Continuous Graph Pattern Matching Over Knowledge Graph Streams

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[Outline]

- ✓ Knowledge Graph (KG) Processing in general
- ✓ KG Streams' Models
- ✓ Issues and Challengers for Processing KG Streams
- ✓ Pre-processing and pruning of KG events
- ✓ Event-based KG Stream Processing
- ✓ Incremental KG Stream Processing
- ✓ Empirical Evaluation

[The Data Deluge]

- More than 3000 Exabytes (billions GBs) created in 2015 alone
  - Increased from 150 Exabytes in 2005

- Many new sources of data become available
  - ✓ Sensors, mobile devices
  - ✓ Web feeds, social networks
  - ✓ Surveillance video and audio
  - ✓ Knowledge Bases

  ………………

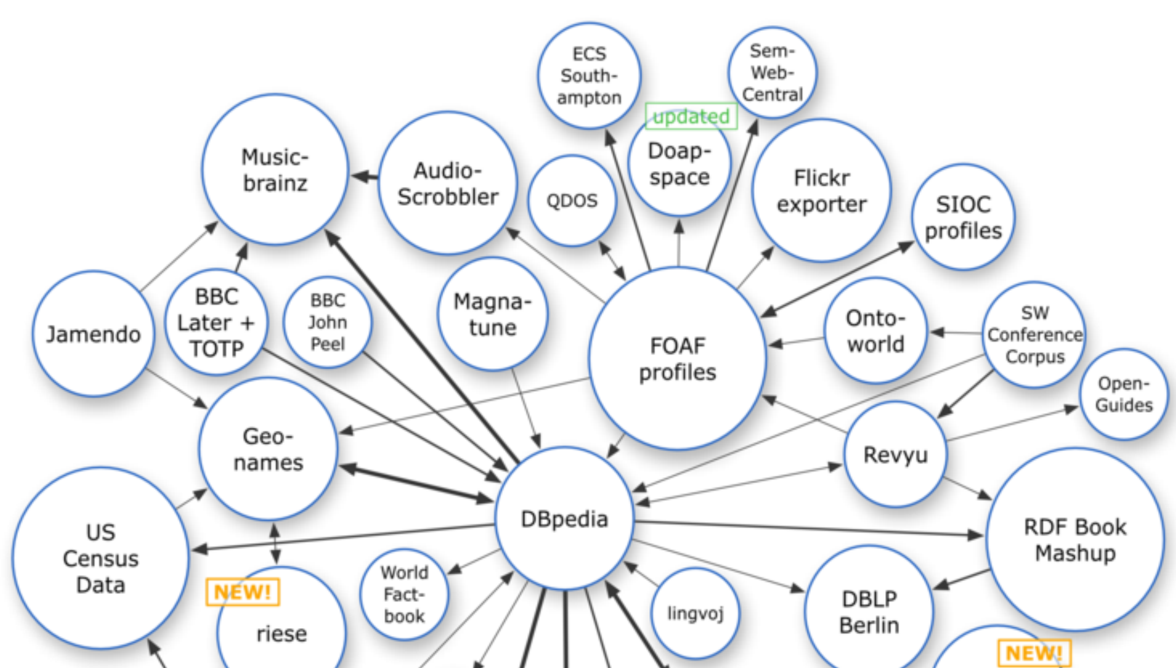


- **Making sense of all data: Stream Processing to the Rescue**
  - ✓ Process data streams on the fly without storage
  - ✓ Limited amount of available memory
  - ✓ Latency of data processing matters

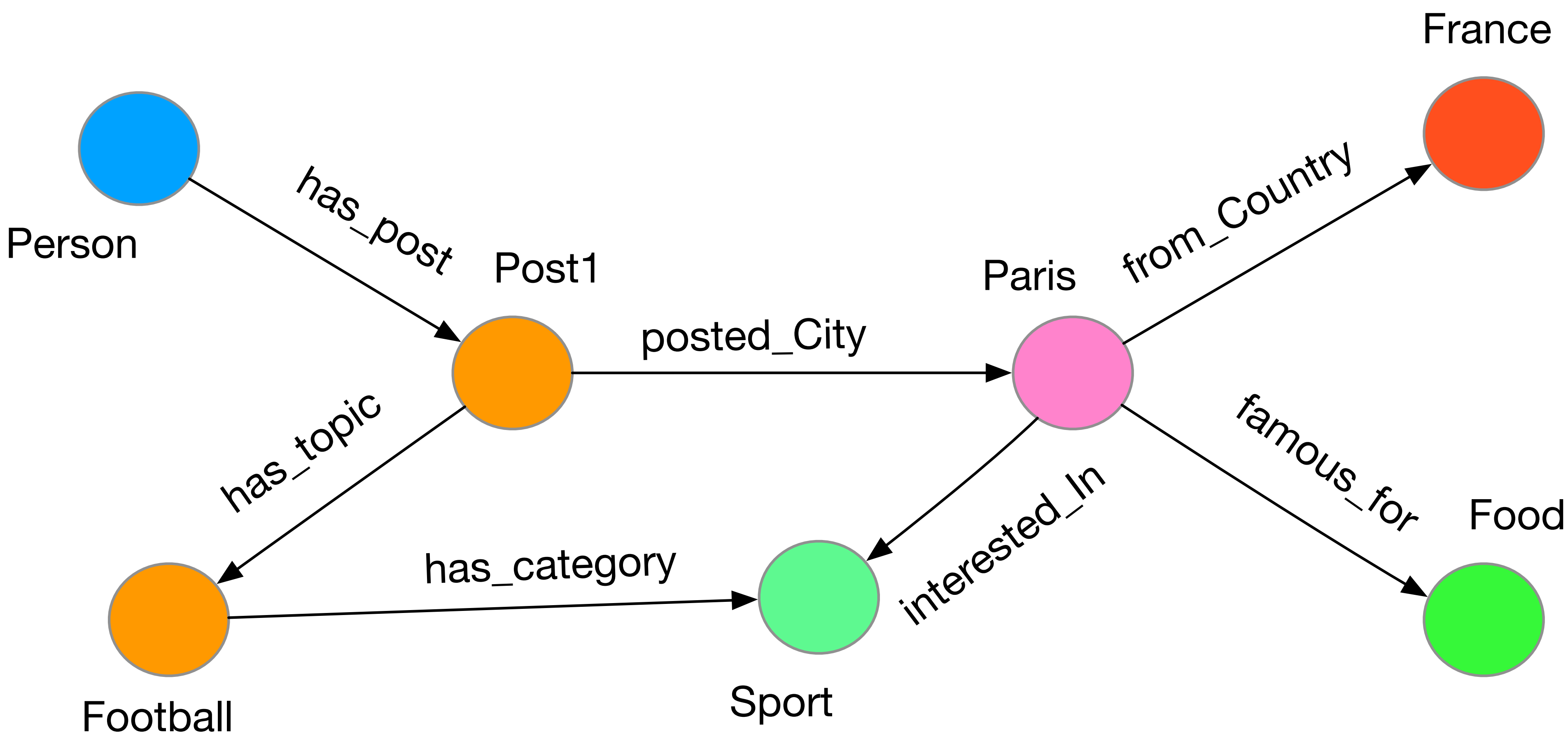
[Stream Processing: is it enough?]

- Nature of the Streams
  - ✓ Heterogeneous stream emanating from multiple sources
  - ✓ Extracting the contextual Knowledge
  - ✓ Seamless Integration of streams

- **Knowledge Graph Data Model**
  - ✓ Lifting streaming data to a semantic model
  - ✓ Schema-less model allows integration of heterogeneous streams
  - ✓ Integration of external sources using Link Data collections
  - ✓ New breed of applications

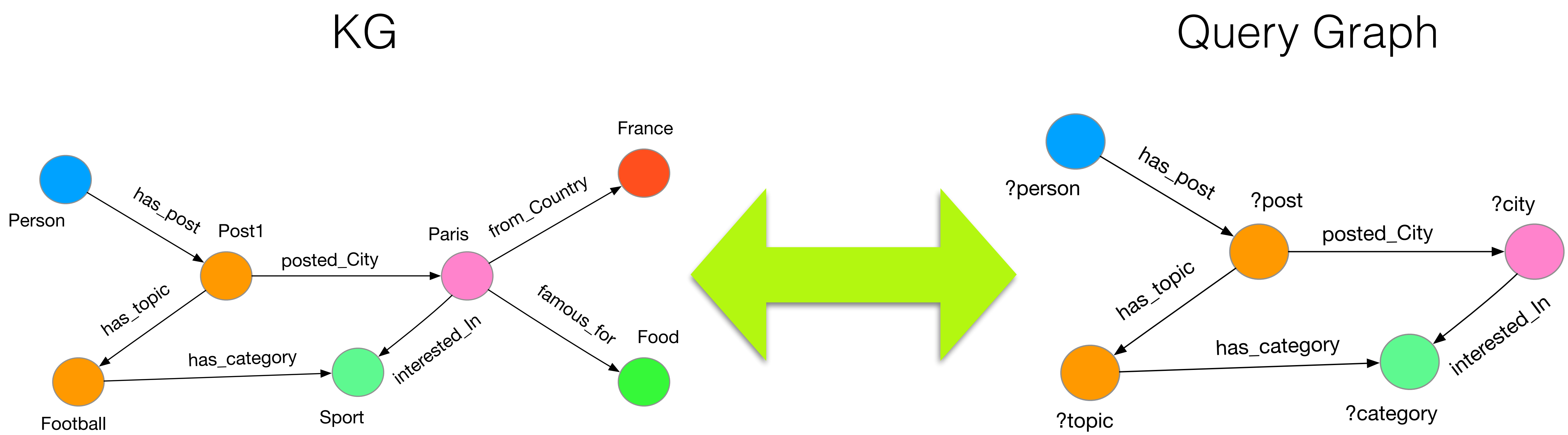


[Knowledge Graph Model]



- ✓ Set of entities and directed relations between them
- ✓ Constraints on type and attributes of the entities and their relations
- **For RDF model**:
  - ✓Entities are IRIs, Blank Nodes, Literals (only for outer edges)
  - ✓Relations are IRI's
  - ✓Set of triples (*subject, predicate, object*)

[Knowledge Graph Model]

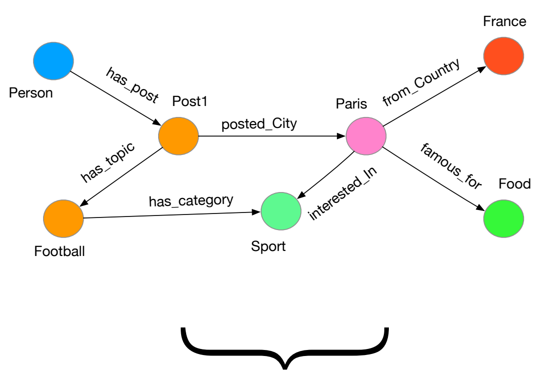


Pattern Matching/Subgraph Isomorphism (homomorphism)

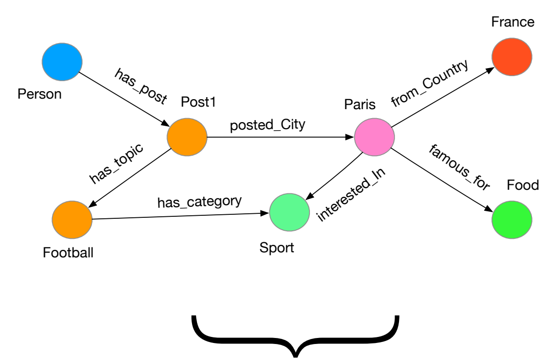
✓ NP-Complete Problem
✓ Require sophisticated Indexing

[Adding Temporal Dynamics to KGs]

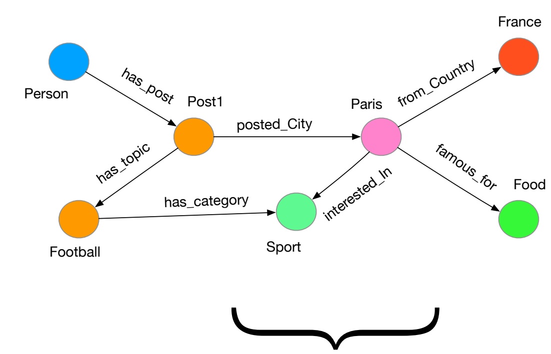
Event/batch-based Model



(KG_1,T_1)

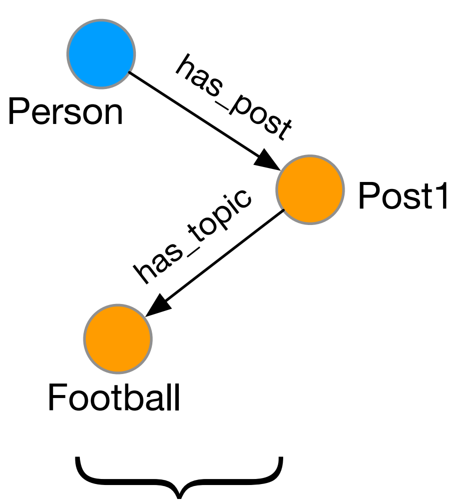


(KG_2,T_2)

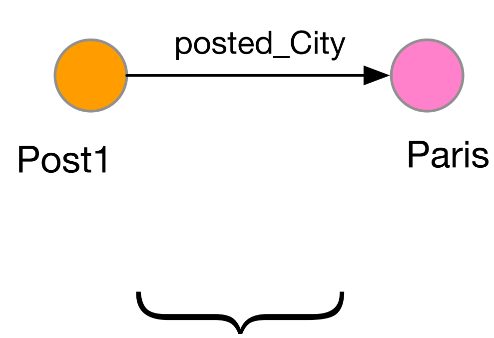


(KG_3,T_3)

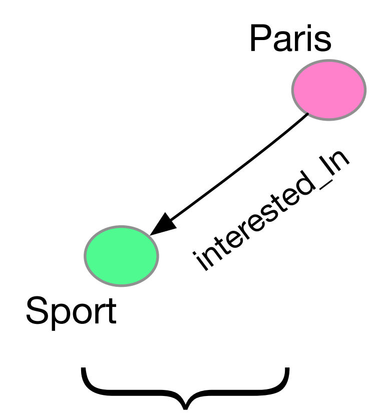
Edge/Incremental Model



$(\Delta KG_1,T_1)$

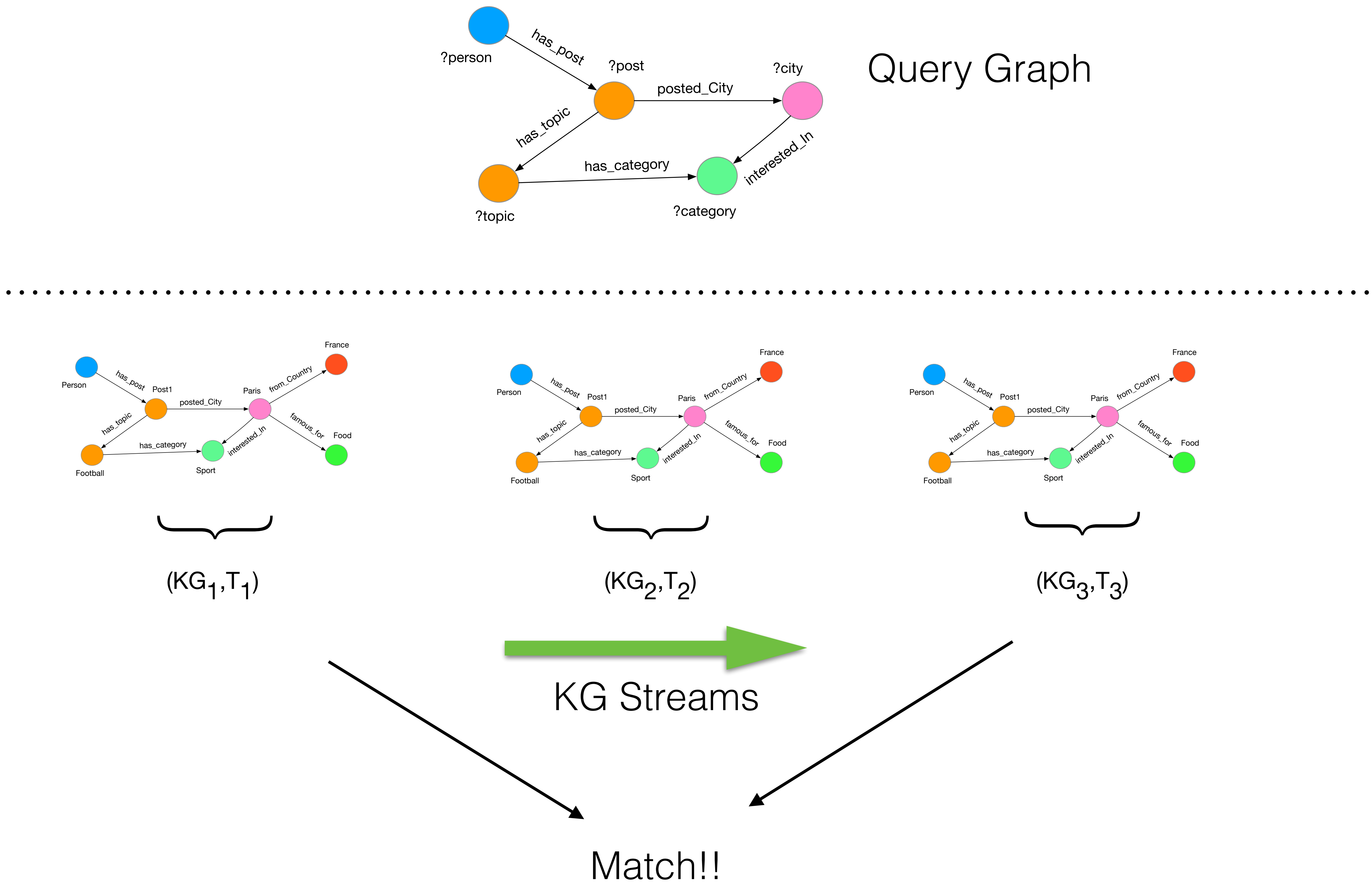


$(\Delta KG_2,T_2)$



$(\Delta KG_3,T_3)$

[KG Stream Processing]



[KG Stream Processing: Issues and Challenges]

- Traditional Static/dynamic Solutions
  - ✓ Graph-based storage and exploration-based querying
  - ✓ Tabular-based storage and join-based querying
  - ✓ Re-evaluation of computed query matches

- Both techniques utilised **index-store-query** model
  - ✓ Expensive indexing to accelerate query processing (O(n^4))
    - ✓ Clustered B-+ Trees

Require on-the-fly KG stream processing

- ✓ Avoid expensive indexing
- ✓ Light-weight data structure
- ✓ Incremental computation of matches

[What We Offer!!]

- ✓ Continuous GPM over both Event and Incremental Model for Tumbling Windows
- ✓ *Query-based graph pruning* techniques for KG events
- ✓ Hybrid *join-and-explore* matching technique to avoid expensive indexing
- ✓ Light-weight *multi-bidirectional* data structure to comply with streaming settings
- ✓ Automata-based executional framework for processing of KG events

Event-based Continuous Graph Pattern Matching

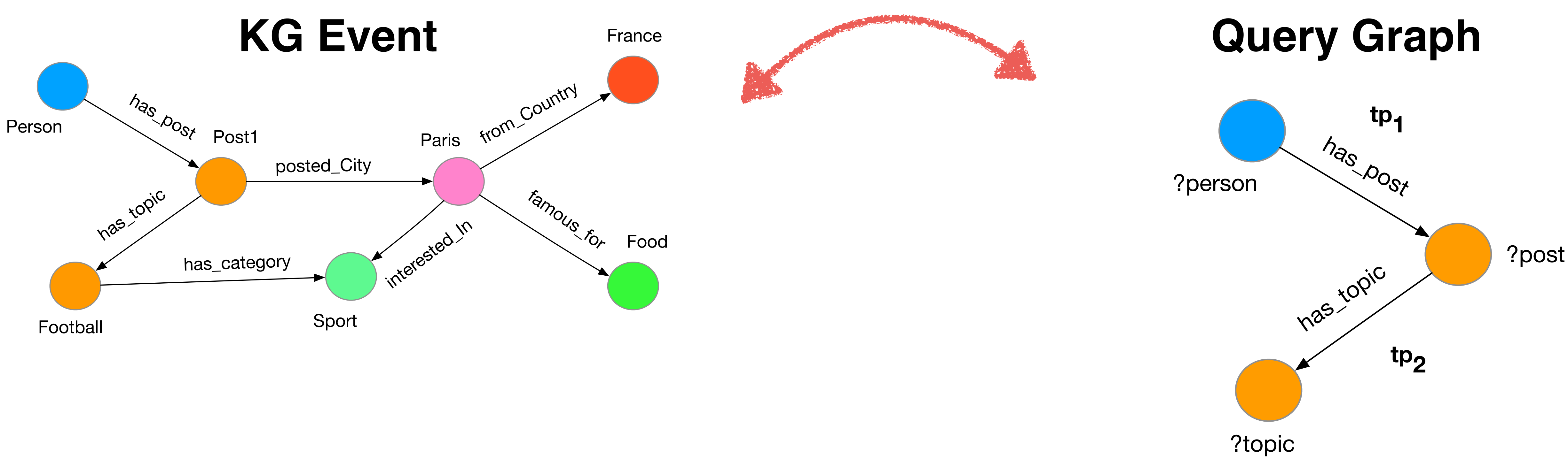
PROBLEM 1 (EVENT-BASED CGPM). *Given (i) a query graph Q, (ii) a* KG *stream $\mathcal{G}$, and (iii) a matching function M,* Event-based CGPM *amounts to continuously compute the function $M(Q, (G^i, \tau_i))$ for each event within the* KG *streams.*

[Pruning KG Events]

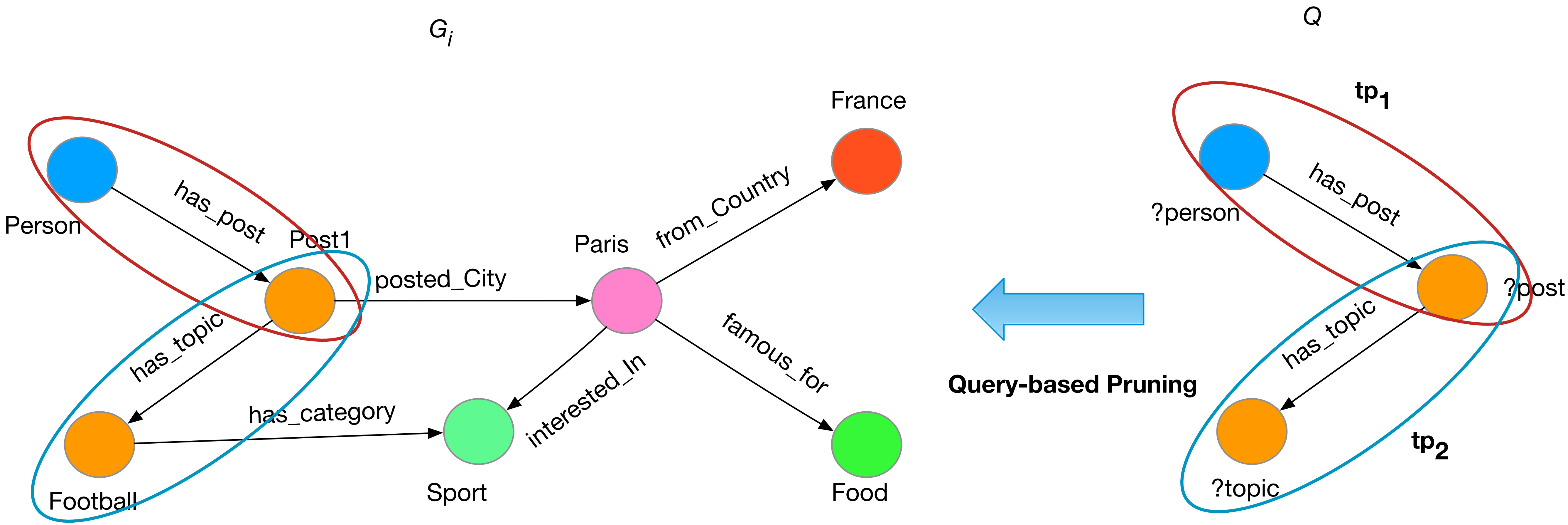
OBSERVATION 1. *Given a query graph* Q *and a* KG *event* (G^i, τ_i), *the number of edges* $|E_Q| \in Q$ *is less than or equal to the number of edges* $|E^i| \in G^i$.

Queries are register beforehand!!

Utilise structural attributes of query graph for pruning



[Pruning KG Events]



Materialisation into Vertically Partitioned Tables

has_post	S	O
	Person	Post1

$\mathbb{T}_1$

has_topic	S	O
	Post1	Football

$\mathbb{T}_2$

Dictionary Encoding (Strings to Numeric Ids)

tp$_1$

4	S	O
	2	3

$\mathbb{T}_1$

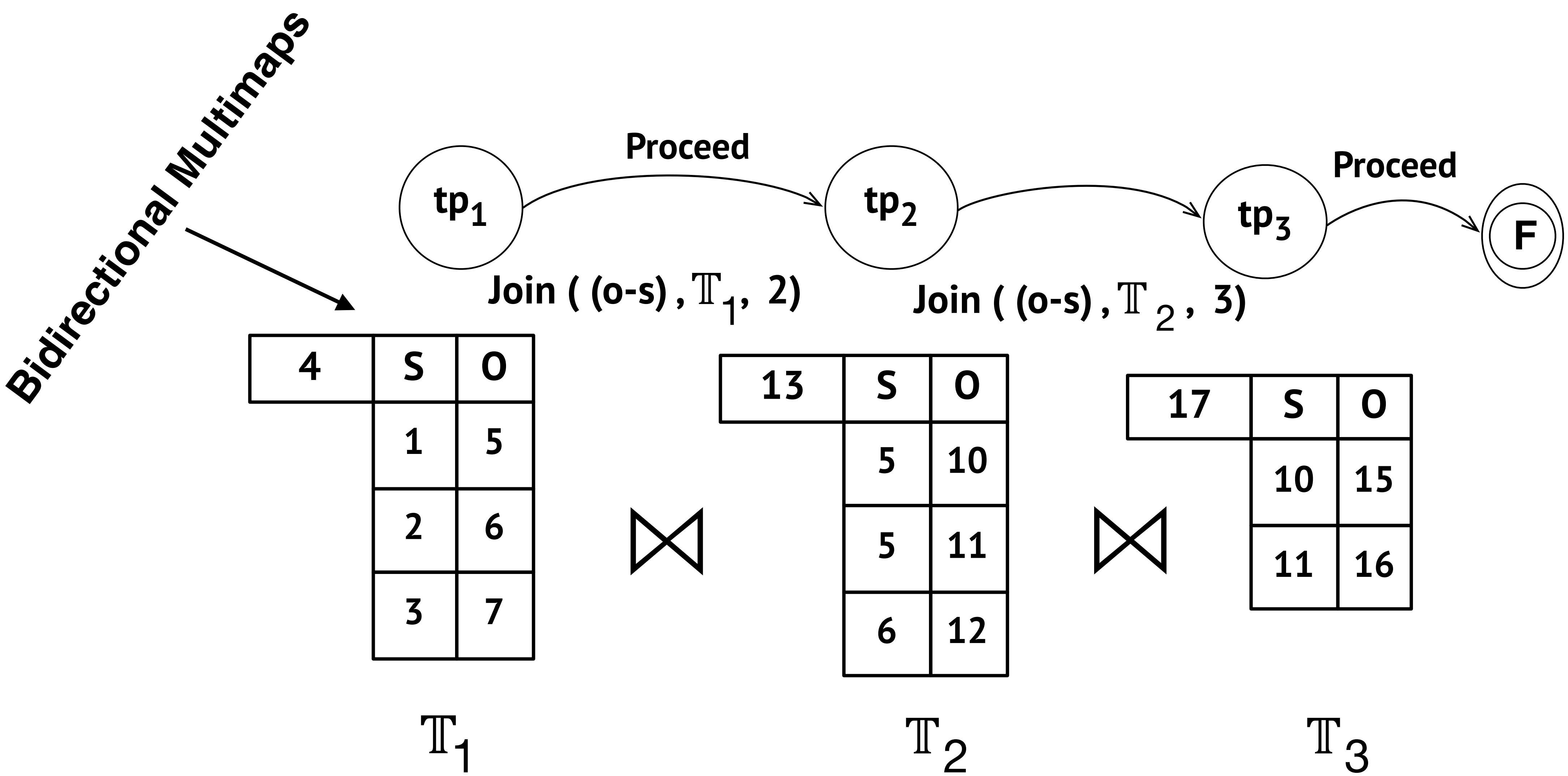
tp$_2$

6	S	O
	3	5

$\mathbb{T}_2$

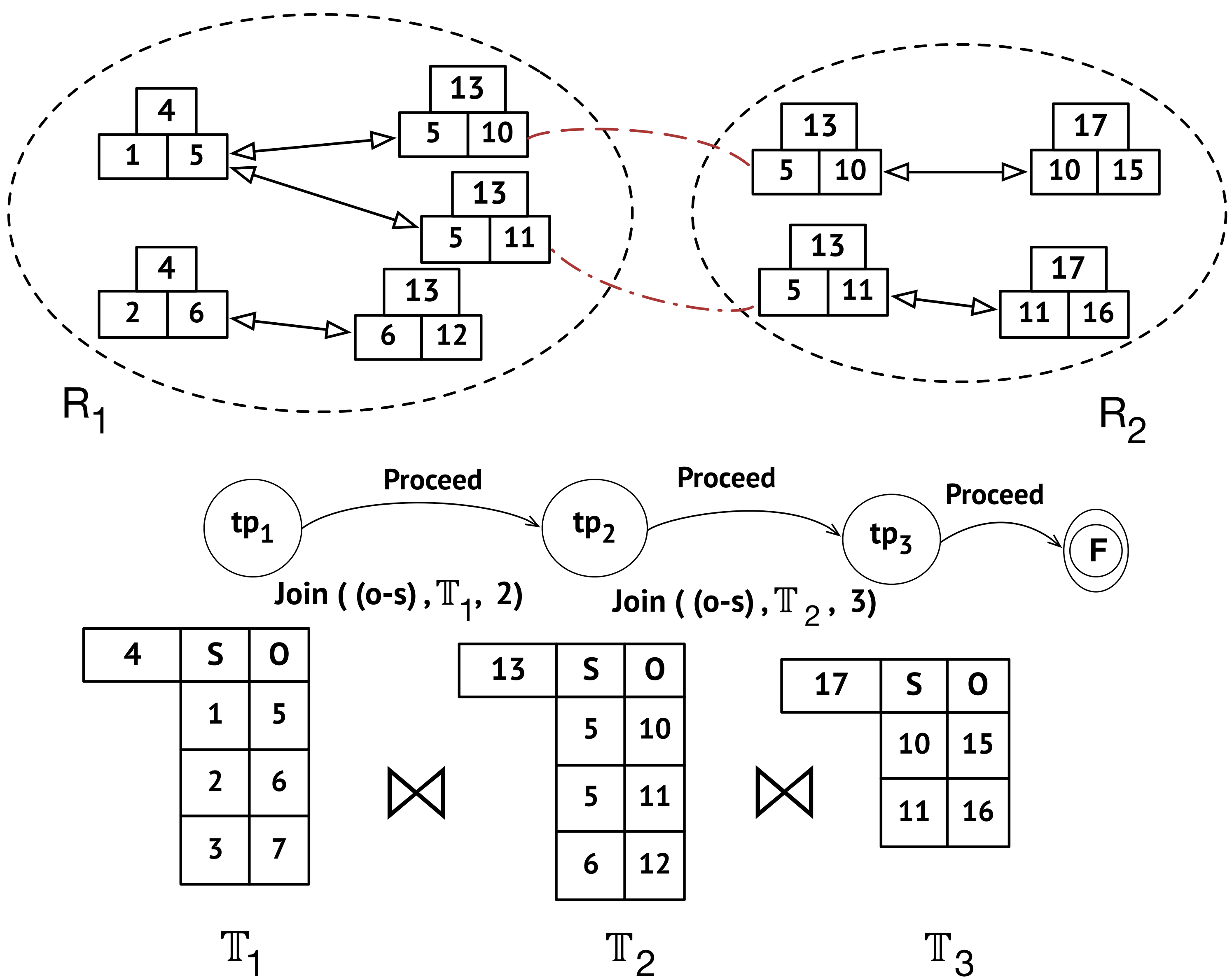
[TP-Join Automata]

- ✓Automate an old friend of pattern matching
- ✓Percolation property for on-the-fly processing
- ✓Map the set of triple patterns (tp) to automaton states
- ✓Triple patterns' join conditions as transition predicates



[TP-Join Automata]

- ✓Hybrid Join-and-explore
- ✓Join the tables for the dependent triple patterns
- ✓Transit to the next state if join produces results
- ✓Insert the resulted matches in graph-structures (multimaps)
- ✓Explore the graph to produce the matches without creating/using indices



[TP-Join Automata]

- On-the-fly execution
- Each step reduces the search space by removes the “dangling” triples
- Support of start, chain, cyclic queries without incurring the cost of indexing
- Can extend the automata for expressive operators, such as kleen-+, negation
- Process joins only if there is an enough evidence of matching a KG event

Incremental Continuous Graph Pattern Matching

PROBLEM 2 (INCREMENTAL CGPM). *Given (i) a query graph Q, (ii) an evolving* KG G*, and* $(\Delta G^i, \tau_i)$ *as updates to* G*, such that the updates conform to a stream* $\mathcal{G} = \{(\Delta G^1, \tau_1), \ldots, (\Delta G^n, \tau_n)\}$*, and (iii) a matching function* M*,* Incremental CGPM *amounts to continuously compute the changes* $\Delta M_i = M(Q, (\Delta G^i, \tau_i))$ *to the matches such that,*

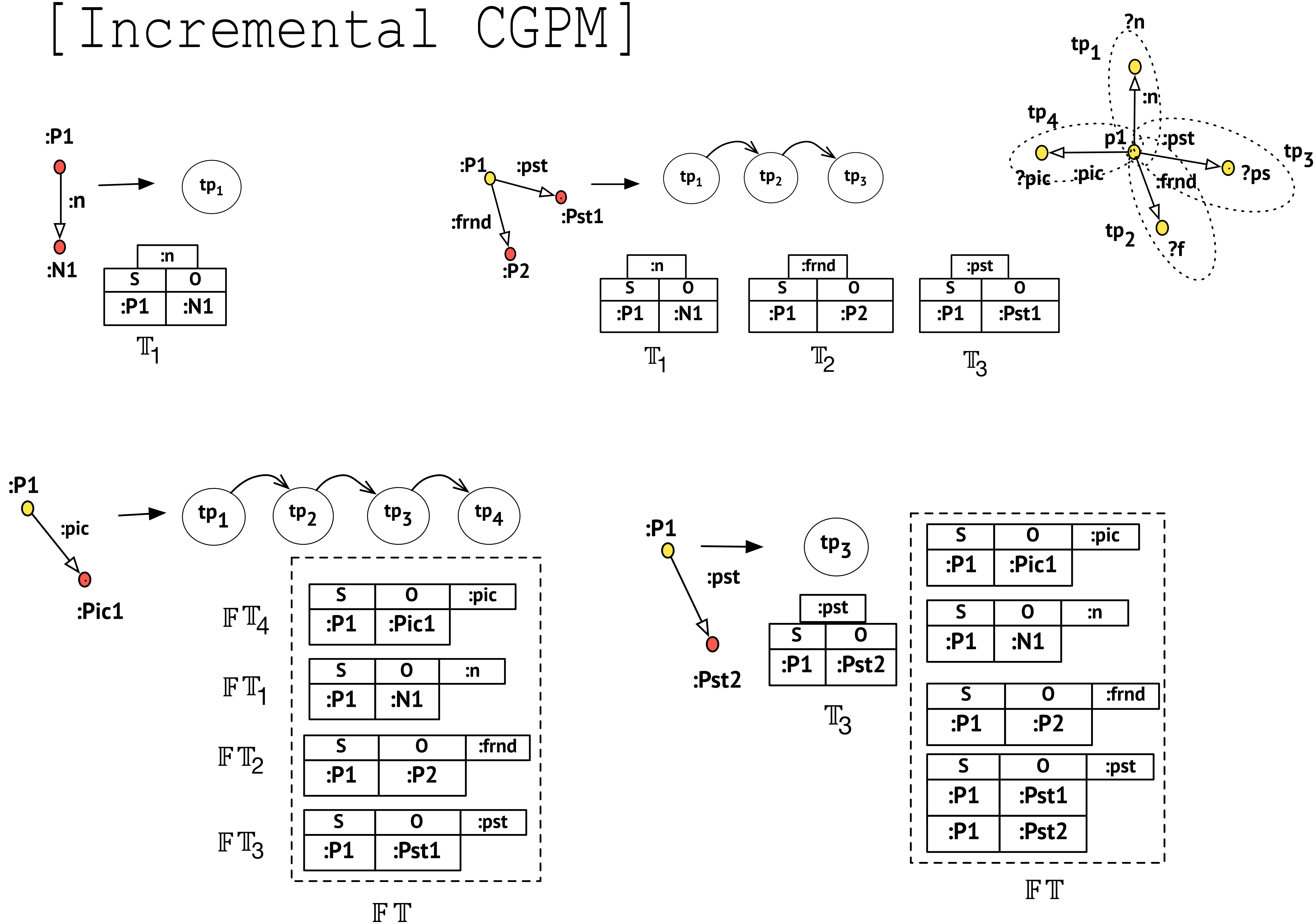
$$M(Q, \bigcup_{k=0}^{i-1}(\Delta G^k, \tau_k) \oplus (\Delta G^i, \tau_i)) = M(Q, \bigcup_{k=0}^{i-1}(\Delta G^k, \tau_k)) \oplus \Delta M_i$$

where operator $\oplus$ *incrementally applies changes to the matched graphs.*

[Incremental CGPM]

- Same approach for pruning events/graph updates
- Extend TP-Join Algorithm:
  - ✓incrementally locate new matches
  - ✓efficiently update the old matches
- Matches emerge slowly during incremental evaluation
- Find partial matches for each update and incrementally process remaining matches
- Lazy Evaluation of joins

[Incremental CGPM]



[Incremental CGPM]

- Lazy Evaluation:
  - ✓Defer the joining process
  - ✓Make sure all the triple pattern has corresponding triples
  - ✓Store the matched results in *Final Tables* (FT) for a defined window
- Utilise final tables to incrementally match the new updates
- Lazy evaluation save useless computations
- Previously matched results are store in Final Tables:
  - ✓Incremental CGPM produces the same result as that of re-evaluation

[Empirical Evaluation]

✓How the system performs as compared to traditionally Index-based solutions

✓How the system performs as compared to re-evaluation based systems

[Empirical Evaluation]

- **Metrics Event-based Evaluation**:

  ✓Varying the number of events and then triples within each event

  ✓Window size would not effect the performance (no aggregate operators used)

- **Metrics Incremental Evaluation**:

✓Varying the window size (w) and evaluate events within the tumbling window

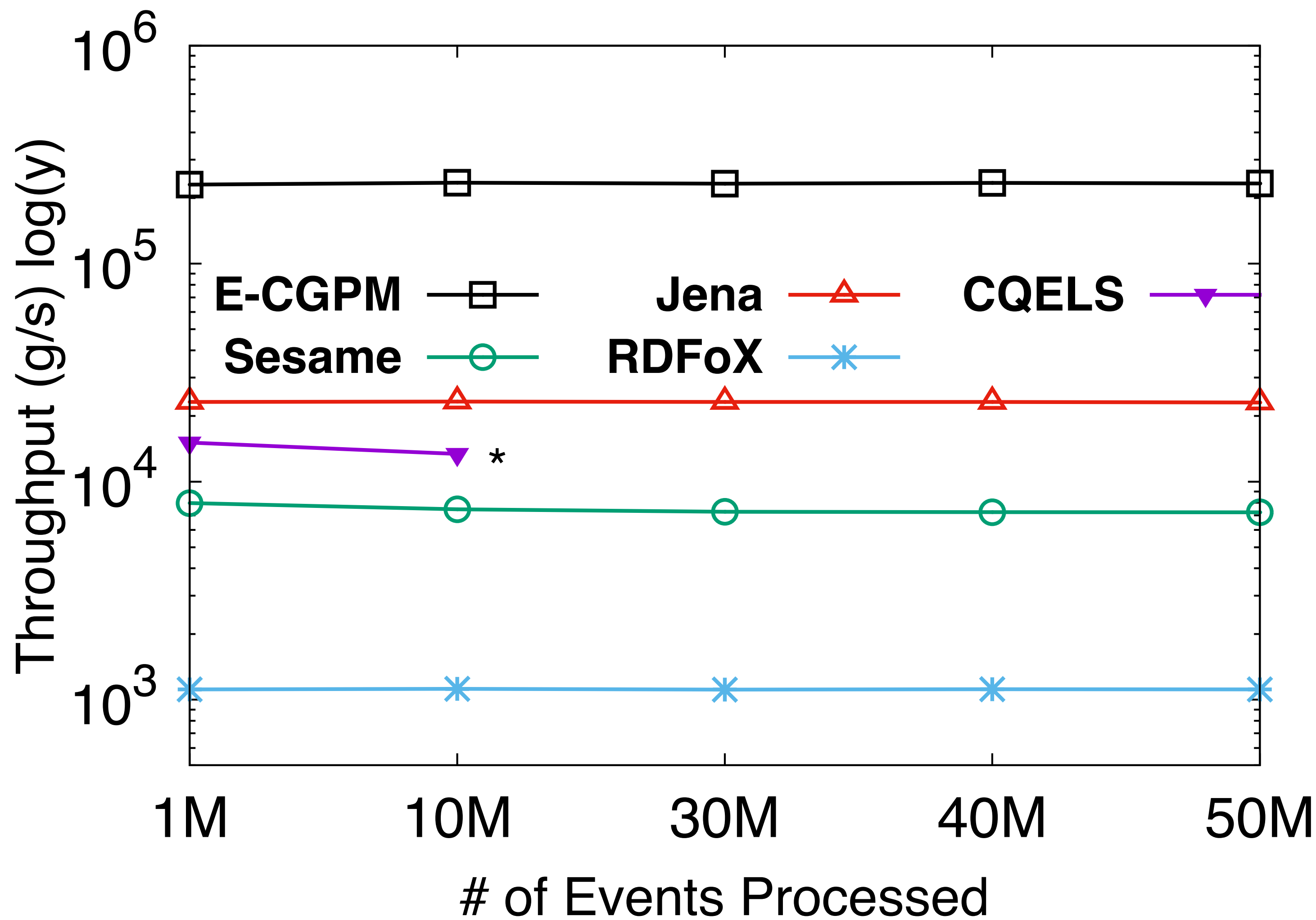
✓Size of the window has direct impact on the performance

[Empirical Evaluation]

- Datasets:
  - ✓NY Taxi dataset with 50 million taxi related events, each event containing 24 triples
  - ✓Social Network Benchmark (SNB) containing 50 million triples

- Queries:
  - ✓ Three NY Taxi data queries containing start, chain and combination of both
  - ✓Three SNB queries from the use cases described in the benchmark (star, chain and cyclic)
  - ✓ Three LsBench Queries customised for SNB dataset (Used for RSP)

[Event-based Evaluation (NY-Taxi)(NY-Q1)]



✓Set-sized sized events
✓Optimisation has not much of effect

✓**CQELS:** RDF stream processing system

✓**Jena,Sesame,RDFox**: In-memory triple stores and static RDF data processing

[Event-based Evaluation (SNB-Q1)]

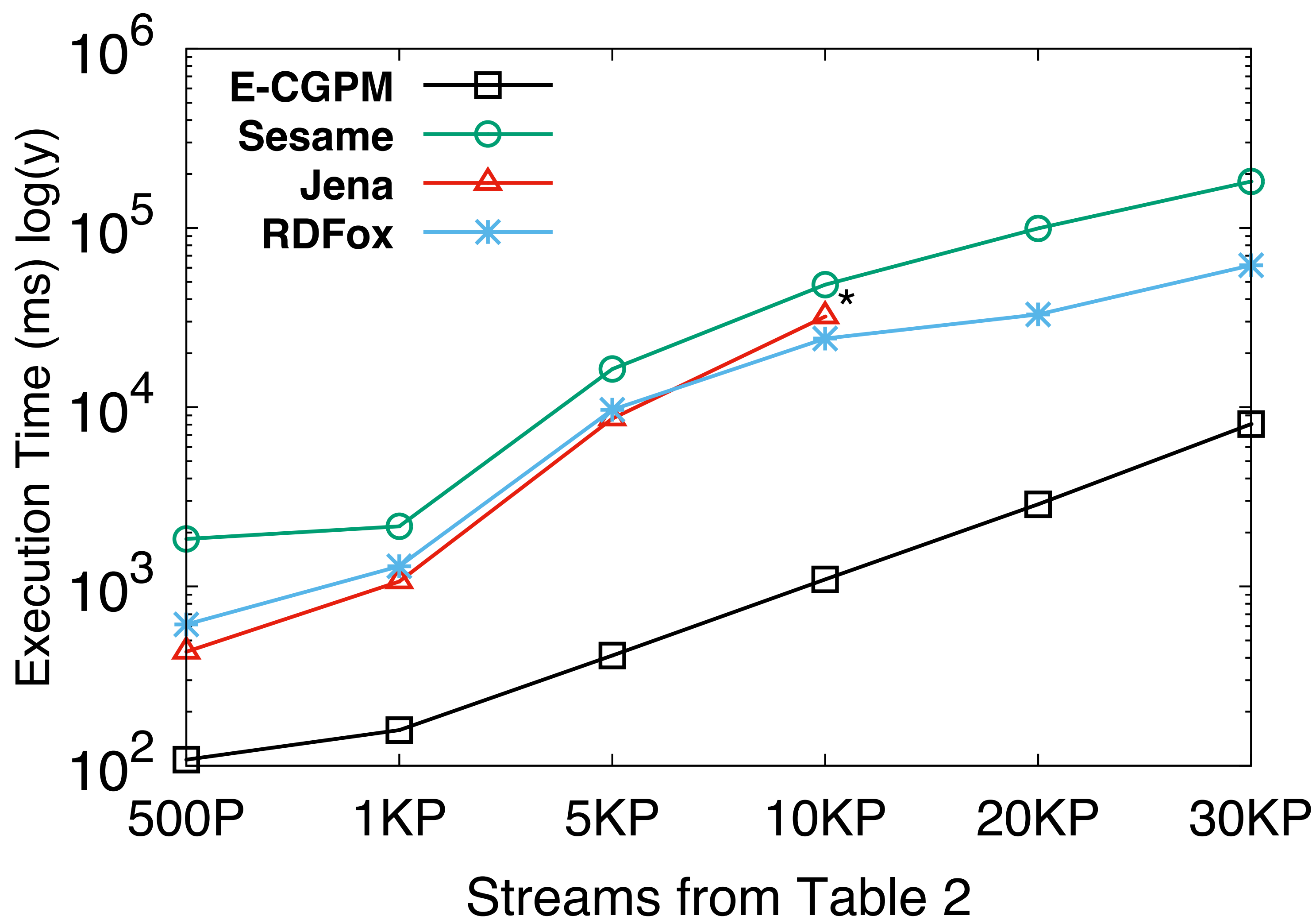
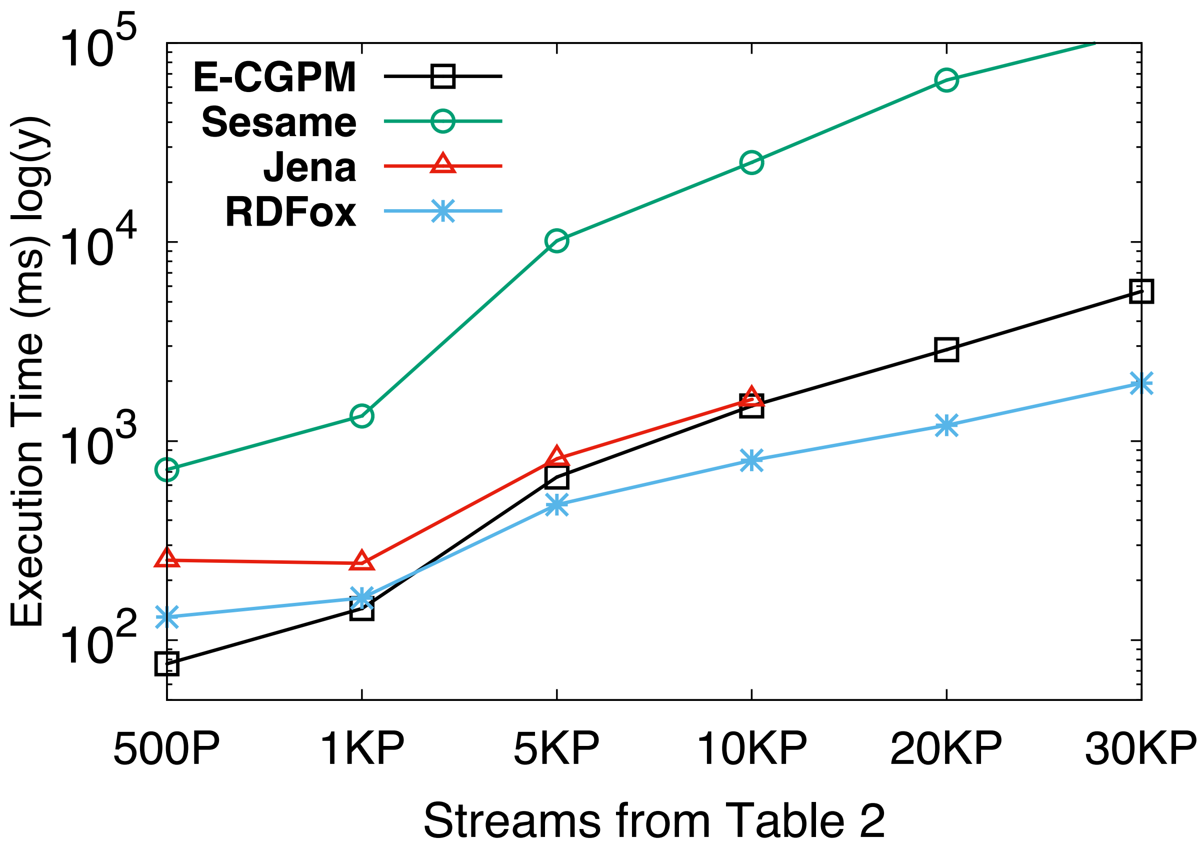


Table 2: *Dataset distribution for large-scale CGPM, Min and Max describes the range of no. of triples for each event of SNB streams*

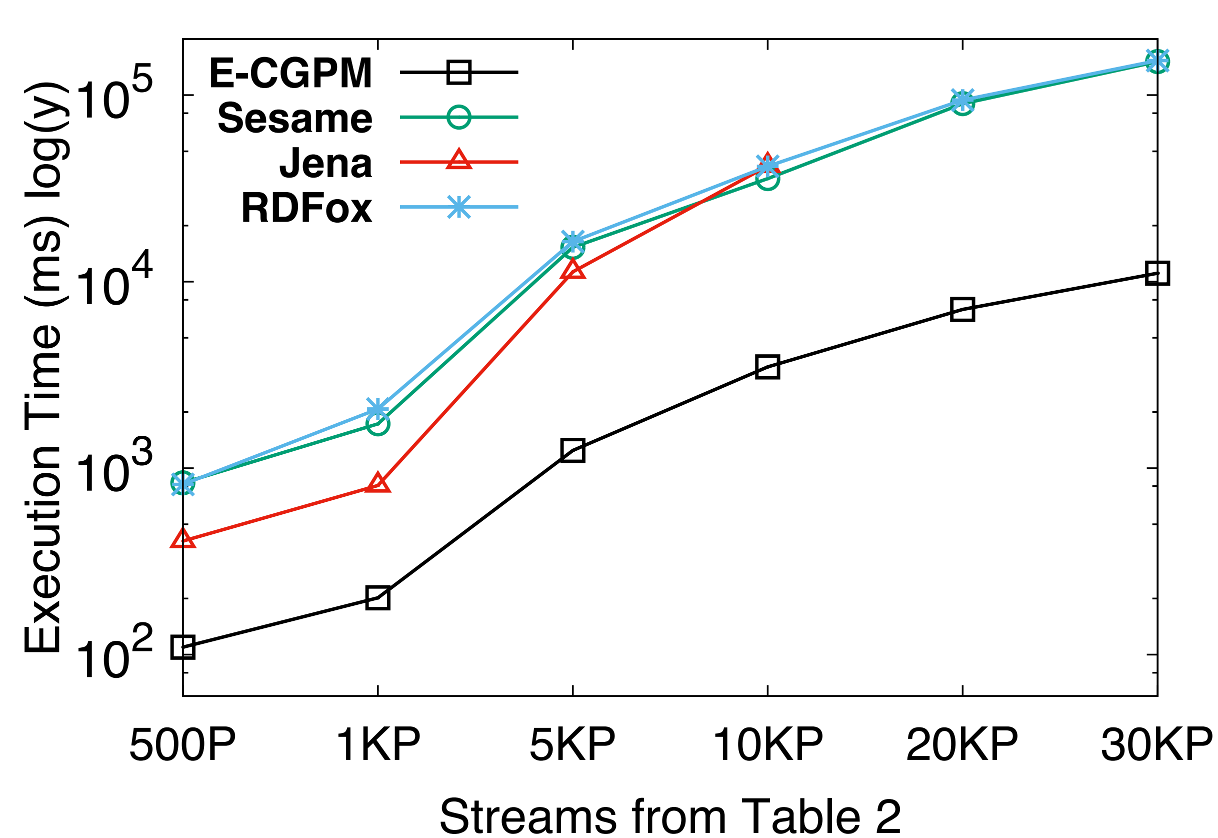
Dataset(streams)	Min (triples/event)	Max (triples/event)
500P	783	148K
1KP	2340	397K
5KP	217K	301K
10KP	50K	805K
20KP	115K	1.9M
30KP	145K	3.2M

✓Variable sized events
✓E-CGPM shows considerable performance improvements

[Event-based Evaluation (SNB-Q1)]

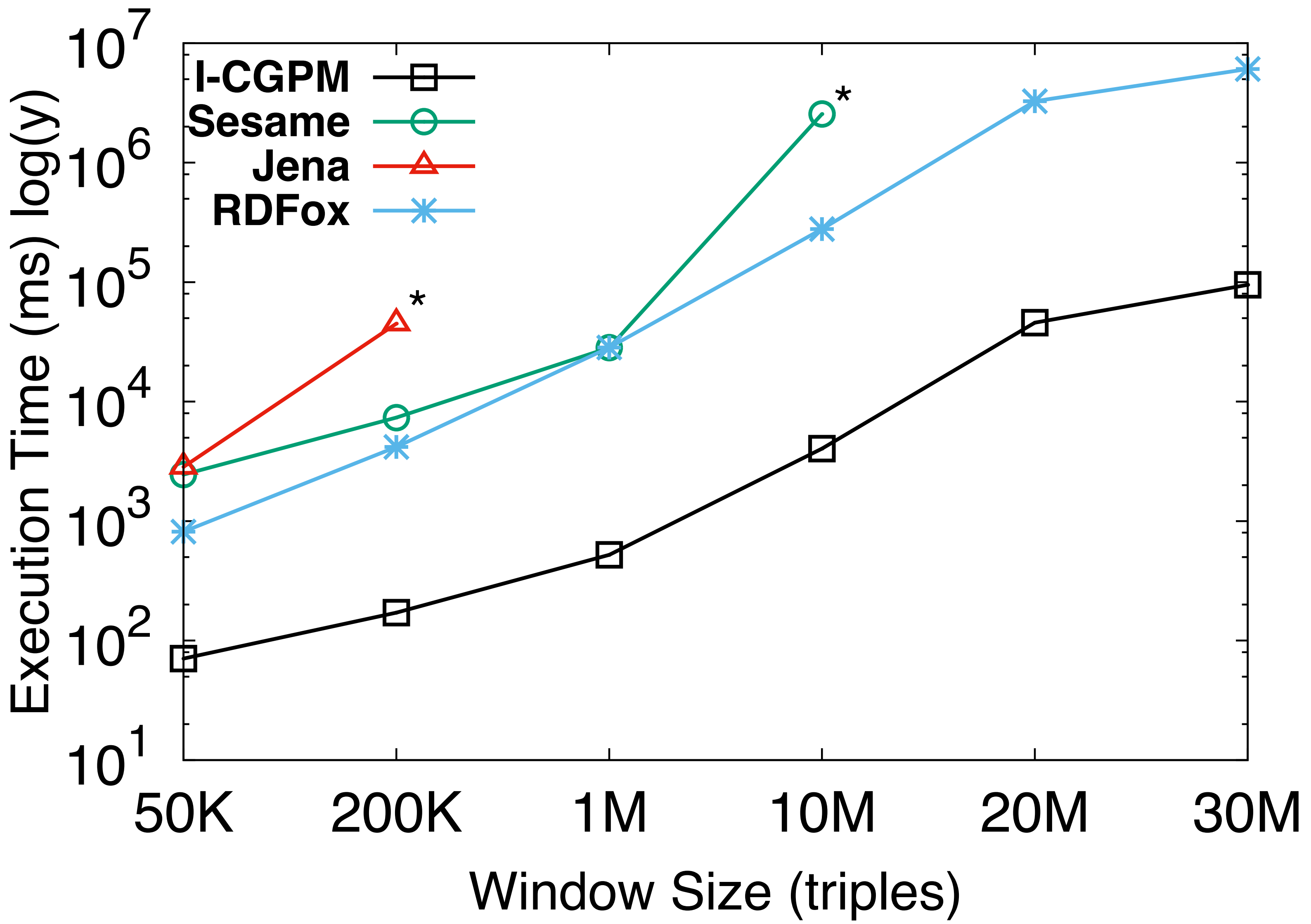


Query Processing Time



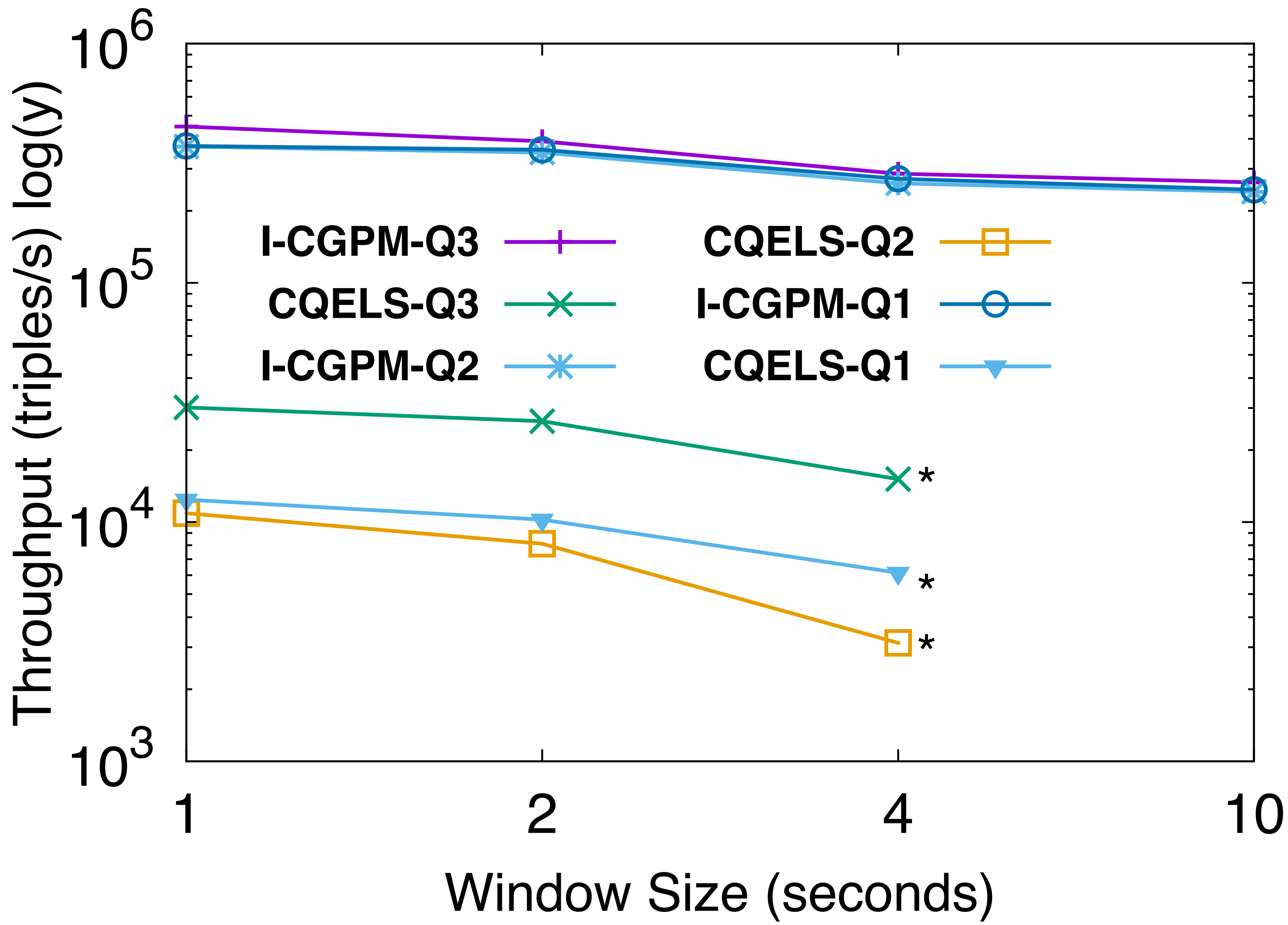
Latency (Data insertion time)

[Incremental Evaluation (SNB-Q1)]



✓Incremental Vs re-evaluation techniques
✓Linear response with the increase in the window size

[Incremental Evaluation (Ls-Bench)]



- ✓CQELS RSP system performs poorly for large datasets
- ✓Lazy Evaluation pays off with less number of join operations

[Conclusion]

- Expensive indexing-based solutions add quite a lot of latency for KG streams
- By leveraging the hybrid join-and-explore technique such latency can be reduced
- on-the-fly processing go KG streams requires customised data structures
- Incremental Evaluation outperforms re-evaluation techniques by an order of magnitude

[Questions?]

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