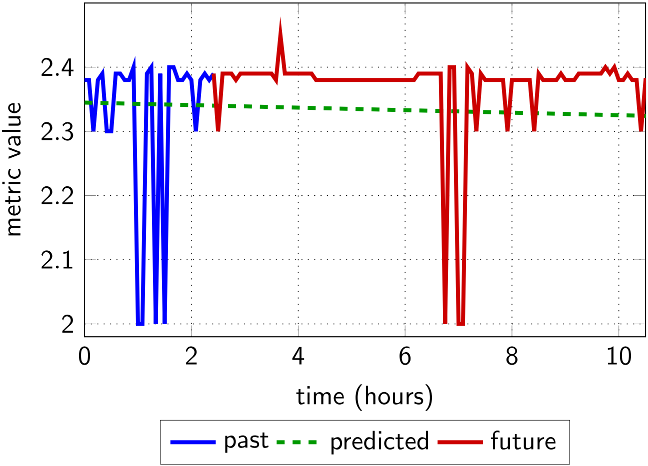

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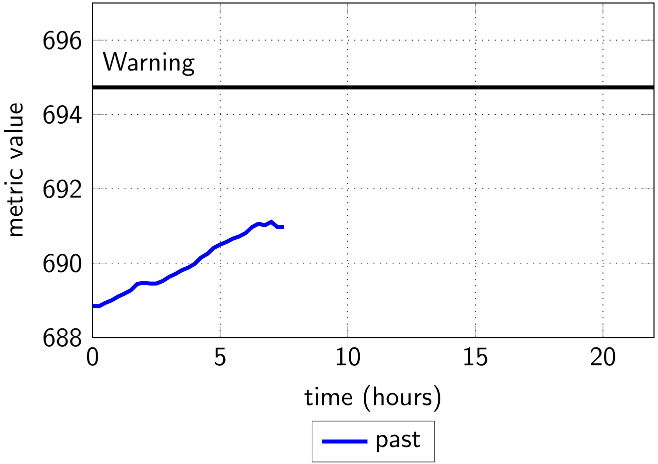

Figure: disk partition

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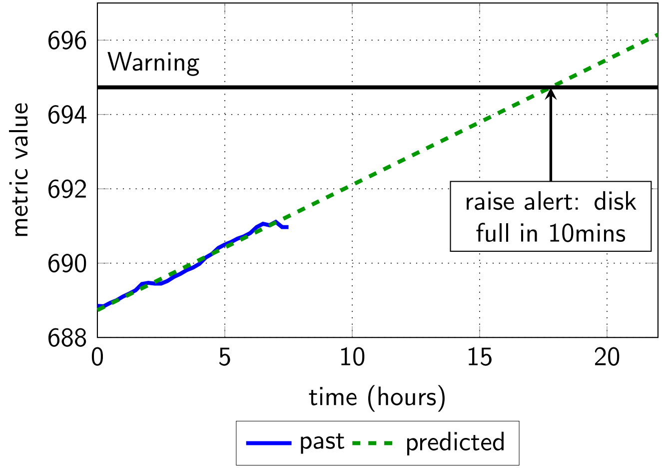

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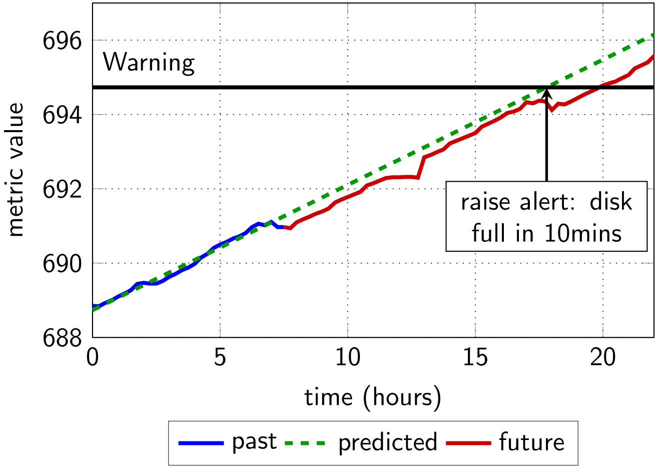

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Metric blacklisting

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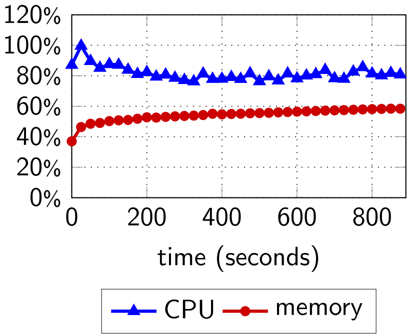
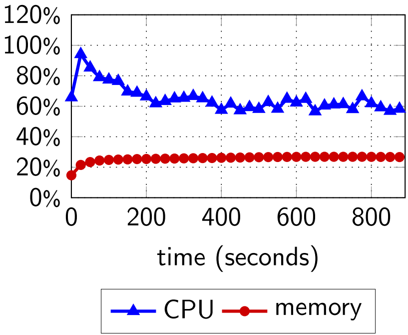
- Metrics (temporarily) blacklisted if their RMSE $>$ threshold
- 58.5% of the metrics have a low RMSE $\rightarrow$ good predictions

Evaluation

CPU load and memory consumption



(a) master



(b) slave-1

Figure: Running on 4 machines and 100 cores for 15 minutes.

Evaluation

Time repartition

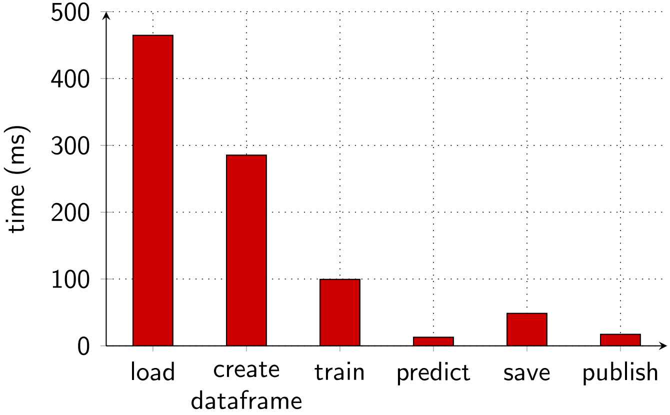


Figure: Time repartition for predicting a metric.

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Load handling

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- One monitoring server (with 24 cores) can handle the load of 1440 metrics (at worst), which is 85 servers on average.

Evaluation

Load handling: linear scaling

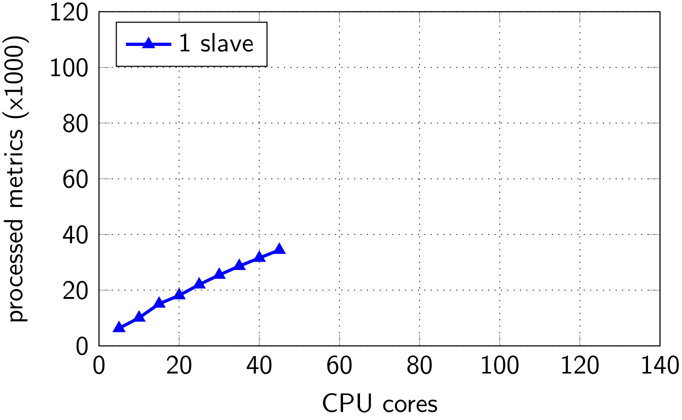
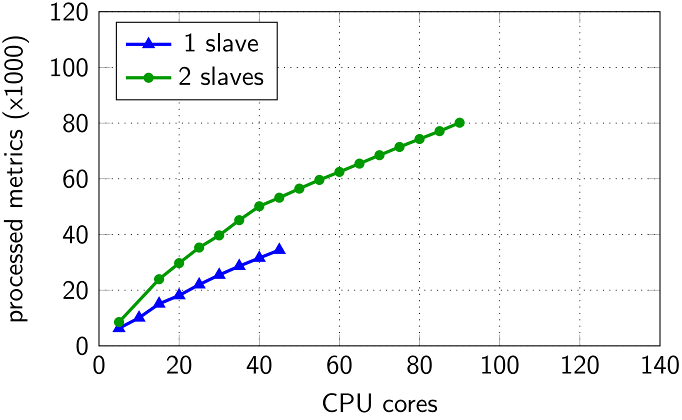


Figure: Amount of metrics handled in 15 minutes.

Load handling: linear scaling



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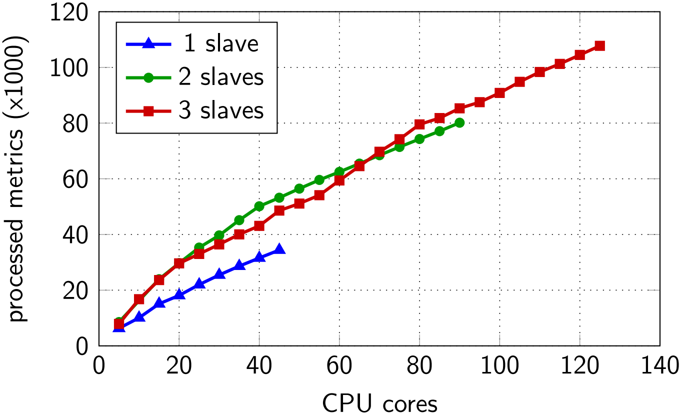

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Related work

Positioning

No published work exhibits the same system (end-to-end system for monitoring metrics prediction, storage and blacklisting).

Prediction models

- Hardware failures [CAS12]

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- Datacenter temperature (e.g. Thermocast [LLL+11])

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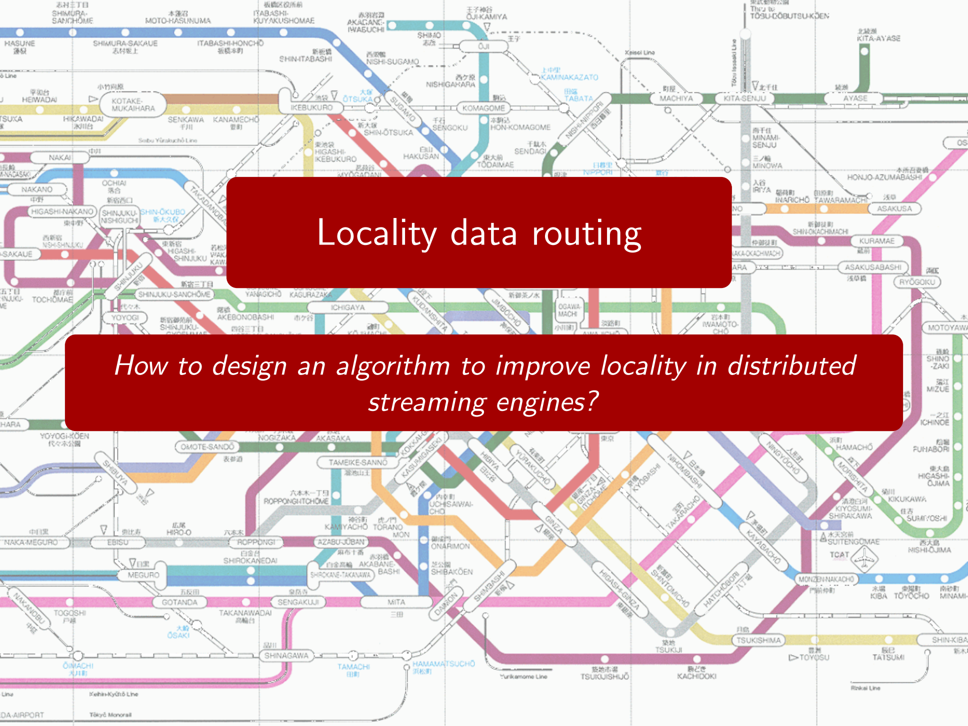
- Hardware failures [CAS12]
- Capacity planning (e.g. Microsoft Azure [mic])
- Datacenter temperature (e.g. Thermocast [LLL+11])
- Monitoring metrics (e.g. Zabbix [zab] with manual tuning)

Locality data routing

How to design an algorithm to improve locality in distributed streaming engines?



Actors

Collaboration with **Vincent Leroy** (SLIDE)
and **Ahmed El-Rheddane** (ERODS).

Distributed streaming engines

Goals

- Real-time message handling

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- Real-time metric calculations
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- Fault-tolerance

Distributed streaming engines

Apache Storm → topologies.

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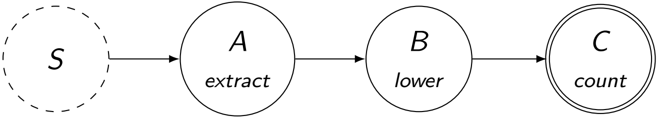

Figure: Trending hashtags topology.

S sends tweets, operator A extract hashtags, B converts them to lowercase, and C counts the frequency of each hashtag.

Distributed streaming engines

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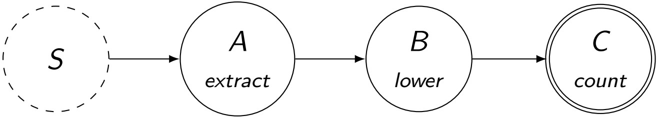

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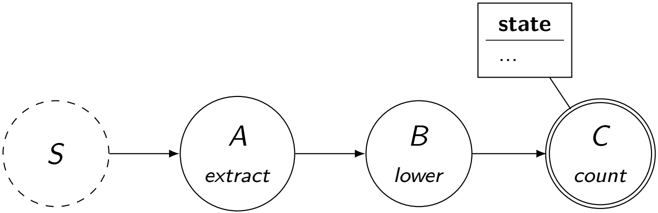
Division into tasks → distribution and parallelization made easy.

Stateful operators

States are associated to keys

For example, the operator C can keep the list of trending hashtags (values) per location (keys).



Stateful operators

Parallelization

To keep a consistent state, same keys must be routed to the same instance.

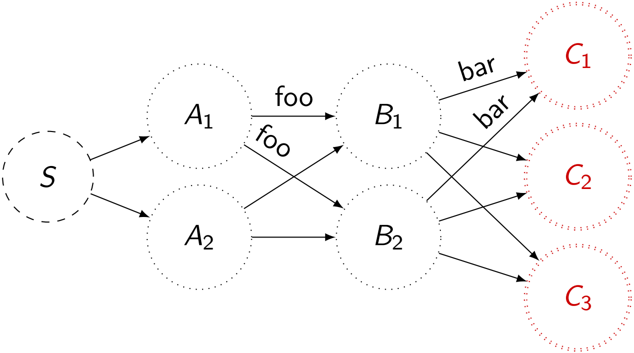
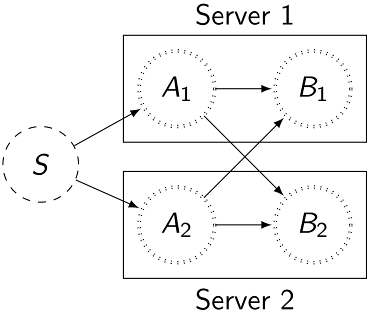


Figure: Tasks A and B are stateless, C is stateful.

Situation

Let's have two stateful operators, each with two instances.



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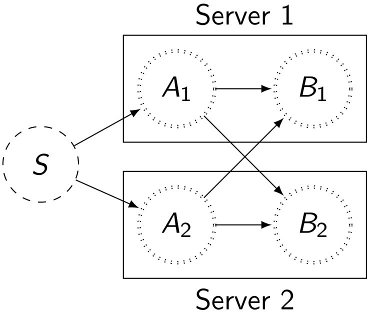

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Minimize the traffic between the machines: $A1 \rightarrow B2$ and $A2 \rightarrow B1$.
By default, $\mathit{locality} = 1/\mathit{parallelism}$

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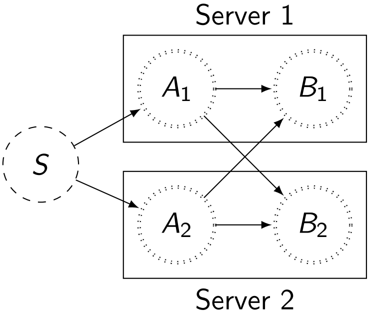

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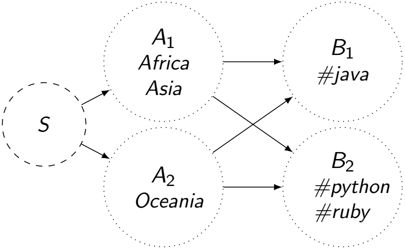
Constraint

Keep a good load balance between the machines.

Keys correlation

Dynamically instrument the keys couples and represent them with a bipartite graph.



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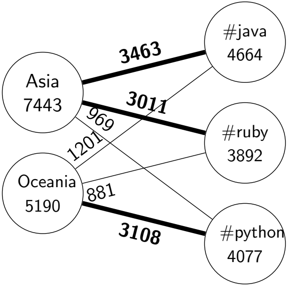

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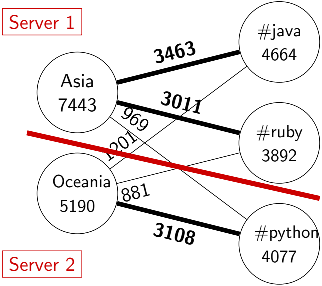
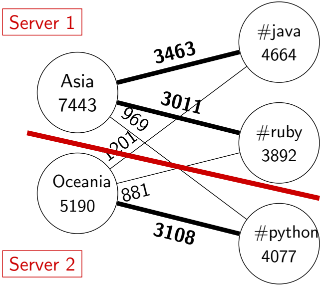


Routing tables

- S: $Asia \rightarrow A_1$
  $Oceania \rightarrow A_2$
- A_1: **#java** $\rightarrow$ $\mathbf{B_1}$
  #ruby $\rightarrow$ $\mathbf{B_1}$
  #python $\rightarrow B_2$
- A_2: **#python** $\rightarrow$ $\mathbf{B_2}$
  #java $\rightarrow B_1$
  #ruby $\rightarrow B_1$

Keys correlation

Dynamically instrument the keys couples and represent them with a bipartite graph.

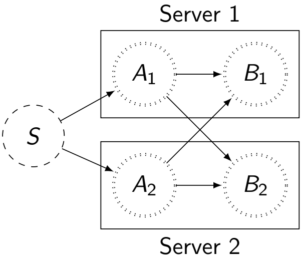


Routing tables

- S: $Asia \rightarrow A_1$
  $Oceania \rightarrow A_2$
- A_1: $\mathbf{\#java \rightarrow B_1}$
  $\mathbf{\#ruby \rightarrow B_1}$
  $\#python \rightarrow B_2$
- A_2: $\mathbf{\#python \rightarrow B_2}$
  $\#java \rightarrow B_1$
  $\#ruby \rightarrow B_1$

Graph partitioning $\rightarrow$ optimized routing, favorizing local links.

Message:
Posted from:



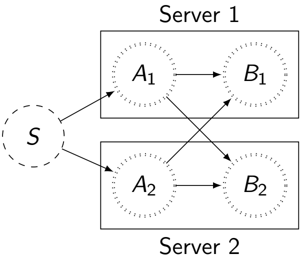
S

key	route

A

key	route

Message: #python doesn't have braces
Posted from: Oceania



S

key	route

A

key	route

Locality data routing

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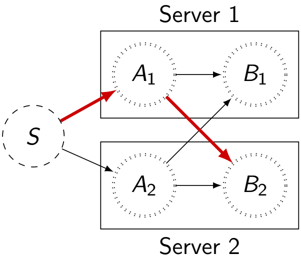


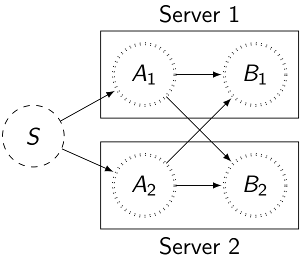
S

key	route
Oceania	A1

A

key	route
python	B2

Message: #java is a verbose language
Posted from: Asia

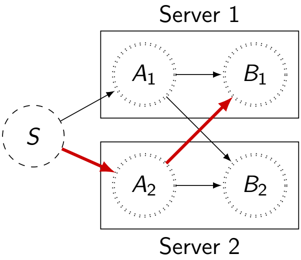


S

key	**route**
Oceania	A1

A

key	**route**
python	B2



Message: #java is a verbose language
Posted from: Asia

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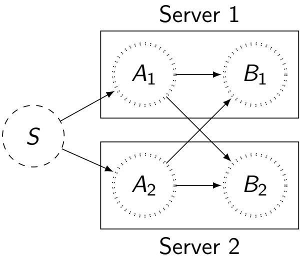
key	route
Oceania	A1
Asia	A2

A

key	route
python	B2
java	B1

Message:
Posted from:



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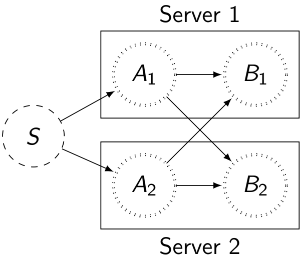
key	**route**
Oceania	A1
Asia	A2

A

key	**route**
python	B2
java	B1

Reconfiguration is computed and applied

Message:
Posted from:



S

key	**route**
Oceania	A1
Asia	A2

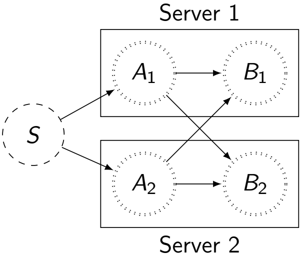
A

key	**route**
python	B1
java	B2

Reconfiguration is computed and applied

Correlation between **Oceania**/**python** and **Asia**/**java**

Message: #python is pretty cool!
Posted from: Oceania



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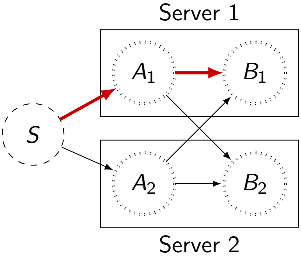

S

key	**route**
Oceania	A1
Asia	A2

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python	B1
java	B2

Trends evolve with time

Correlations between keys change frequently.

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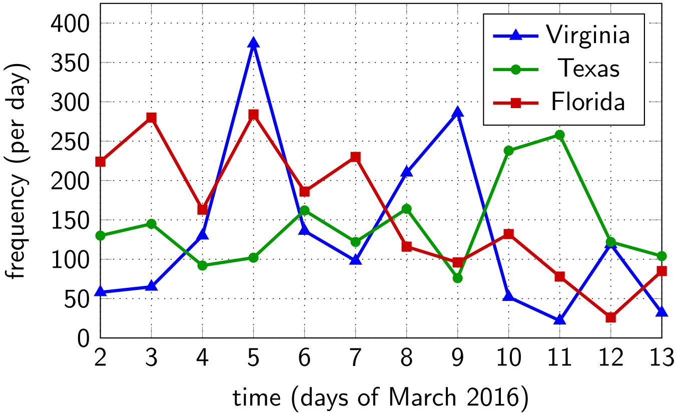

Figure: #nevertrump, in March 2016

Locality decay

- Keys correlations evolve with time.

Locality data routing

Locality decay

- Keys correlations evolve with time.
- Routing tables optimized by examining old data lead to decreased locality.

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Reconfiguration

- We re-compute the tables every N minutes.

Locality decay

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- Routing tables optimized by examining old data lead to decreased locality.

Reconfiguration

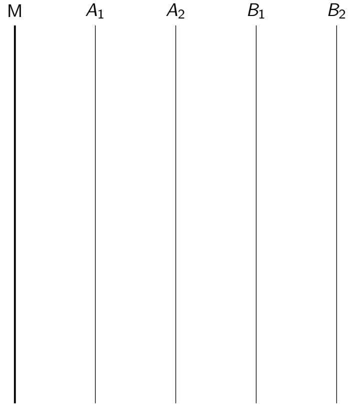
- We re-compute the tables every N minutes.
- Difficulty: keep the state consistent.

Reconfiguration protocol

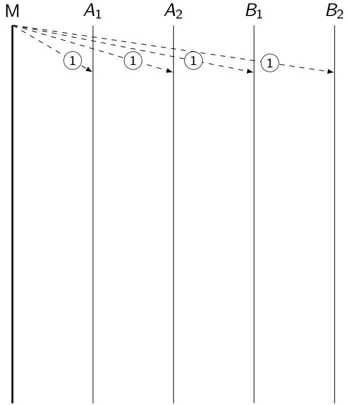
Solution: online reconfiguration protocol

- update the routing tables in a live system
- without losing any message and state

Reconfiguration protocol

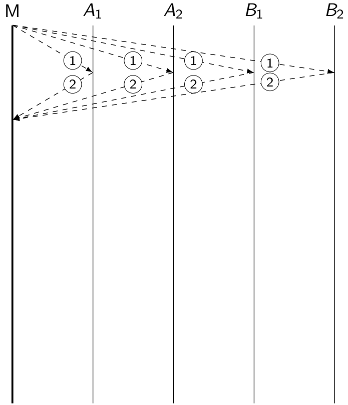


Reconfiguration protocol



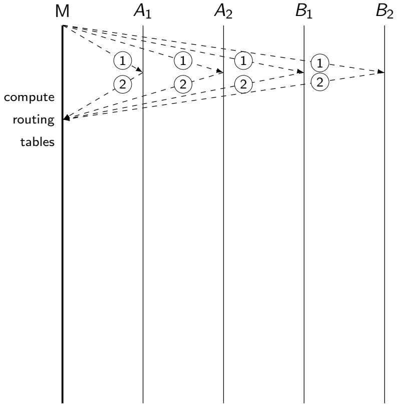
1 Get statistics

Reconfiguration protocol



1. Get statistics
2. Send statistics

Reconfiguration protocol

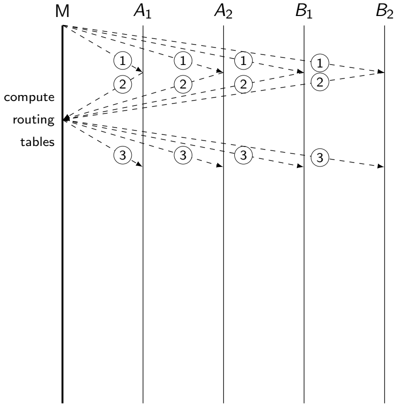


① Get statistics

② Send statistics

Partition graph, compute routing tables

Reconfiguration protocol



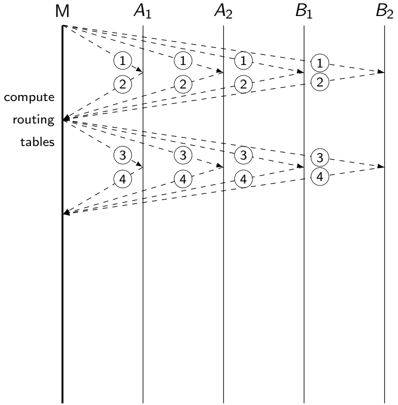
① Get statistics

② Send statistics

Partition graph, compute routing tables

③ Send reconfiguration

Reconfiguration protocol

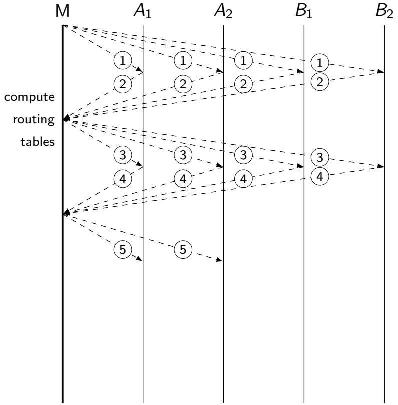


1. Get statistics
2. Send statistics

Partition graph, compute routing tables

3. Send reconfiguration
4. Send ACK

Reconfiguration protocol



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Partition graph, compute routing tables

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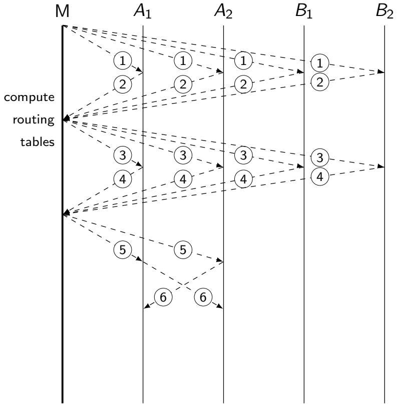
5. Propagate

Reconfiguration protocol



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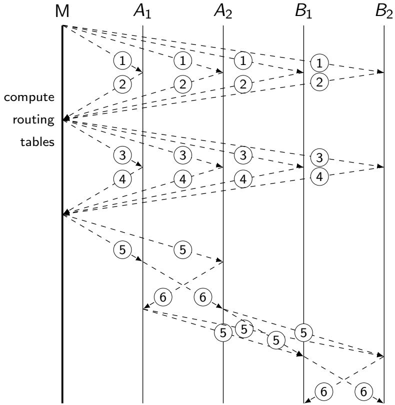
6. Transfer key states

Reconfiguration protocol



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Partition graph, compute routing tables

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Propagate to next operator

Evaluation

Datasets

- From Flickr and Twitter
- Fields: location (country or place), hashtag
- Size: 173M records (Flickr), 100M (Twitter)

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Setup

- 8× 128 GB RAM, 20 cores.
- Computation of aggregated statistics (stateful workers).
- Parallelism (2..6), network speed (1Gb/s | 10Gb/s), message size (0..20kB).

Evaluation

Great speed-up when network is the bottleneck.

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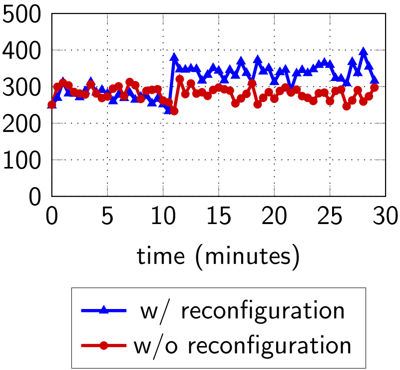
Great speed-up when network is the bottleneck.

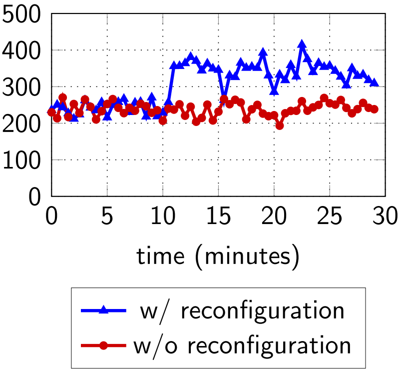
Highly dependent on message size.

Evaluation – Flickr

Throughput (Ktuples/s) on 10Gb/s network, parallelism 6



(a) message size=4kB

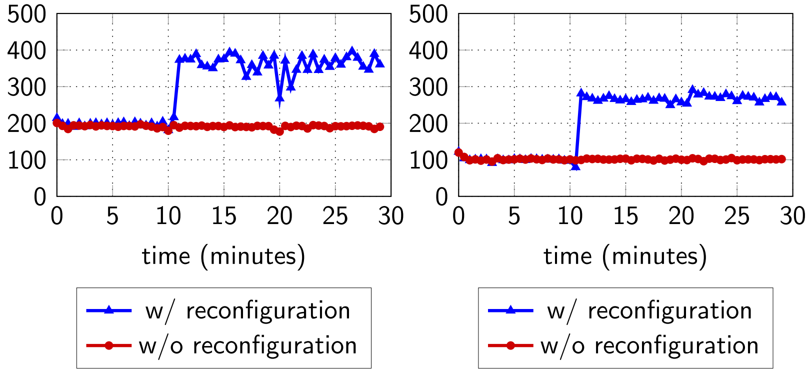


(b) message size=8kB

Locality data routing

Evaluation – Flickr

Throughput (Ktuples/s) on 1Gb/s network, parallelism 6



(a) message size=4kB

(b) message size=8kB

Evaluation – Flickr

Average throughput with 1Gb/s network, 4kB message size

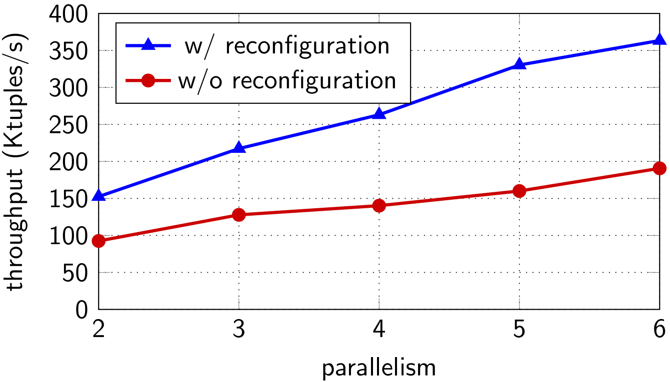
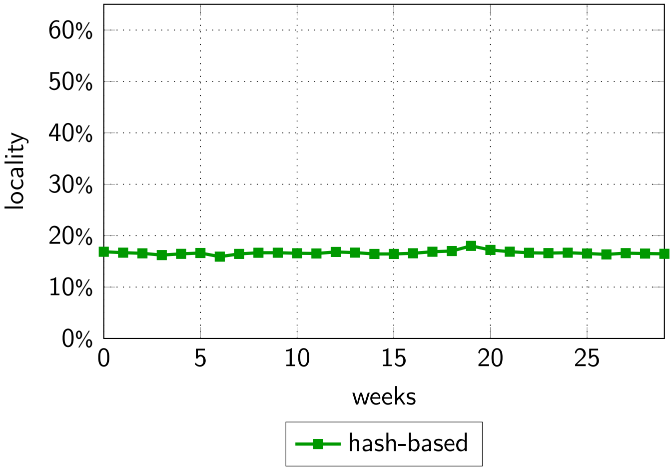


Figure: Average throughput, measured after the first reconfiguration.

Evaluation – Flickr

Locality, with parallelism 6



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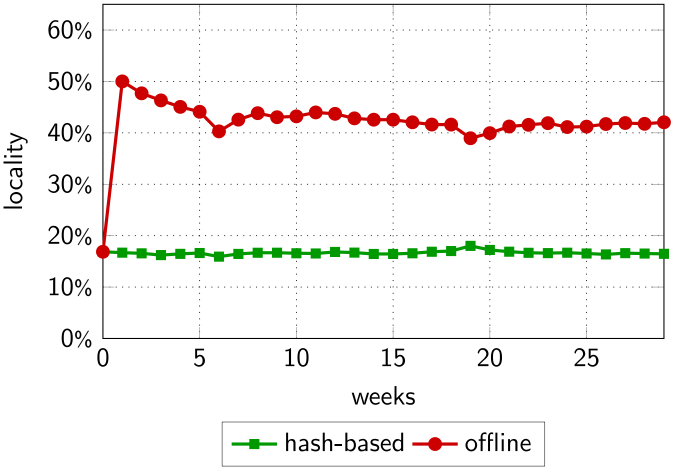

Evaluation – Flickr

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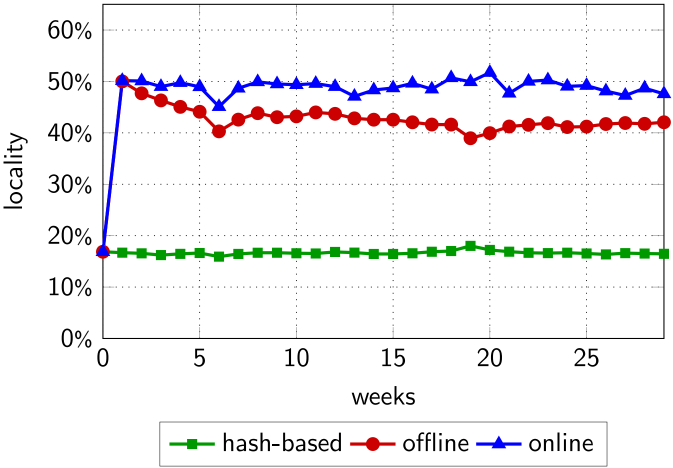
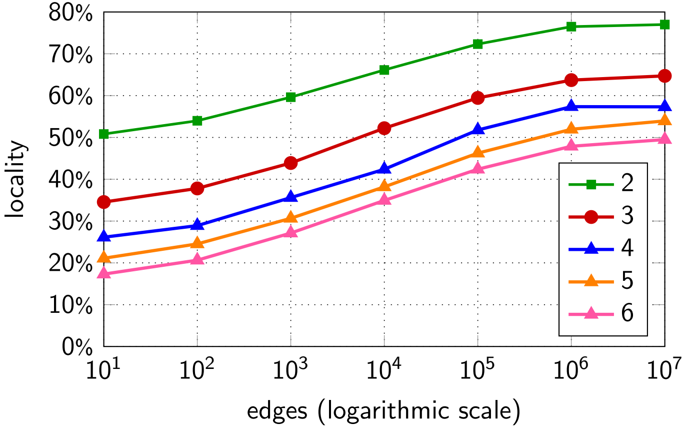


Evaluation – Flickr

Locality when changing the number of collected key correlations



Related work

Scheduling: placement of operators on servers

- Using the topology [ABQ13]
- Using observed communication patterns [ABQ13]
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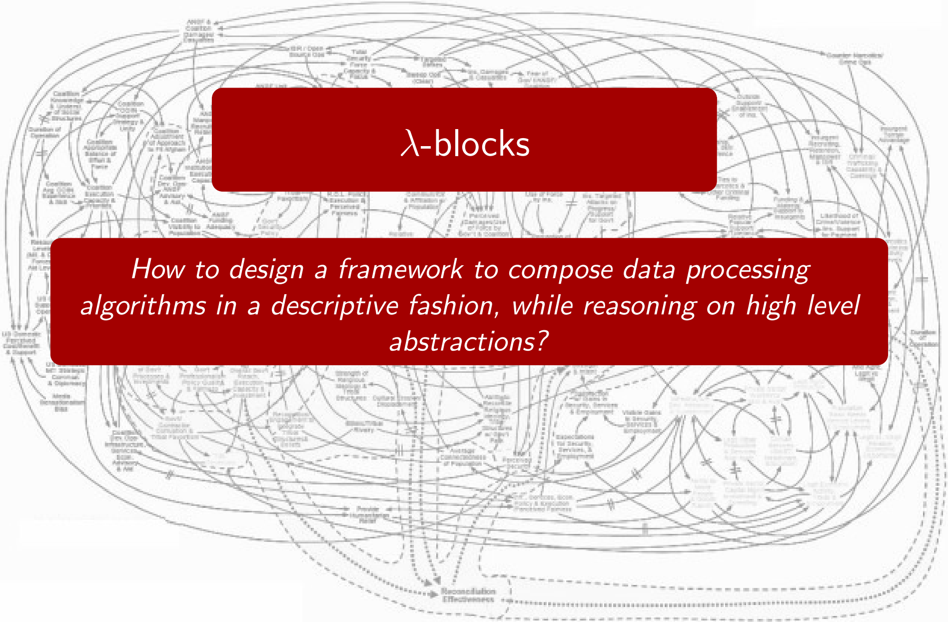
Co-location of correlated keys

- Databases partitions [CJZM10], social networks [BJJL13]

GOTO E SPAGHETTI CODE



λ-blocks

How to design a framework to compose data processing algorithms in a descriptive fashion, while reasoning on high level abstractions?

Design goals

- A data processing abstraction

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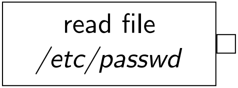
- Graph manipulation toolkit
- Bring simplicity to large-scale data processing

Topologies



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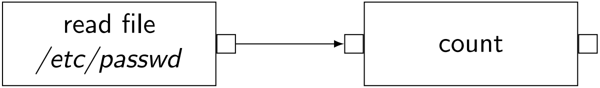

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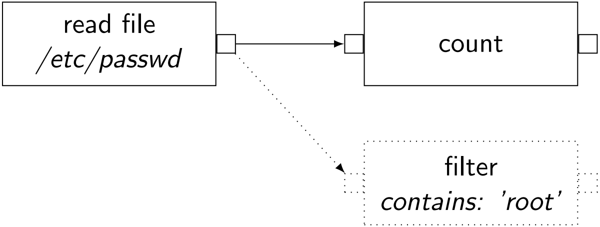

Topologies

```python
"""Counts system users.
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def main():
    with open('/etc/passwd') as f:
        return len(f.readlines())

if __name__ == '__main__':
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```

~~$ wc -l /etc/passwd~~

Topologies

```yaml
---
name: count_users
description: Count number of system users
modules: [lb.blocks.foo]
---
- block: readfile
  name: my_readfile
  args:
    filename: /etc/passwd

- block: count
  name: my_count
  inputs:
    data: my_readfile.result
```

Blocks

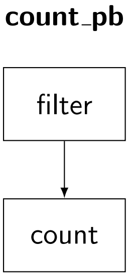
- read_http
- plot_bars
- show_console
- write_line
- write_lines
- split
- concatenate
- map_list
- flatMap
- flatten_list
- group_by_count
- sort
- get_spark_context
- spark_readfile
- spark_text_to_words
- spark_map
- spark_filter
- spark_flatMap
- spark_mapPartitions
- spark_sample
- spark_union
- spark_intersection
- spark_distinct
- spark_groupByKey
- spark_reduceByKey
- spark_aggregateByKey
- spark_sortByKey
- spark_join
- spark_cogroup
- spark_cartesian
- spark_pipe
- spark_coalesce
- spark_repartition
- spark_reduce
- spark_collect
- spark_count
- spark_first
- spark_take
- spark_takeSample
- spark_takeOrdered
- spark_saveAsTextFile
- spark_countByKey
- spark_foreach
- spark_add
- spark_swap
- twitter_search
- cat
- grep
- cut
- head
- tail

Blocks

```python
@block(engine='localpython')
def take(n: int=0):
    """Truncates a list of integers.

    :param int n: The length of the desired result.
    :input List[int] data: The list of items to truncate.
    :output List[int] result: The truncated result.
    """
    def inner(data: List[int])->ReturnType[List[int]]:
        assert n <= len(data)
        return ReturnEntry(result=data[:n])
    return inner
```

Sub-topologies



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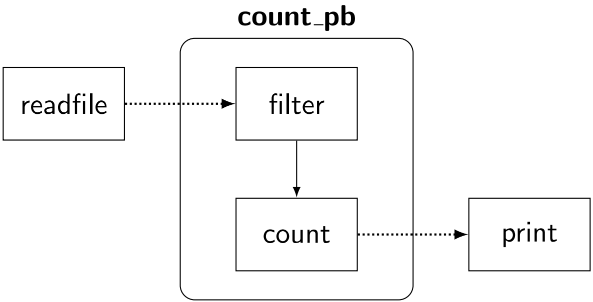


Sub-topologies

```
---
name: count_pb
---
- block: filter
  name: filter
  args:
    contains: error
  inputs:
    data: $inputs.data
- block: count
  name: count
  inputs:
    data: filter.result
```

Sub-topologies

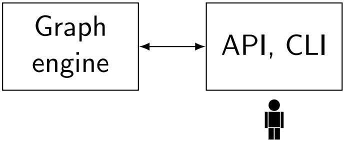
```yaml
---
name: count_pb
---
- block: filter
  name: filter
  args:
    contains: error
  inputs:
    data: $inputs.data
- block: count
  name: count
  inputs:
    data: filter.result
```

```yaml
---
name: foo_errors
---
- block: readfile
  name: readfile
  args:
    filename: foo.log

- topology: count_pb
  name: count_pb
  bind_in:
    data: readfile.result
  bind_out:
    result: count.result

- block: print
  name: print
  inputs:
    data: count_pb.result
```

Architecture



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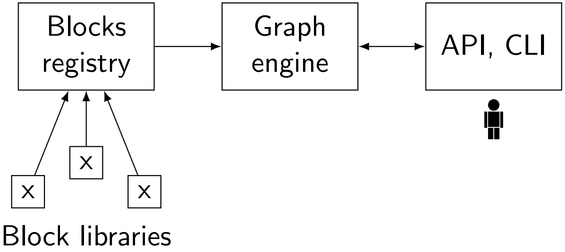

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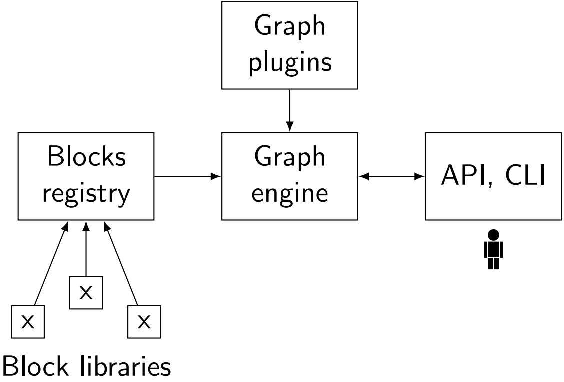

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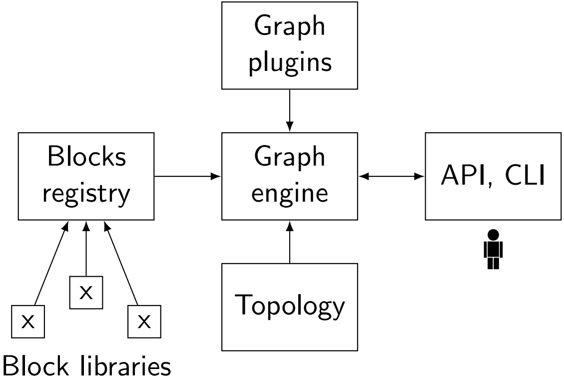

Graph manipulations

- Verification (e.g. type checking)

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- Reasoning on the computation graph as a high-level object

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Graph manipulations

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  - **`after_block_execution`**
    observation

Graph manipulation example: instrumentation (excerpt)

```python
by_block = {} # timing by block: begin, duration

@before_block_execution
def store_begin_time(block):
    name = block.fields['name']
    by_block[name]['begin'] = time.time()
```

Graph manipulation example: instrumentation (excerpt)

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by_block = {} # timing by block: begin, duration

@before_block_execution
def store_begin_time(block):
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@after_block_execution
def store_end_time(block, results):
    name = block.fields['name']
    by_block[name]['duration'] = \
      time.time() - by_block[name]['begin']
```

Graph manipulation example: instrumentation (excerpt)

```
@after_graph_execution
def show_times(results):
    longest_first = sorted(by_block, reverse=True)
    for blockname in longest_first:
        print('{}\t{}'.format(
            blockname,
            by_block[blockname]['duration'])
```

Graph manipulation example: instrumentation

block	**duration (ms)**
read http	818
write lines	54
grep	49
split	20

Evaluation

Setup

- Wordcount over https: local machine, 8 cores, 16 GB RAM
- Wordcount over disk: local machine, 8 cores, 16 GB RAM
- PageRank on Spark: Spark on 1 server (24 cores, 128 GB RAM)

Evaluation

Performances

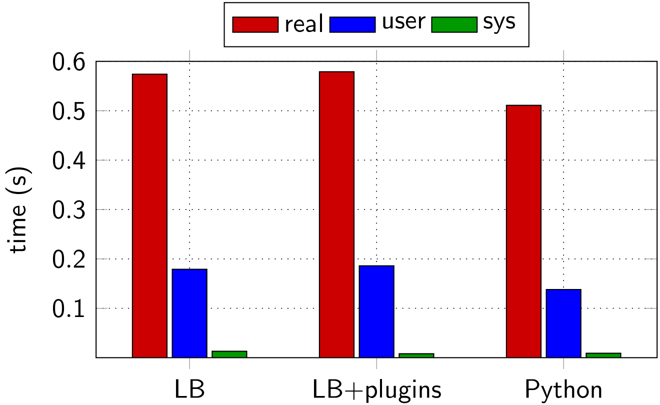

Figure: Wordcount over https: Twitter feed.

Performances

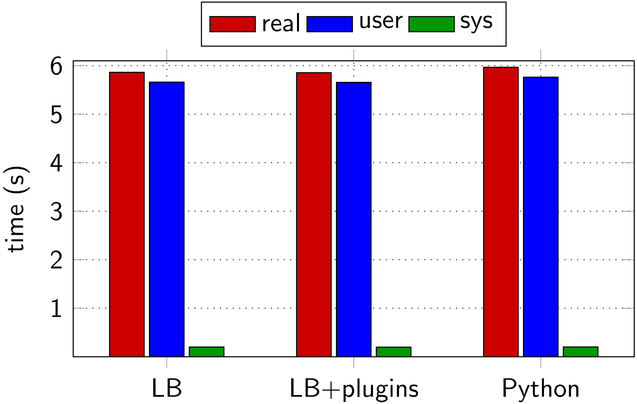

Figure: Wordcount over disk: Wikipedia dataset.

Evaluation

Performances

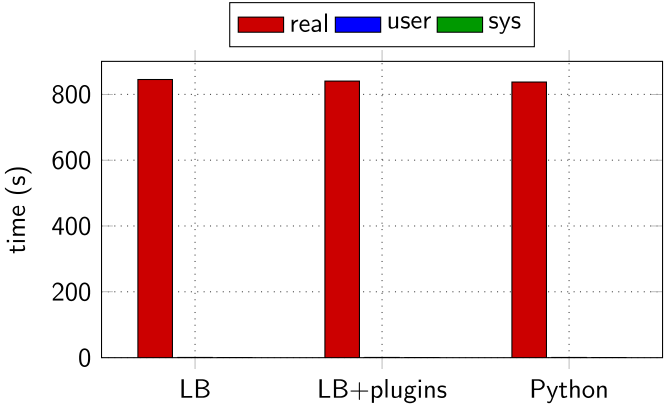

Figure: PageRank on Wikipedia hyperlinks with Spark.

Evaluation

Maximum overhead measured per topology: 50 ms

Related work

Dataflow programming

- ML pipelines: scikit-learn [PVG+11], Spark [The17a], Orange framework [DCE+13]
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Other

- "Serverless" architectures and stateless functions [JVSR17]

Context

Computer systems to process large quantities of data.

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Problems: how to design. . .

- An industrial system to handle monitoring data and make predictions about future failures?
- An algorithm to improve locality in distributed streaming engines?
- A framework to compose data processing algorithms in a descriptive fashion, while reasoning on high level abstractions?

Contributions

Metrics prediction	Locality routing	λ-blocks

Contributions

	Metrics prediction	**Locality routing**	**λ-blocks**
What it is	Industrial system	Online routing library	Data processing abstraction

Contributions

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Layer	End-to-end	Low	High

Contributions

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What it is	Industrial system	Online routing library	Data processing abstraction
Layer	End-to-end	Low	High
Improves	**Uptimes**	**Throughput**	**Programmability**

Future work

Metrics prediction in monitoring systems

- Predictions on long-term global trends
- Ticketing mechanism

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Metrics prediction in monitoring systems

- Predictions on long-term global trends
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Locality data routing

- Replace binary locality/non-locality with distance
- Smarter way to determine when to reschedule
- Extend to more complex topologies

Future work

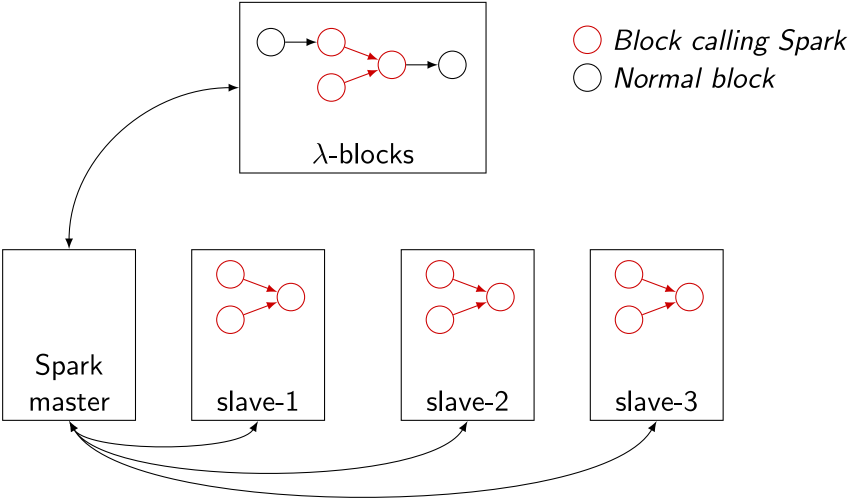
λ-blocks

- Explore more graph manipulation abstractions (complexity analysis, serialization, verification...)
- Streaming and online operations
- Tight integration with clusters (data storage, caches, etc)

Thanks! Questions?

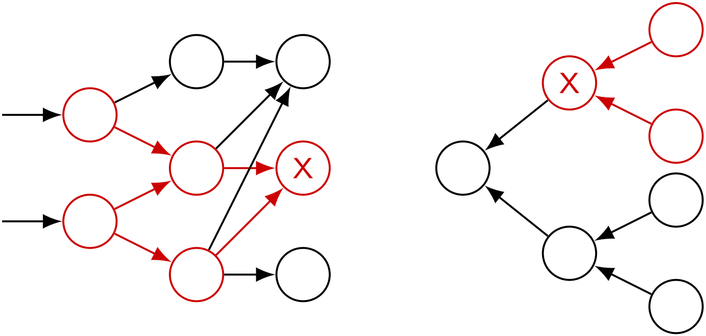
λ-blocks

Using a Spark cluster



λ-blocks

Signature algorithm



$$
\begin{aligned}
H(B) = h(&B.name, && \text{block name (not instance name)} \\
&B.args, && \text{list of (name, value) tuples} \\
&B.inputs) && \text{list of (name, H(block), connector) tuples}
\end{aligned}
$$

Engine instrumentation

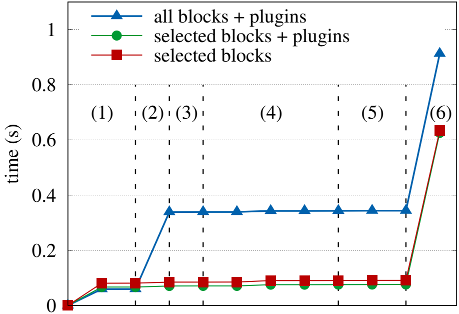


Figure: Wordcount program running under different setups.
(1) Startup (modules import, etc); (2) Blocks registry creation, block modules import; (3) Plugin import; (4) YAML parsing and graph creation; (5) Graph checks; (6) Graph execution.

Database schema

metrics

metric_id	uuid
metric_name	text
group_id	uuid

predictions

metric_id	uuid
timestamp	int
predicted_values	list

measurements

metric_id	uuid
timestamp	int
warn	text
crit	text
max	double
min	double
value	double
metric_name	text
metric_unit	text

Images credits

- *Data Center operators verifying network cable integrity*, CC-BY-SA, https://commons.wikimedia.org/wiki/File:Dc_cabling_50.jpg
- *Tokyo metro map*, http://bento.com/subtop5.html
- *Goto e spaghetti code*, http://blogbv2.altervista.org/HD/il-goto-e-la-buona-programmazione-parte-ii/

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