Complete Event Trend Detection in High-Rate Event Streams

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Real-time Event Trend Analytics

Event trend = event sequence of any length

Traffic control

Event trend:
Aggressive driving

Health care

Event trend:
Irregular heart rate

Cluster monitoring

Event trend:
Uneven load distribution

E-commerce

Event trend:
Items often bought together

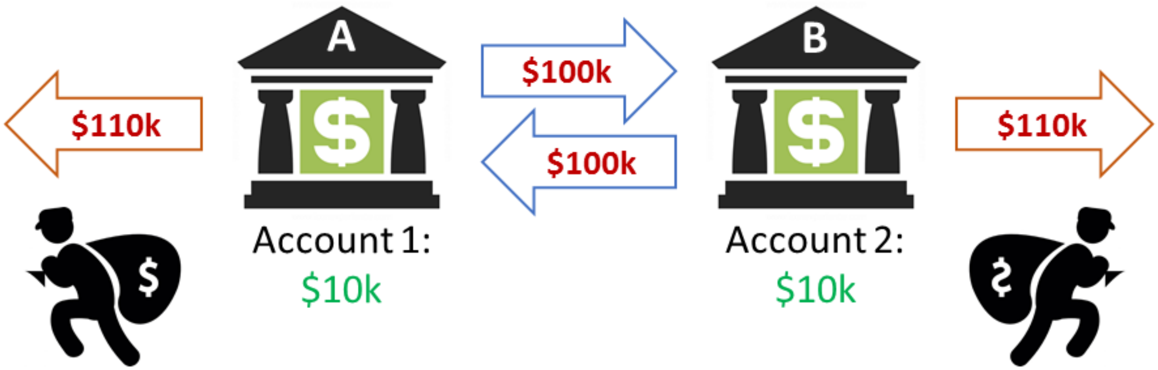
Stock market

Event trend:
Head-and-shoulders

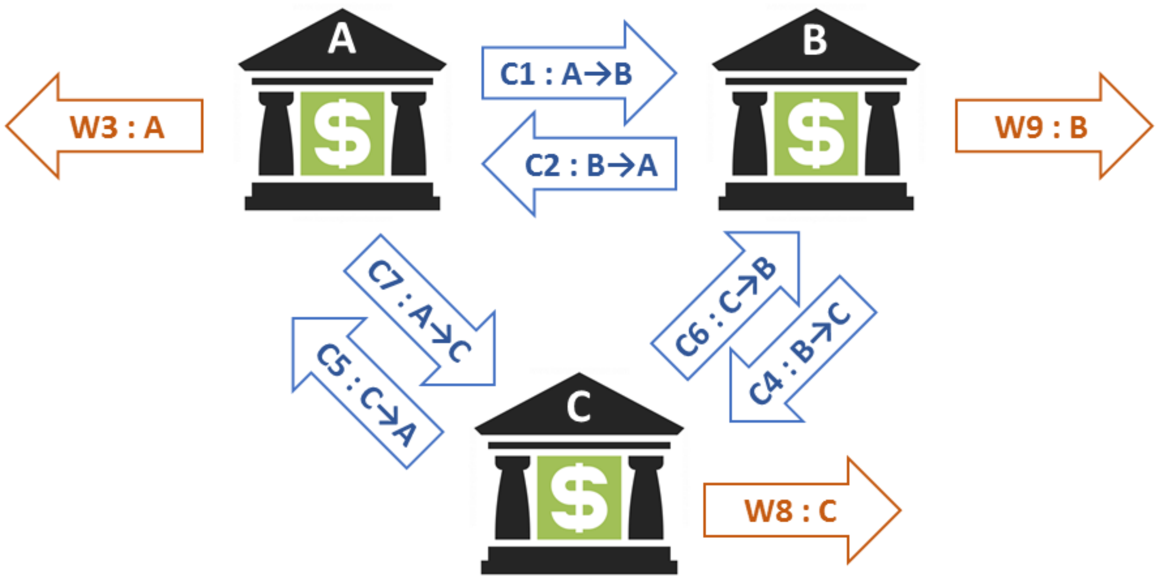
Financial fraud

Event trend:
Circular check kite

Check Kiting Fraud



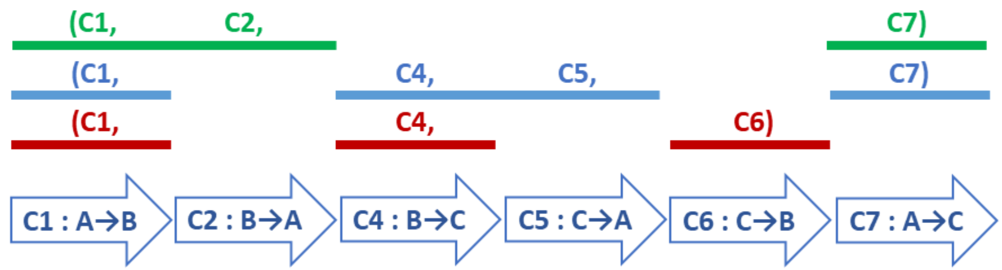
Check Kiting Fraud



- In 2013, a bank fraud scheme netted $5 million from six New York City banks [FBI]
- In 2014, 12 people were charged in a large-scale “bust out” scheme, costing banks over $15 million [The Press Enterprise]

Complete Event Trend Detection

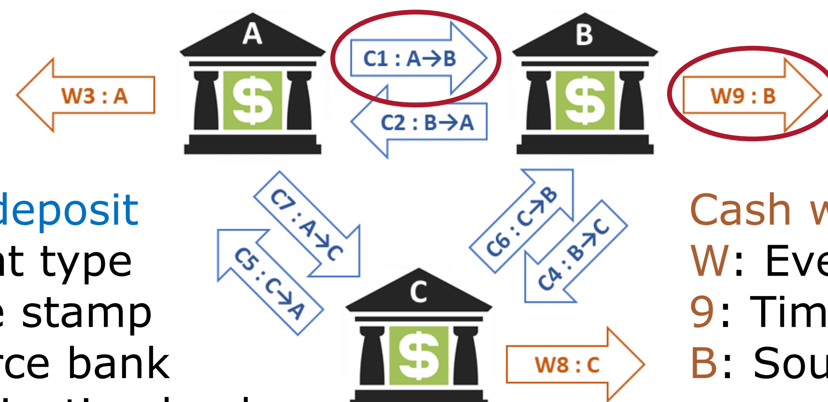
CETs: Complete Event Trends



CET Detection Query

PATTERN Check+ C [ ]
WHERE C.type = not-covered **AND**
C.destination = **Next**(C).source
WITHIN 12 hours **SLIDE** 1 minute

Event Stream



Check deposit
C: Event type
1: Time stamp
A: Source bank
B: Destination bank

Cash withdrawal
W: Event type
9: Time stamp
B: Source bank

Problem Statement & Challenges

Problem Statement

CET optimization problem is to detect all CETs matched by Kleene query q in stream I with minimal CPU processing costs while staying within memory M

Challenges

1. **Expressive yet efficient**
   Exponential number of event trends of arbitrary length

2. **Real-time yet lightweight**
   Common event sub-trend storage versus their re-computation

3. **Optimal yet feasible**
   NP-hard event stream partitioning problem

State-of-the-Art Approaches

1. **Limited expressive power**
   Neither Kleene closure nor the skip-till-any-match semantics are supported [1,2,3]

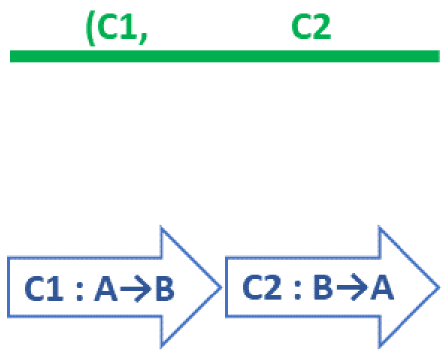
2. **Delayed system responsiveness**
   Common event sub-trends are re-computed [1,2,3,4]

1) Flink. https://flink.apache.org/
2) A.Demers, et al. Cayuga: A General Purpose Event Monitoring System. In CIDR’07.
3) Y.Mei, et al. ZStream: A Cost-based Query Processor for Adaptively Detecting Composite Events. In SIGMOD’09.
4) H.Zhang, et al. On Complexity and Optimization of Expensive Queries in Complex Event Processing. In SIGMOD’14.

Base-Line CET Detection

Cases of the base-line algorithm:
1. **Start a new CET**

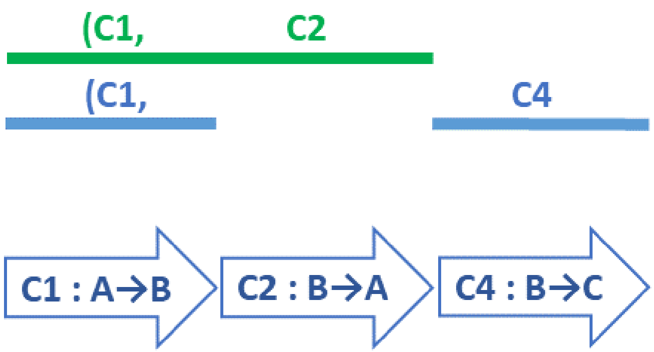
Base-Line CET Detection



Cases of the base-line algorithm:

1. Start a new CET
2. **Append to an existing CET**

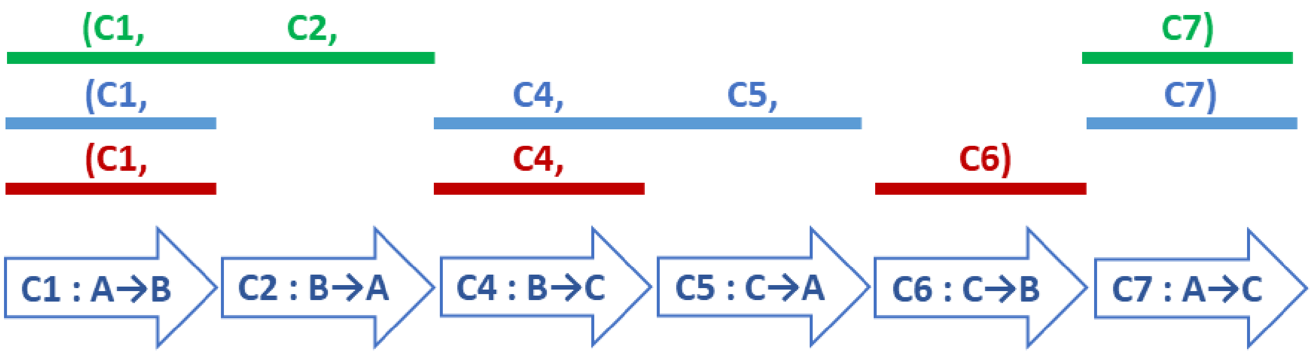
Base-Line CET Detection



Cases of the base-line algorithm:

1. Start a new CET
2. Append to an existing CET
3. **Replicate the prefix of an existing CET and append to it**

Base-Line CET Detection



Problem: Exponential
time & space complexity

Overview of Our CET Approach

Event trend output stream

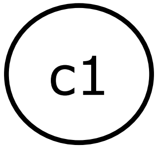
Step 2:
Graph-based CET Detection
Trade-off between time & space complexity

CET graph

Step 1:
Compact CET Encoding as CET Graph
Quadratic time & space complexity

Input event stream

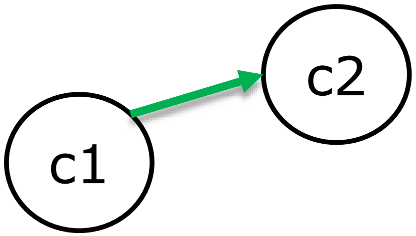
Step 1: CET Graph Construction



Cases of the graph construction algorithm:

1. Start a new CET

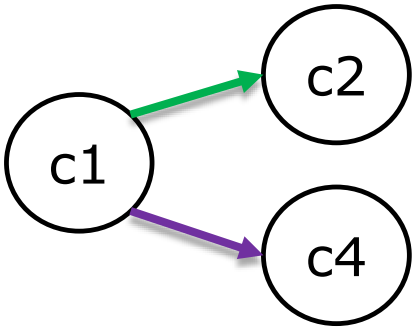
Step 1: CET Graph Construction



Cases of the graph construction algorithm:

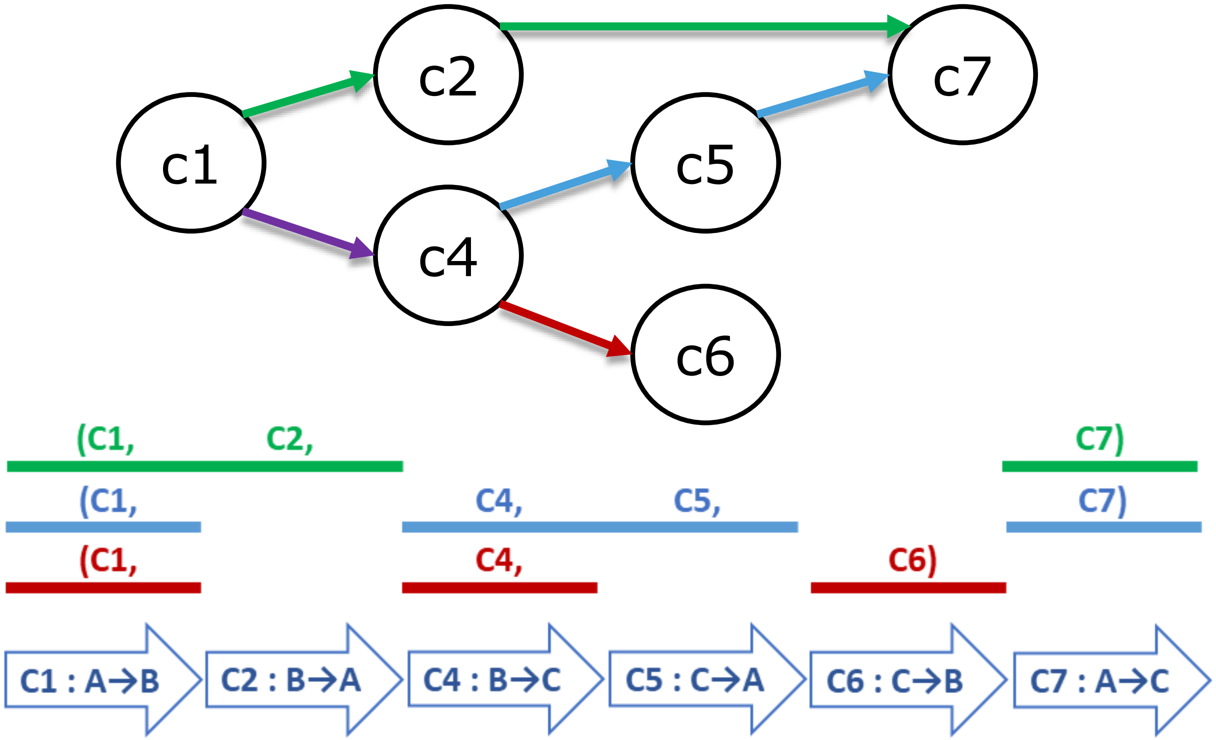
1. Start a new CET
2. **Append to an existing CET**

Step 1: CET Graph Construction



Cases of the graph construction algorithm:
1. Start a new CET
2. Append to an existing CET
3. **Append to the prefix of an existing CET**

Step 1: CET Graph Construction



Compact CET encoding = CET graph

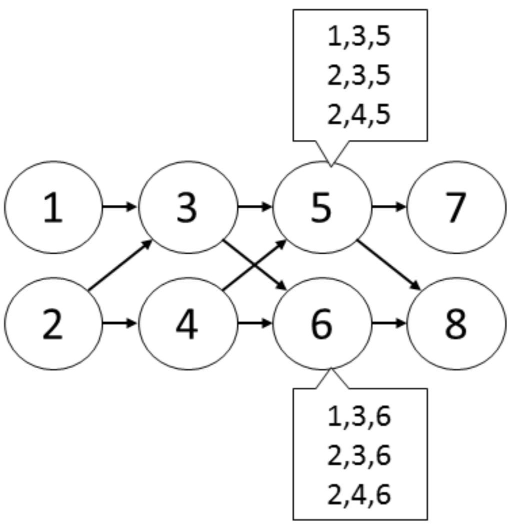
- Matched event = vertex
- Event adjacency relation = edge
- CET = Path through the graph

Quadratic time & space complexity

Step 2: Graph-based CET Detection

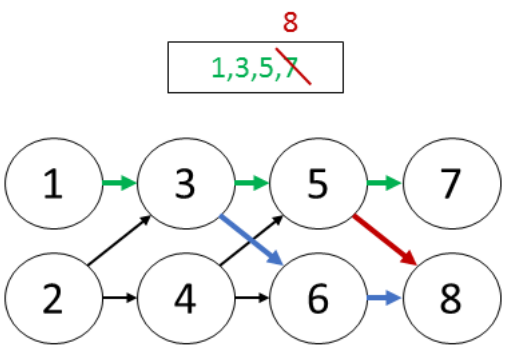
Spectrum of CET Detection Algorithms

T-CET: Time-optimal BFS-based algorithm



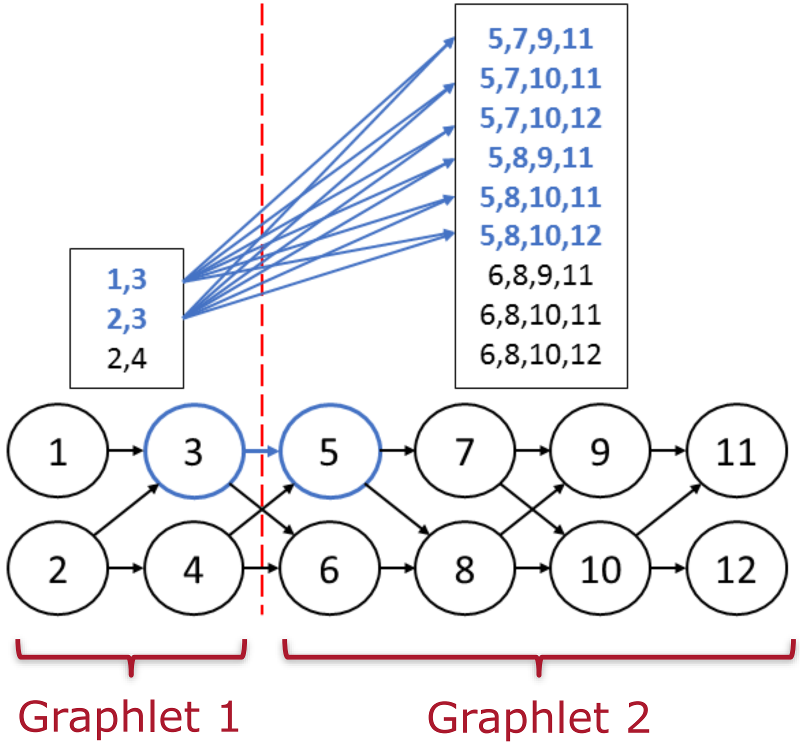
Is a **middle ground** possible?

M-CET: Memory-optimal DFS-based algorithm



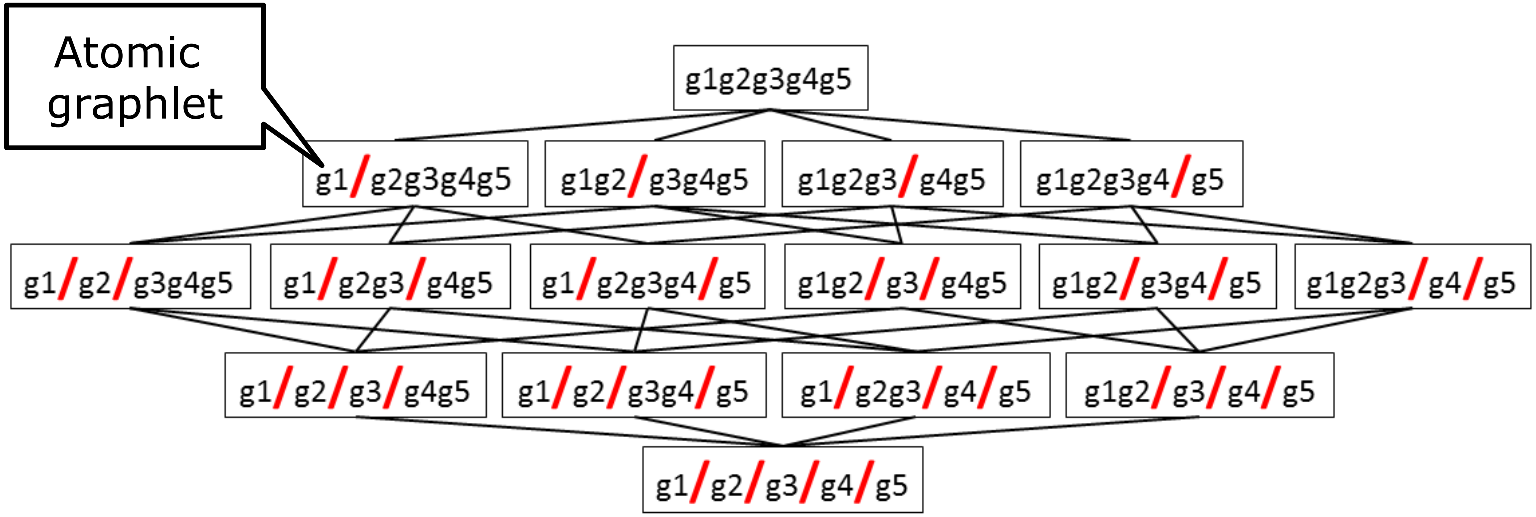
Step 2: Graph-based CET Detection

Our Proposed H-CET (Hybrid) Algorithm



How do we partition the graph?

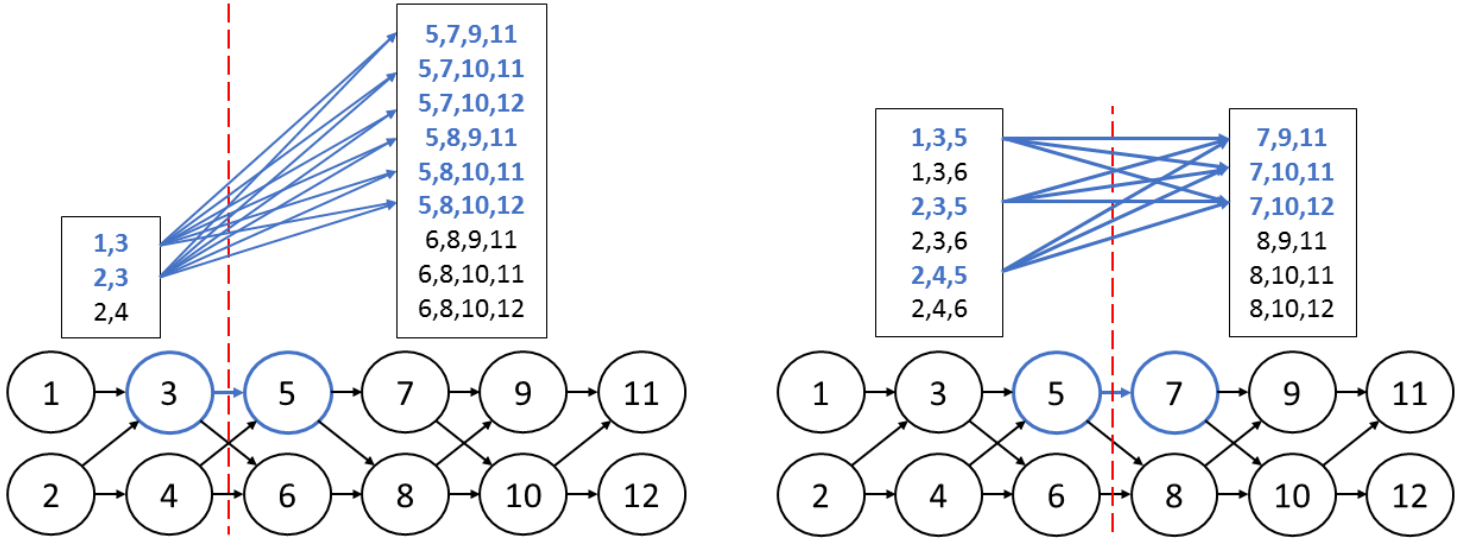
Graph Partitioning Search Space



Graph partitioning search is **exponential** in # of atomic graphlets

<u>Goal:</u> Optimal graph partitioning plan

Balanced Graph Partitioning

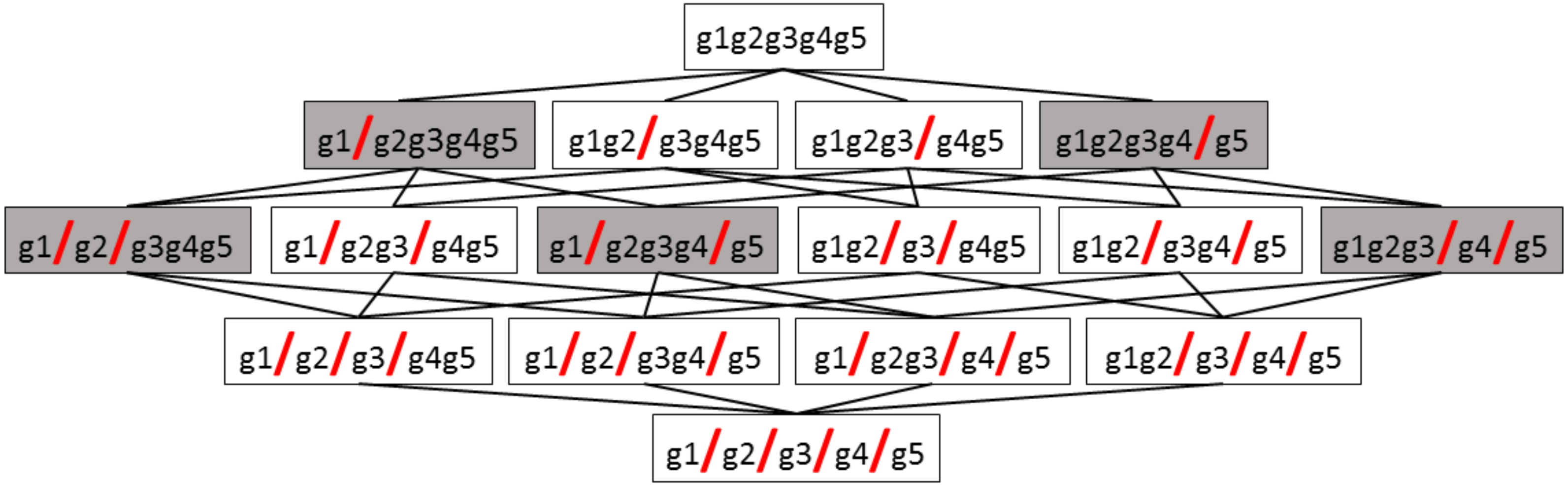


CPU: 27 connect operations
Memory: 42 events

CPU: 27 connect operations
Memory: 36 events

Theorem. The closer a graph partitioning is to balanced, the lower are CPU & memory costs of the CET detection.

Graph Partitioning Algorithm

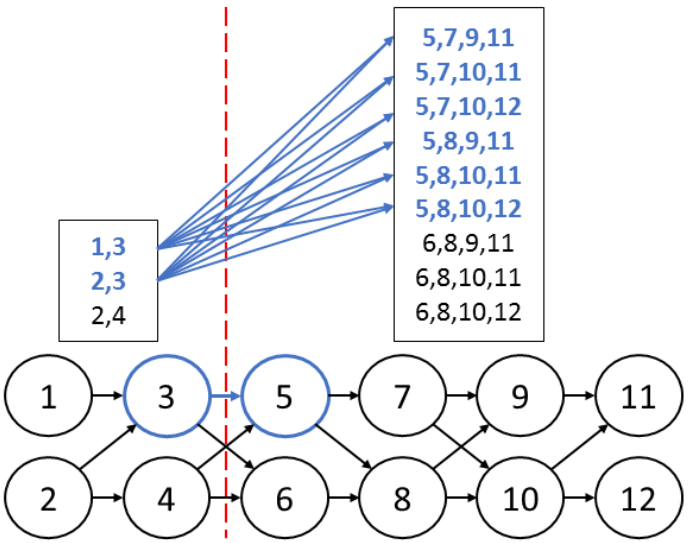


Pruning principles:

1. Unbalanced node pruning

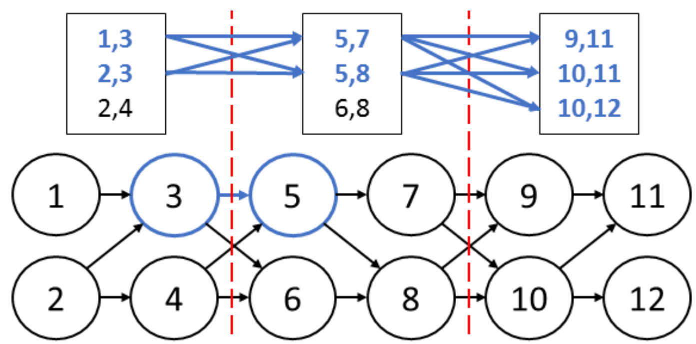
Number of Graphlets

2 Graphlets



CPU: 27 connect operations
Memory: 42 events

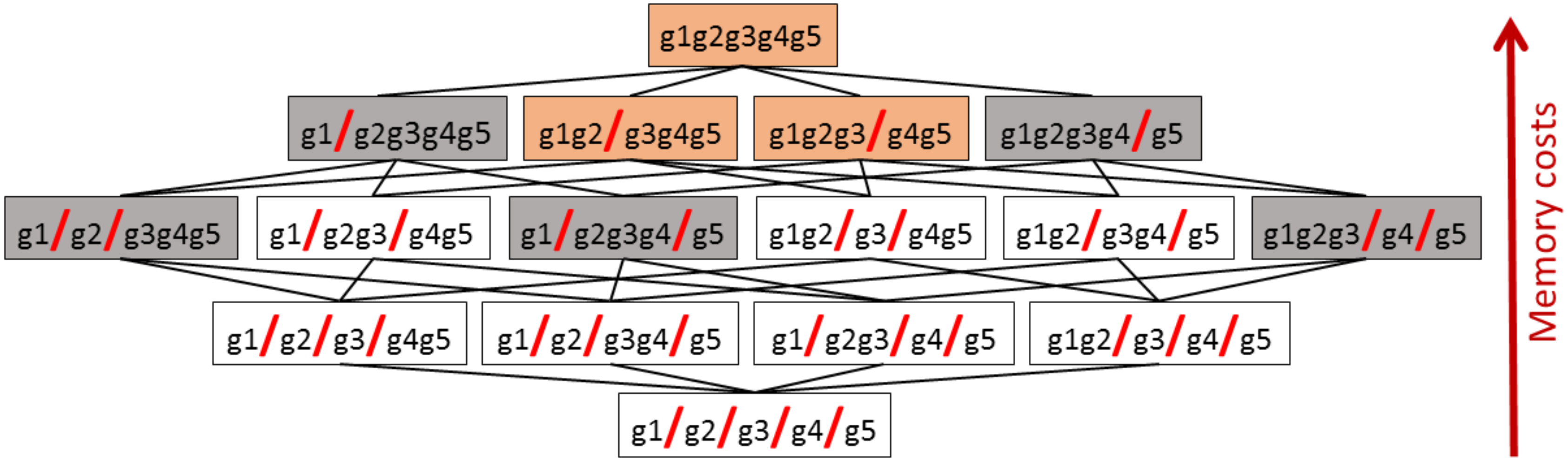
3 Graphlets



CPU: 38 connect operations
Memory: 18 events

Theorem. If we add a cut to the graph, memory costs of CET detection goes down, while CPU processing time goes up.

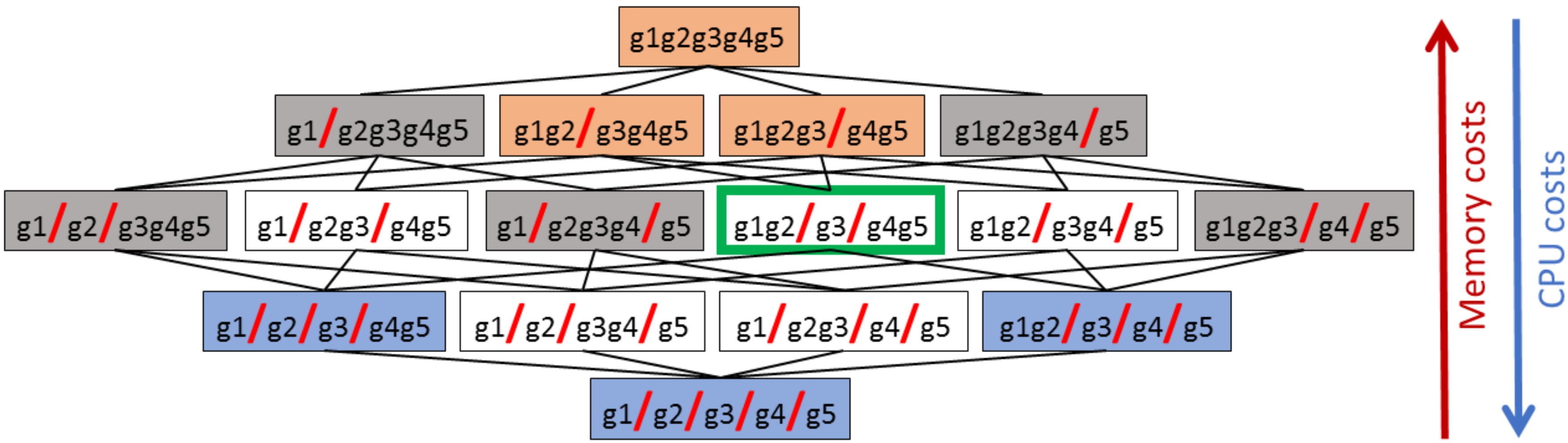
Graph Partitioning Algorithm



Pruning principles:

1. Unbalanced node pruning
2. **Infeasible level pruning**

Graph Partitioning Algorithm



Pruning principles:

1. Unbalanced node pruning
2. Infeasible level pruning
3. **Inefficient branch pruning**

Experimental Setup

Execution infrastructure:

Java 7, 1 Linux machine with 16-core 3.4 GHz CPU and 128GB of RAM

Data sets:

- Stock real data set (ST) [1]

  CETs = Stock trends

- Physical activity monitoring real data set (PA) [2]

  CETs = Behavioral patterns per person

- Financial transaction synthetic data set (FT)

  CETs = Circular check kites

[1] Stock trade traces. http://davis.wpi.edu/datasets/Stock Trace Data/
[2] A. Reiss and D. Stricker. Creating and benchmarking a new dataset for physical activity monitoring. In PETRA, pages 40:1-40:8, 2012.

Experimental Setup

CET detection algorithms:

- Base line (BL) maintains a set of CETs
- SASE++ is memory-optimized [1,2]
- Flink is a popular open-source streaming engine that supports event pattern matching but not Kleene closure. Thus, we flatten our queries [3]

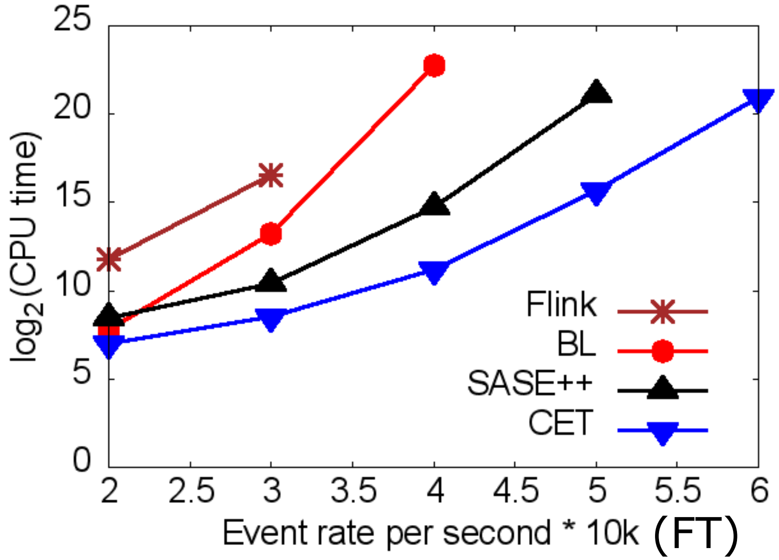
CET graph partitioning algorithms:

- Exhaustive (Exh)
- Greedy
- Branch and bound (B&B)

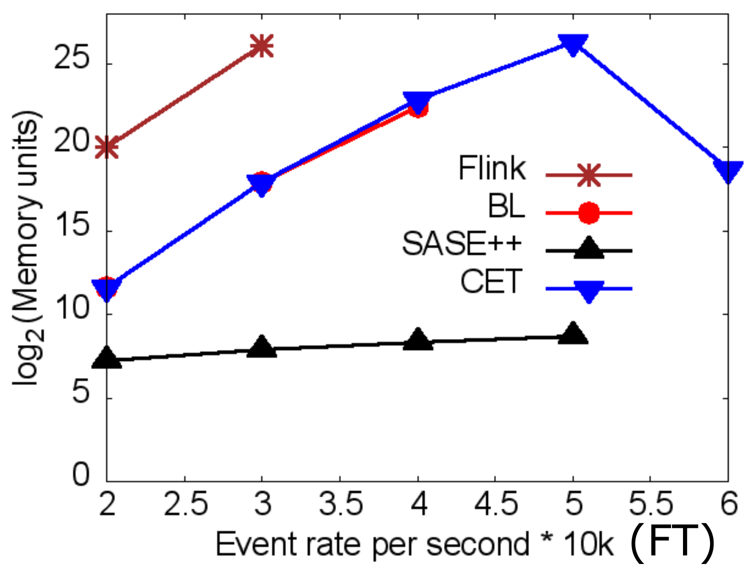
[1] J. Agrawal, Y. Diao, D. Gyllstrom, and N. Immerman. Efficient pattern matching over event streams. In SIGMOD, pages 147-160, 2008.
[2] H. Zhang, Y. Diao, and N. Immerman. On complexity and optimization of expensive queries in Complex Event Processing. In SIGMOD, pages 217-228, 2014.
[3] Apache Flink. https://ink.apache.org/

CET Detection Algorithms

CPU costs



Memory costs

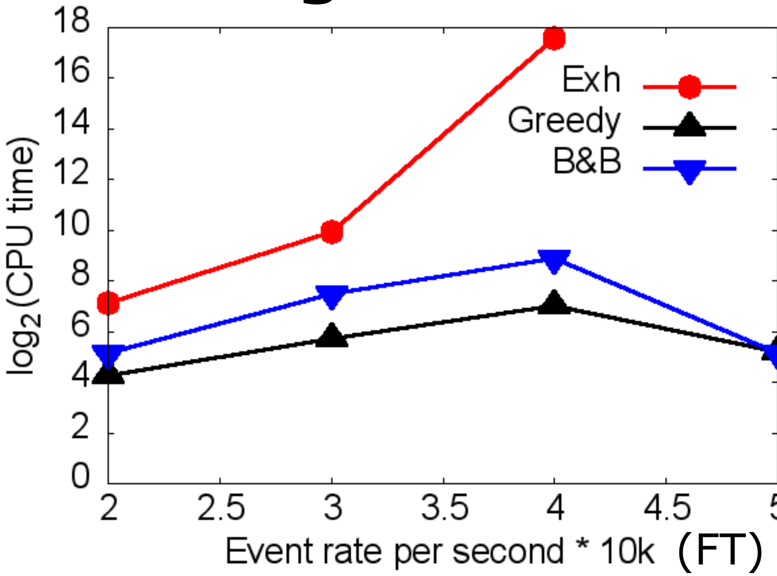


CET

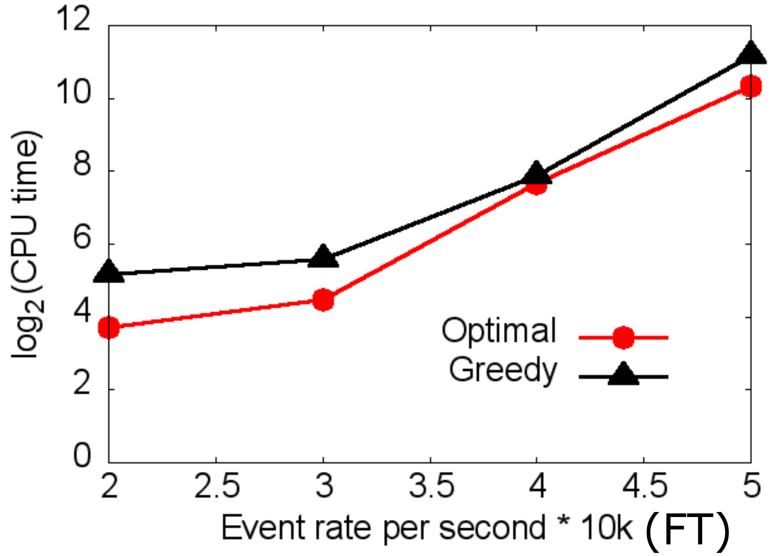
- utilizes available memory to achieve **42-fold** speed-up compared to SASE++
- is **2 orders of magnitude** faster and requires **2 orders of magnitude** less memory than Flink

CET Graph Partitioning

Graph partitioning algorithms



Quality of partitioning plan



B&B is

- **2 orders of magnitude** faster than Exhaustive but **3-fold** slower than Greedy
- CET detection in a greedily partitioned CET graph is almost **3-fold** slower than in an optimally partitioned CET graph

Conclusions

We are the first to enable **real-time Kleene closure computation over event streams under memory constraints**

1. **CET graph** compactly encodes all CETs and defines the spectrum of **CET detection algorithms**
2. **Hybrid CET detection algorithm** utilizes available memory to achieve **42-fold speed-up**
3. **Graph partitioning algorithm** prunes large portions of search to efficiently find an optimal graph partitioning

Acknowledgement

- DSRG group at WPI
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