Towards Hybrid Graphs: Unifying Property graphs and Time series

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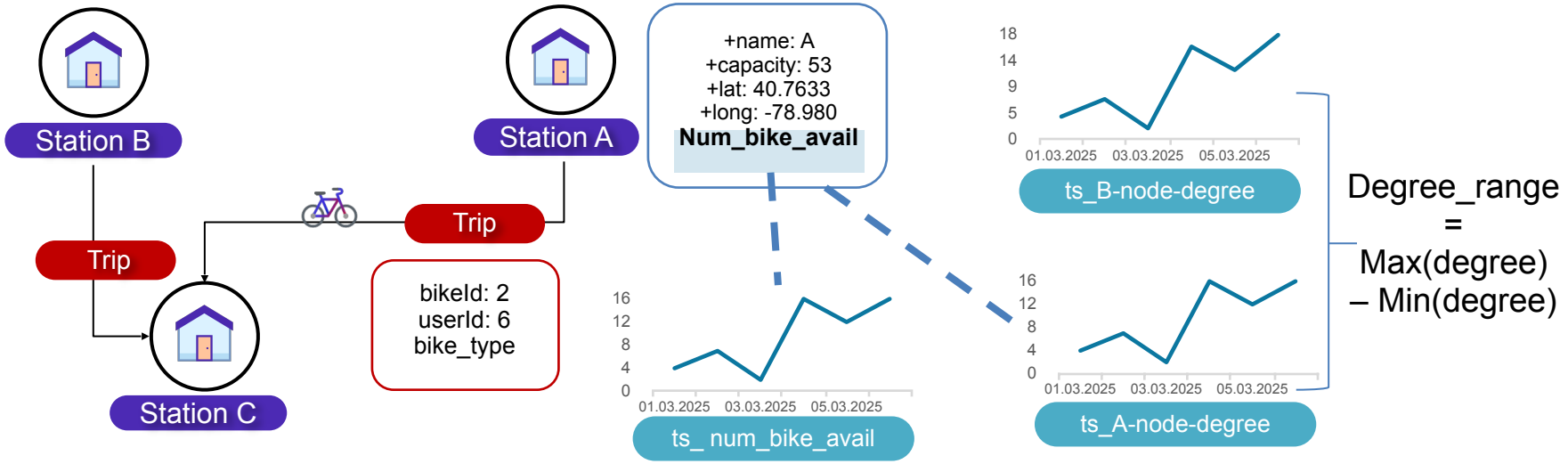
EDBT Conference

26/03/2025

Motivation – Why combining Graphs and Time Series ?

Bike sharing use case with stations and trips:
number of available bikes and degree of station nodes are in **continuous change** and can be represented as time series



Previous Approaches

- **Graph-based models:** rich connectivity → no time-series analytics
- **Time-series models**: time-evolving data→ no relationships, no graph analytics
- **Missing link**: limited previous works to connect Graph and Time Series data

(Temporal)
Property
Graph

(Multivariate)
Time Series

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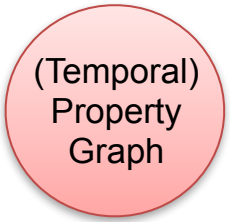

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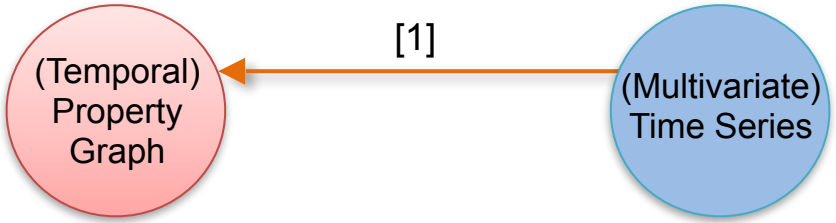

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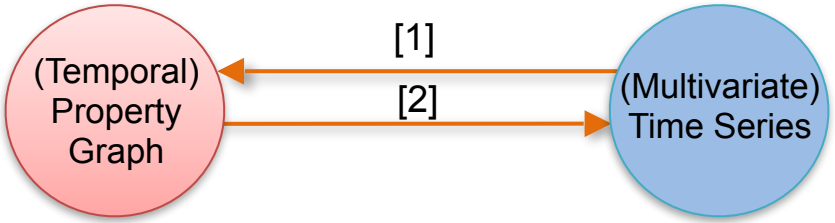

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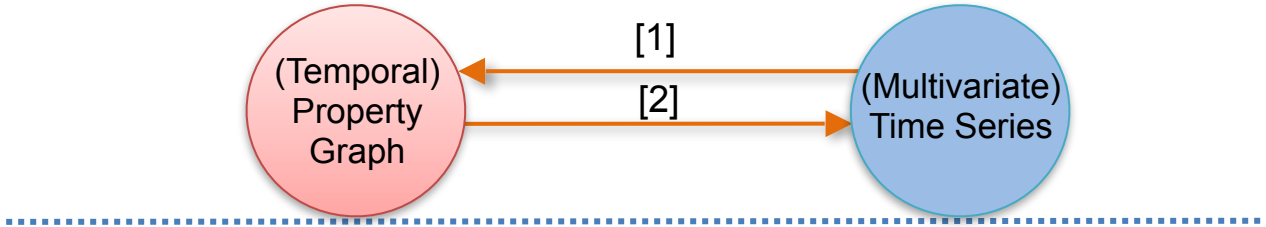

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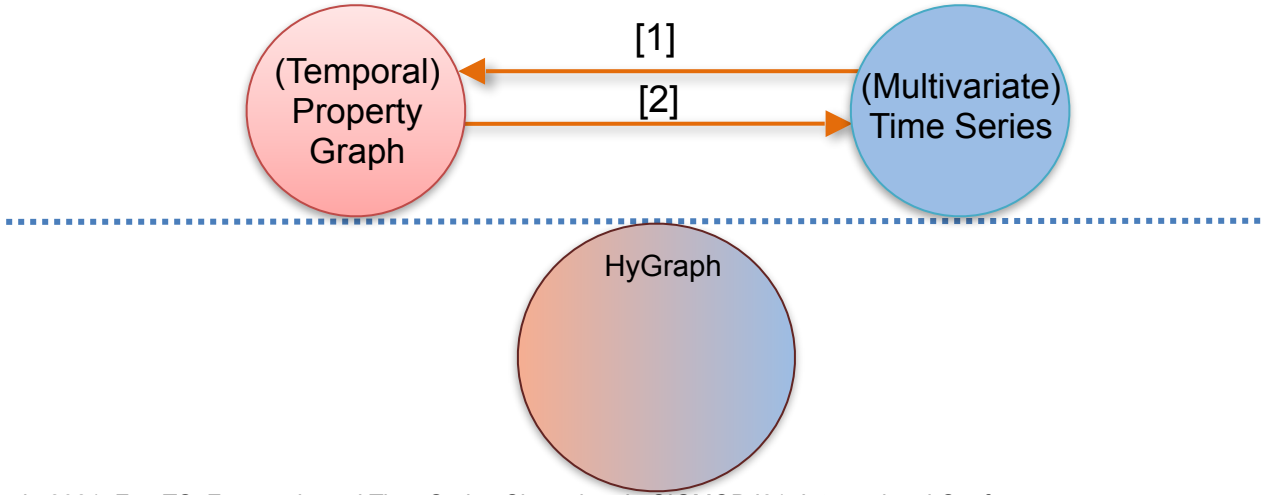

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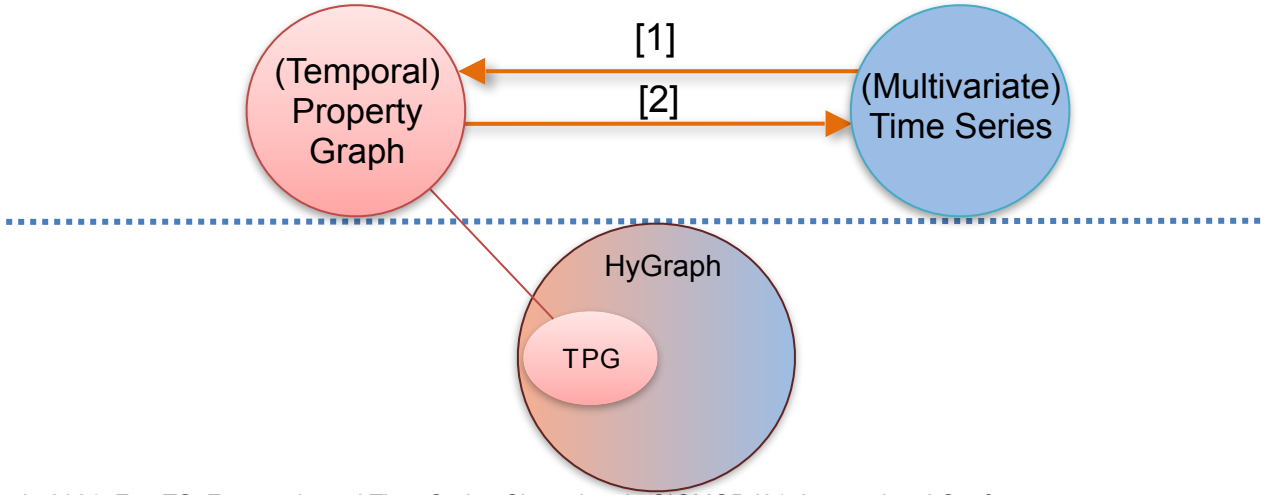

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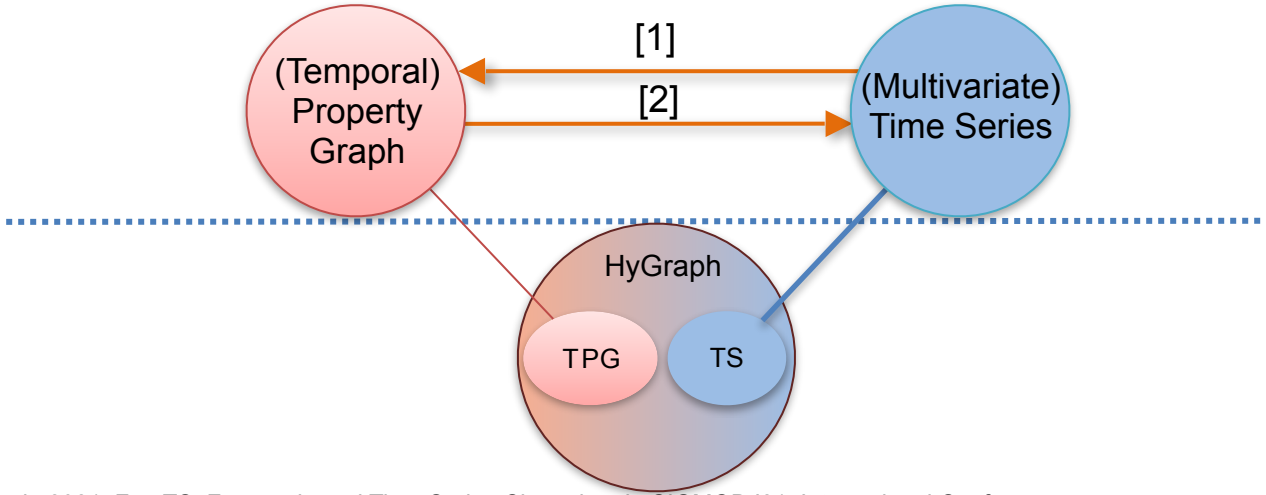

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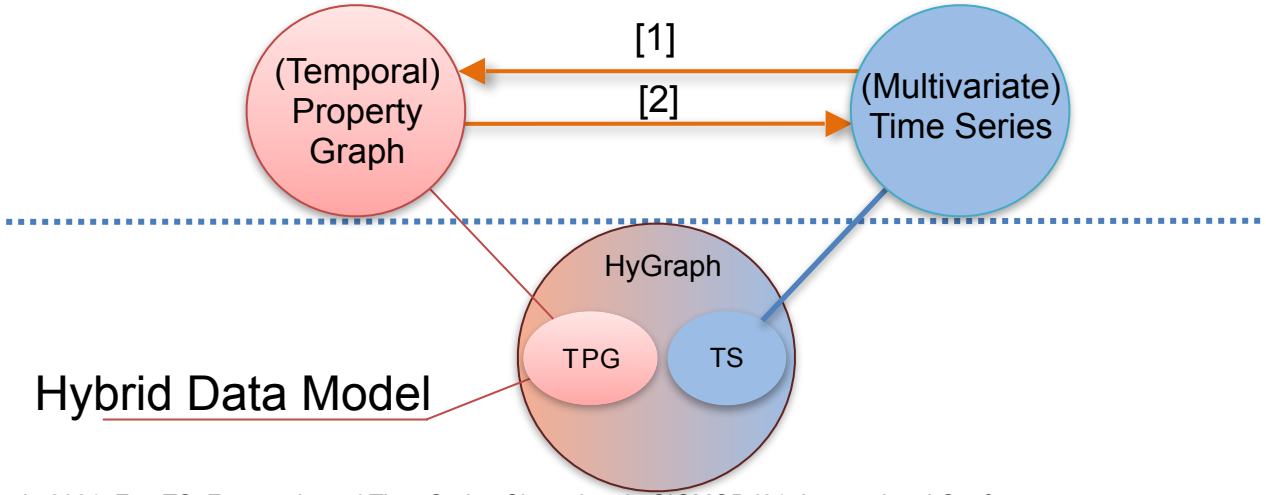

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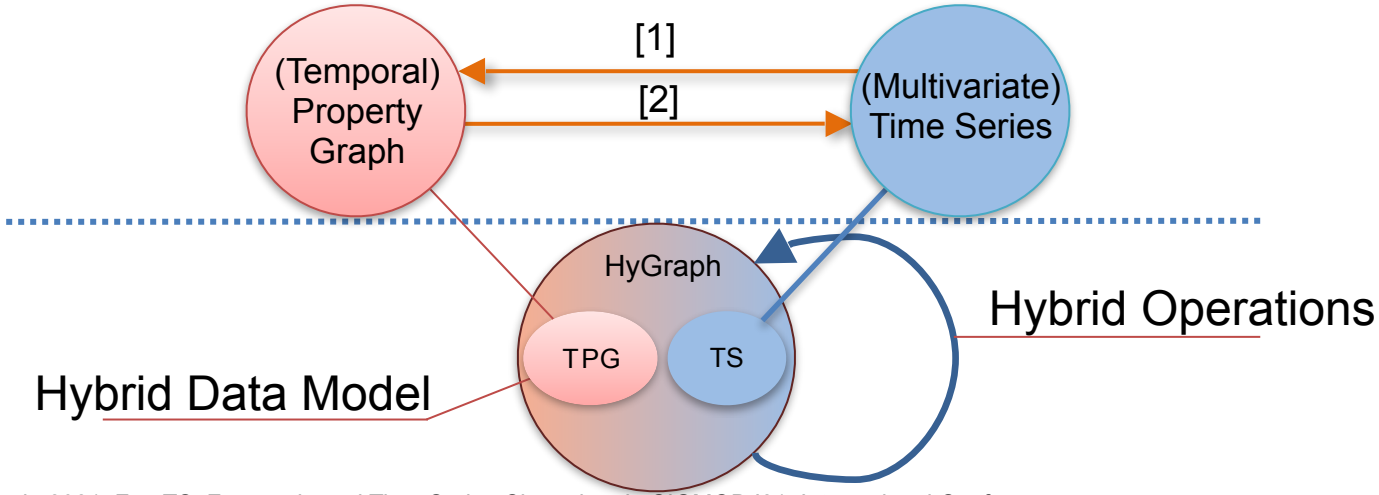

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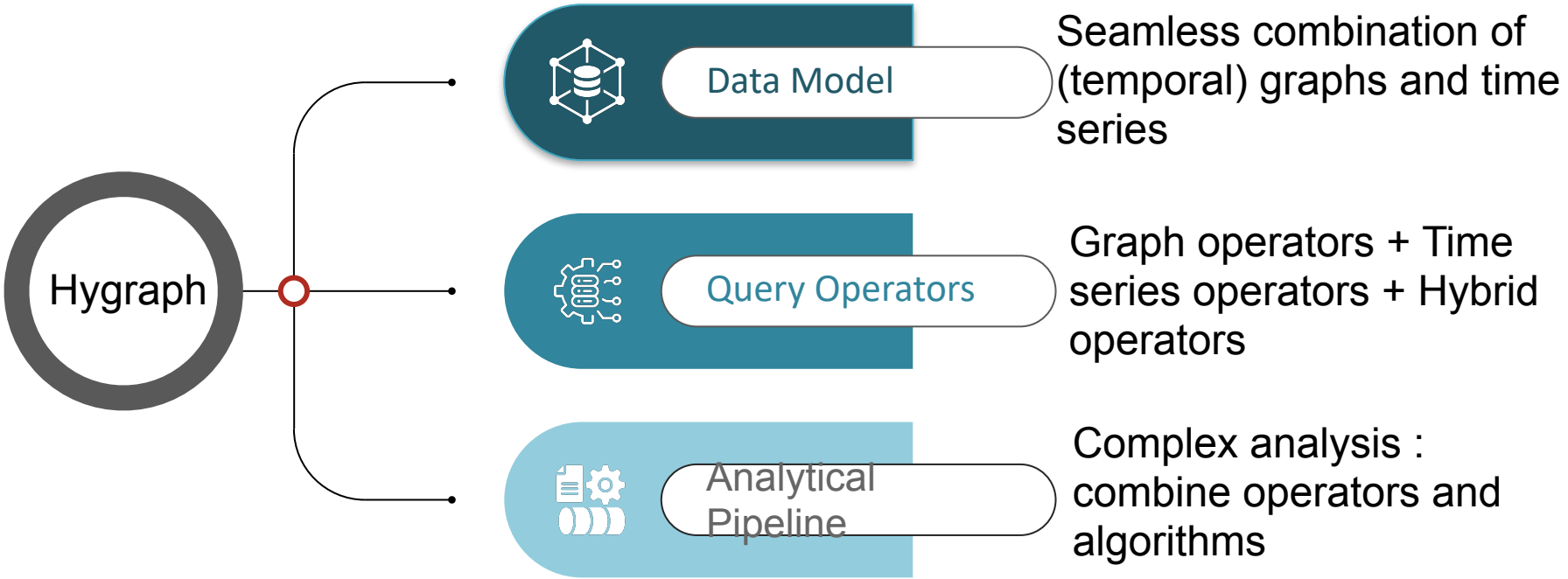
HyGraph's Vision: Combining Graphs and Time Series



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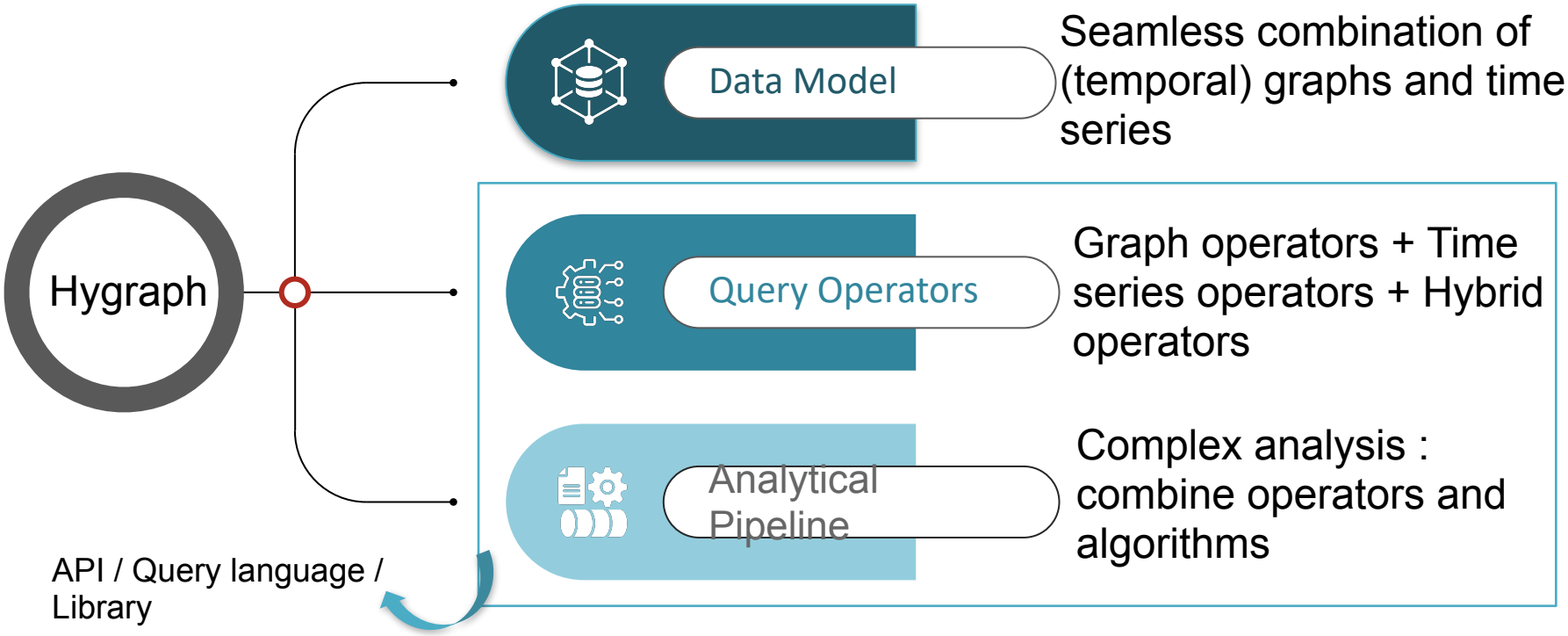

HyGraph's Data Model – extend temporal PG and TS

- Time series as a **Property** for Graph elements
- Time series as **Edge/Vertex** : **PG Vertex** and **TS Vertex**, **PG Edge** and **TS Edge** →Time series as **a first-class** citizen
  - TS Edge and TS Vertex can have label too
  - All edges and vertices are temporal (interval)
- Multivariate time series support
  - $ts = \{(t_1, y_1), (t_2, y_2), \ldots, (t_n, y_n) | n \in N\}$, $y = (val_1, val_2, \ldots, val_k)$.
- Evolving subgraps
  - Mapping function of subgraph to a set of vertices and edges per time: $S \times T \rightarrow P(V) \times P(E)$

Converting Temporal Property Graph & Time Series into HyGraph

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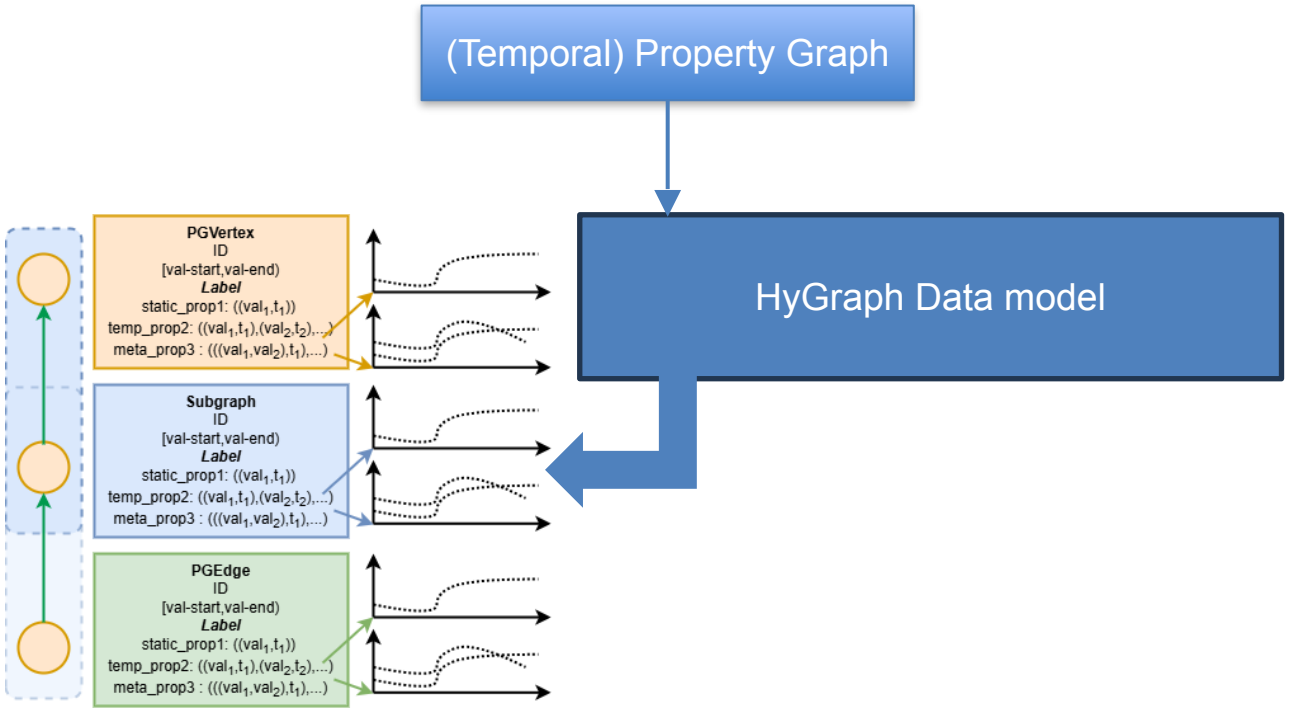

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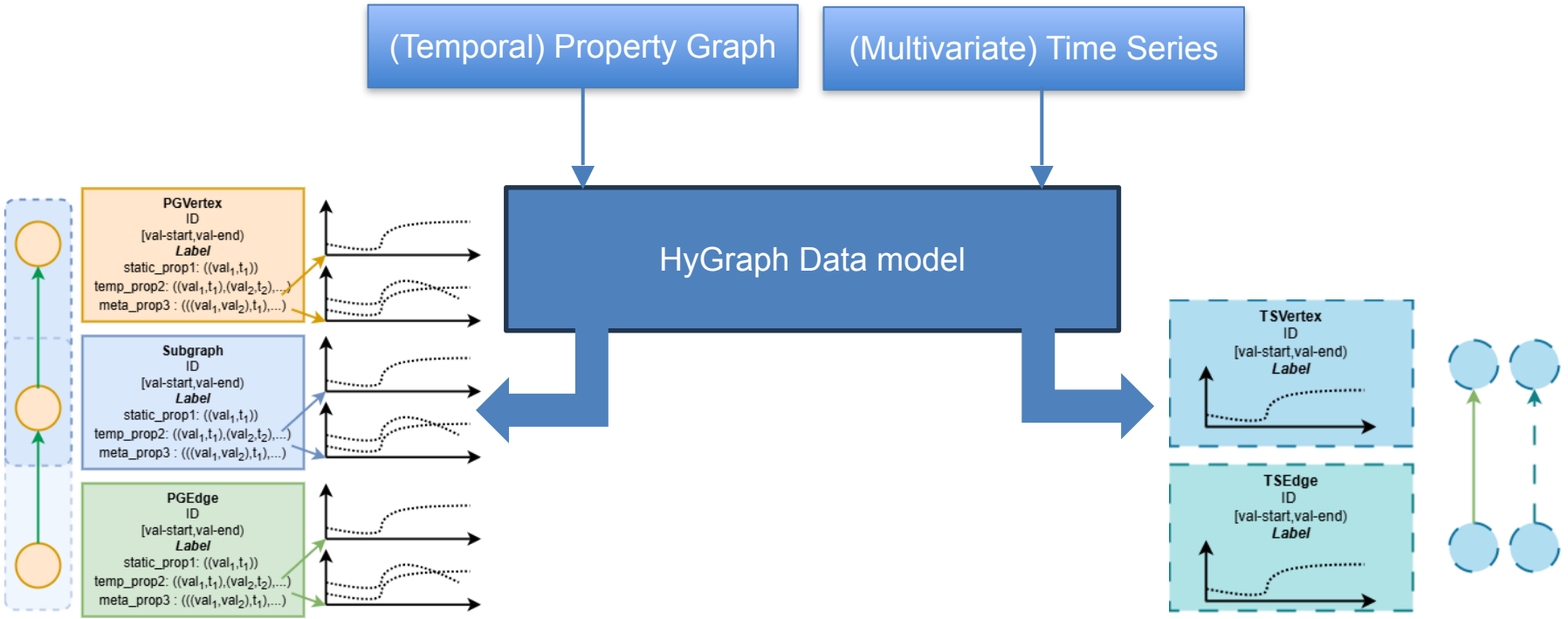
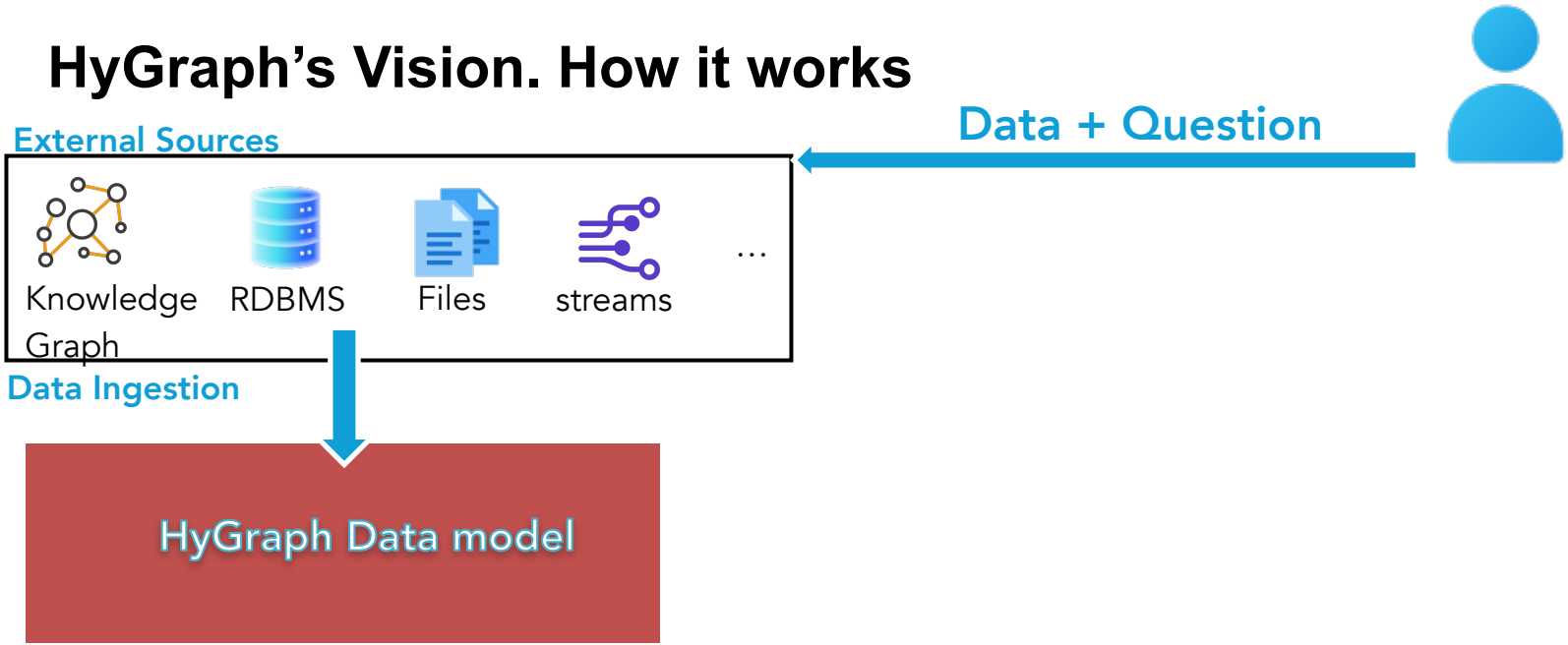


HyGraph's Vision. How it works



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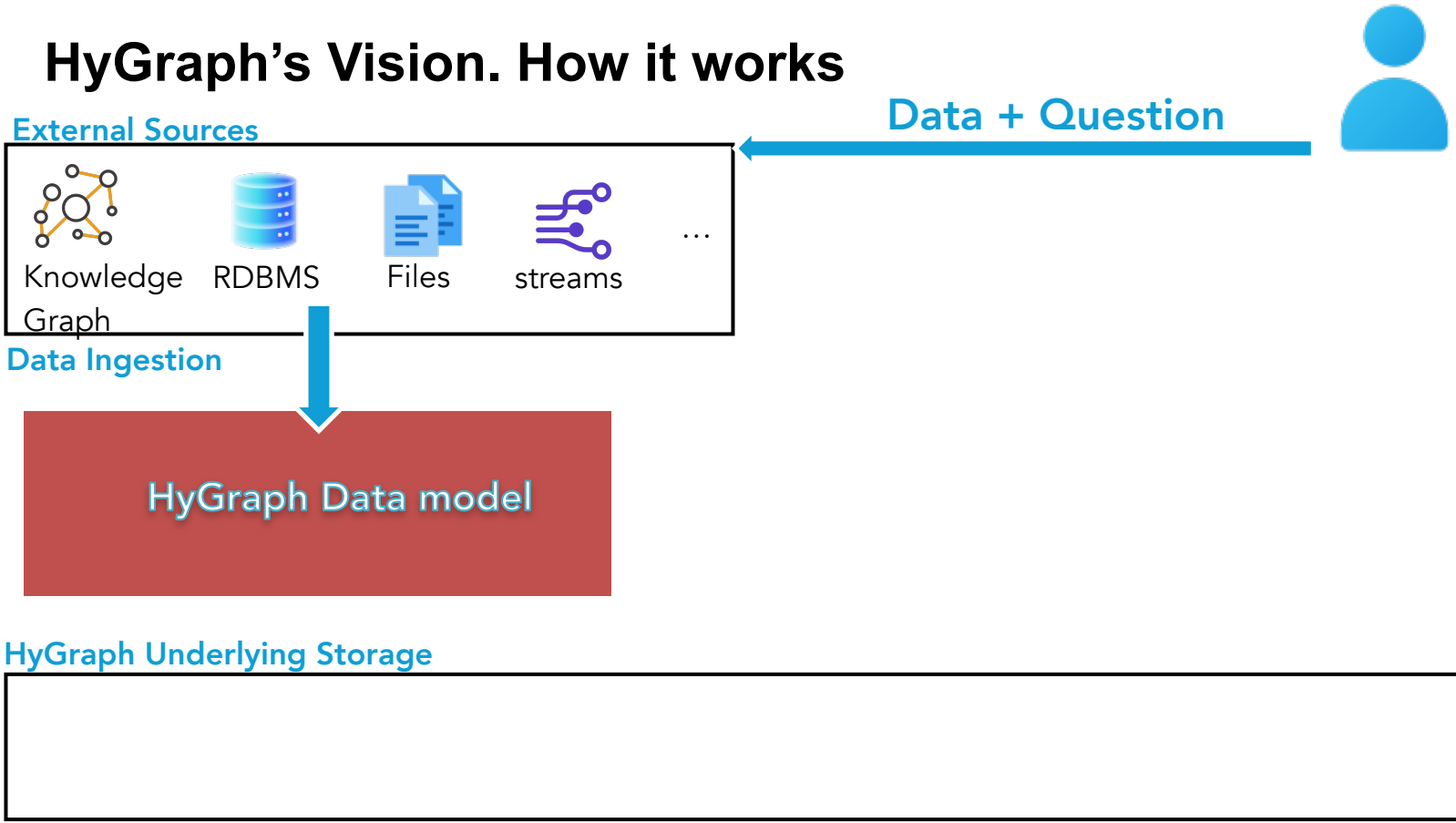

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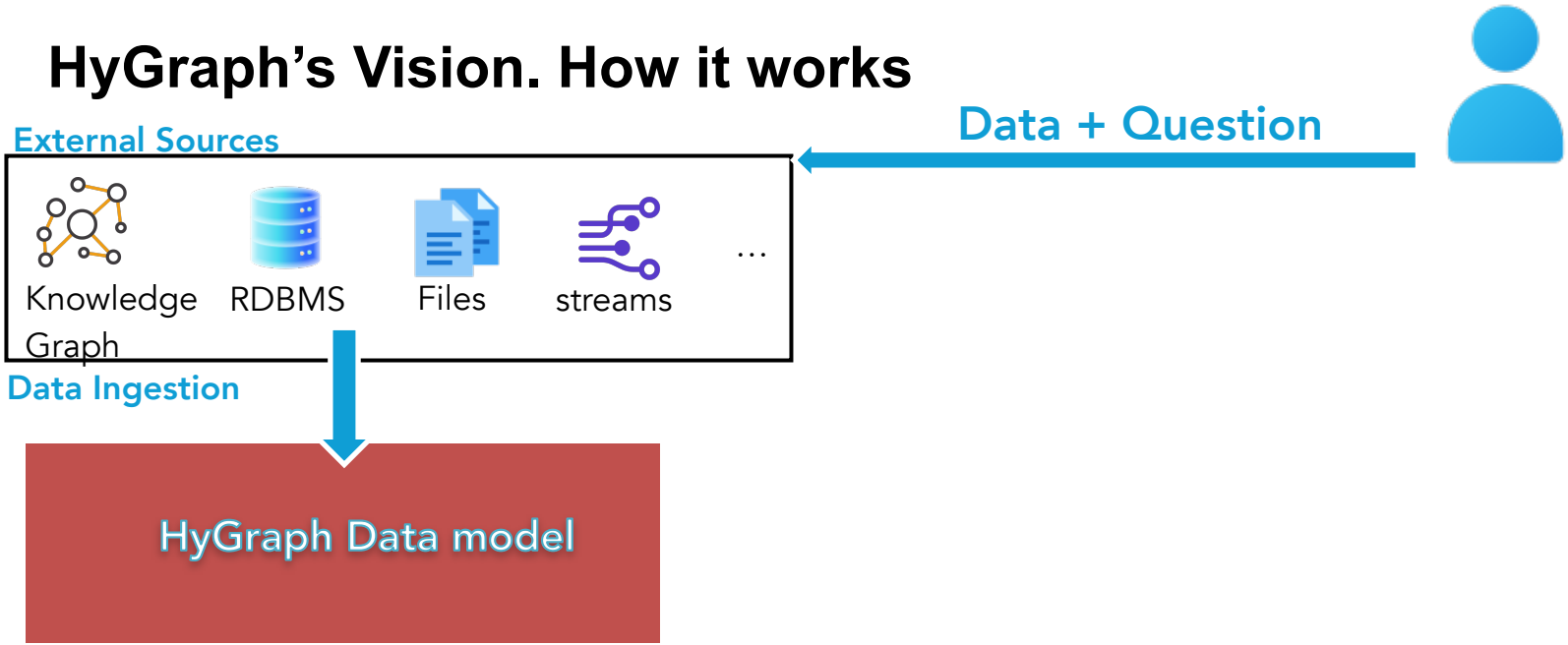

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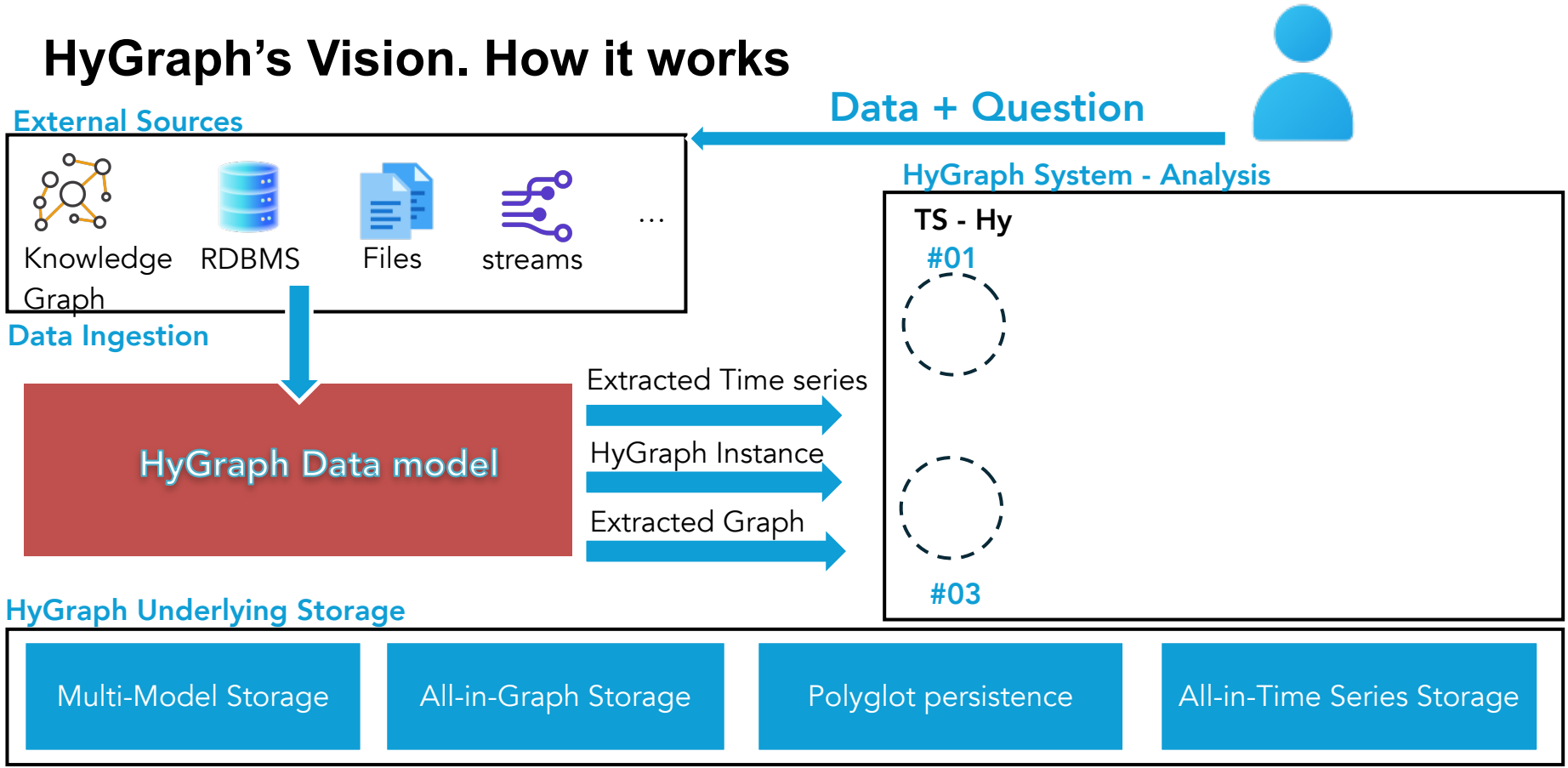

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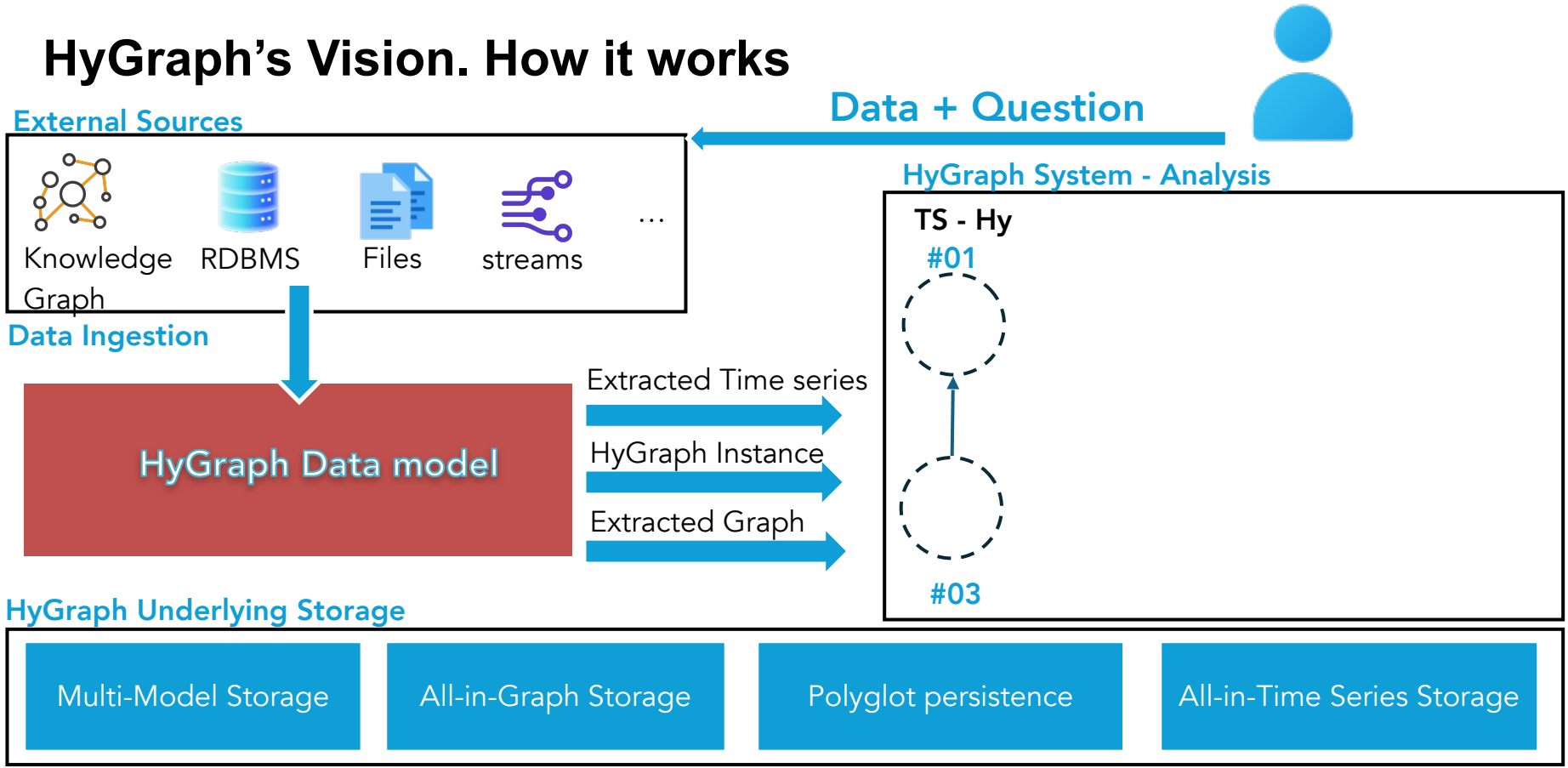

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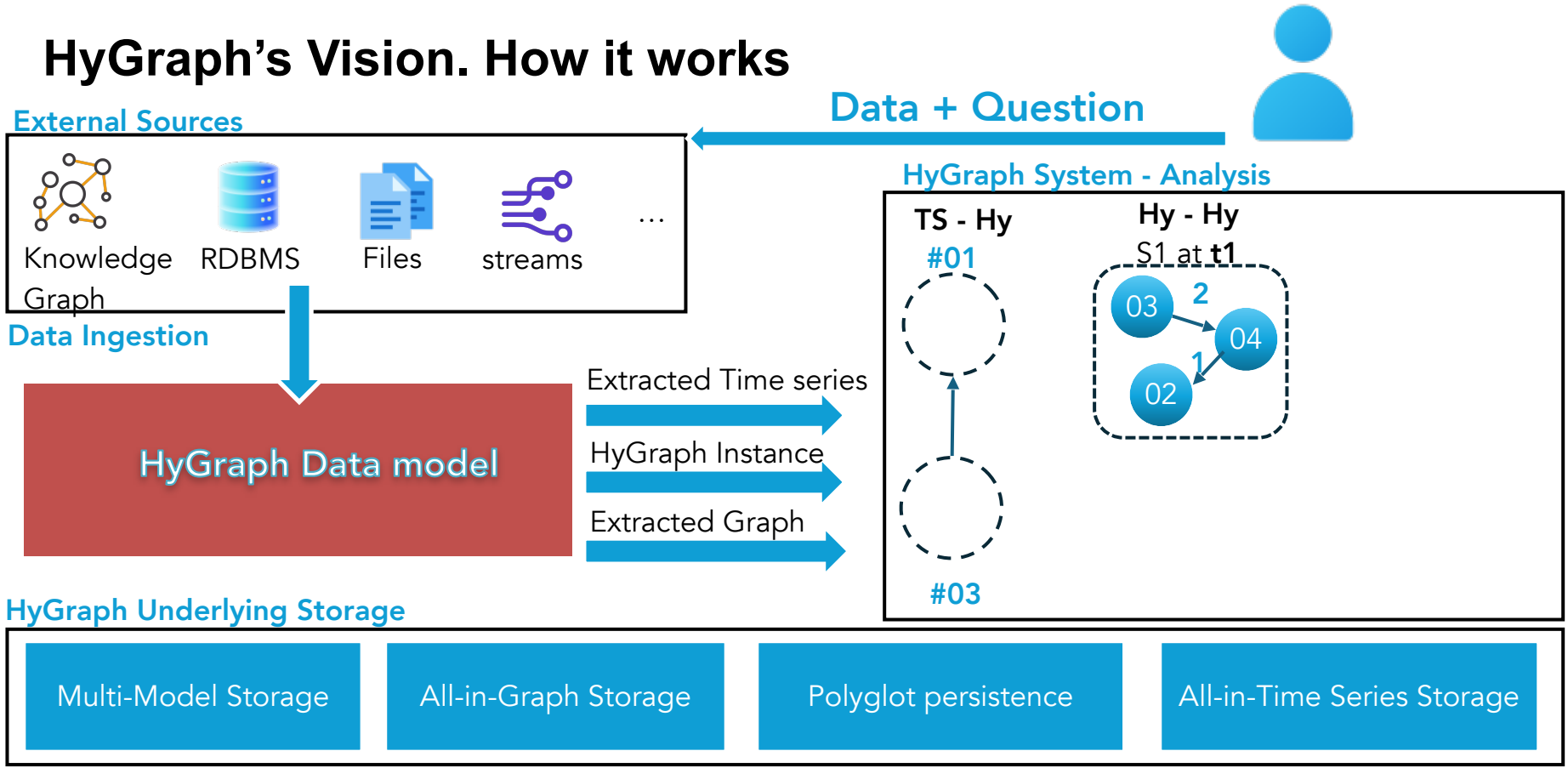

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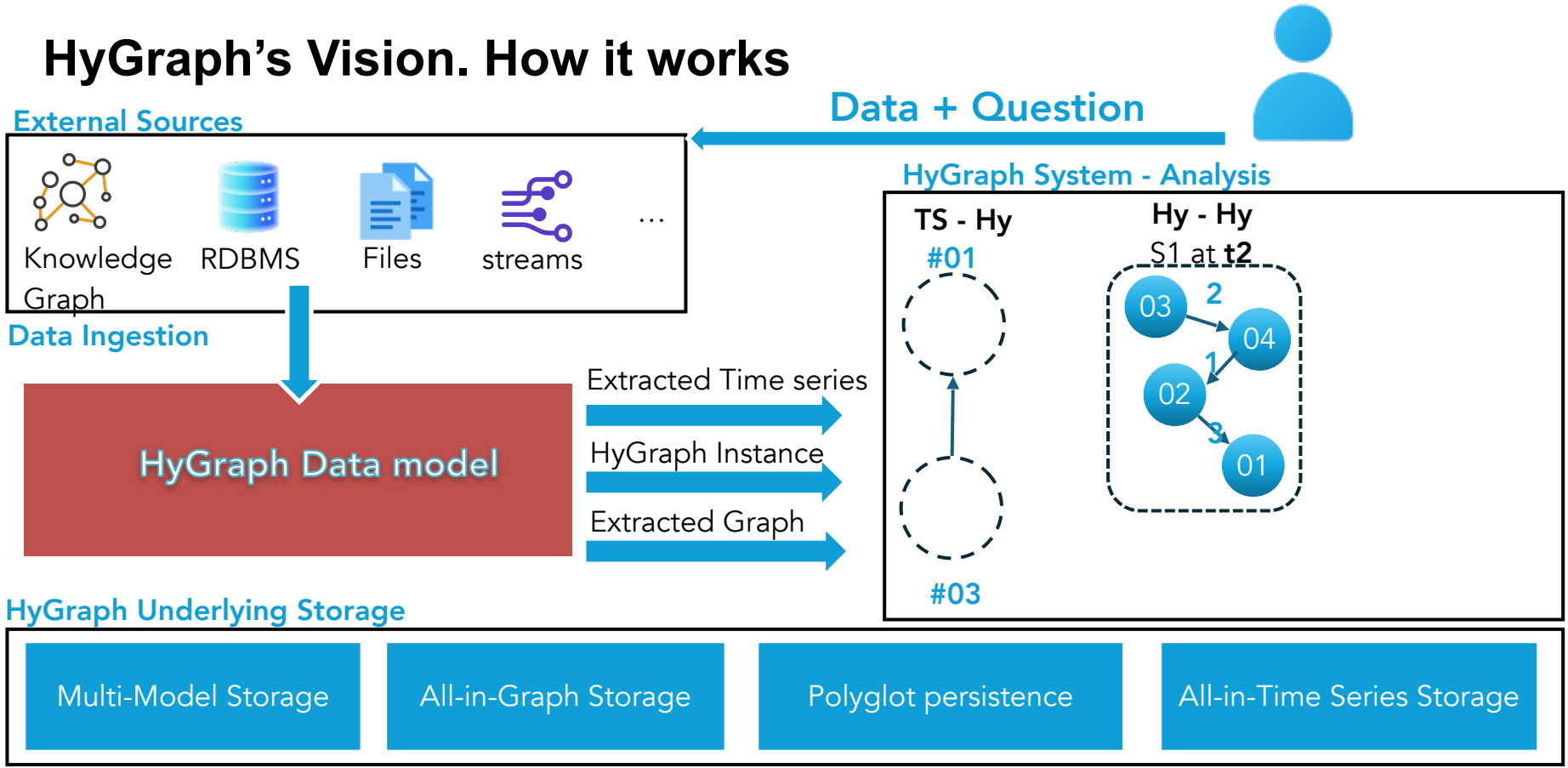

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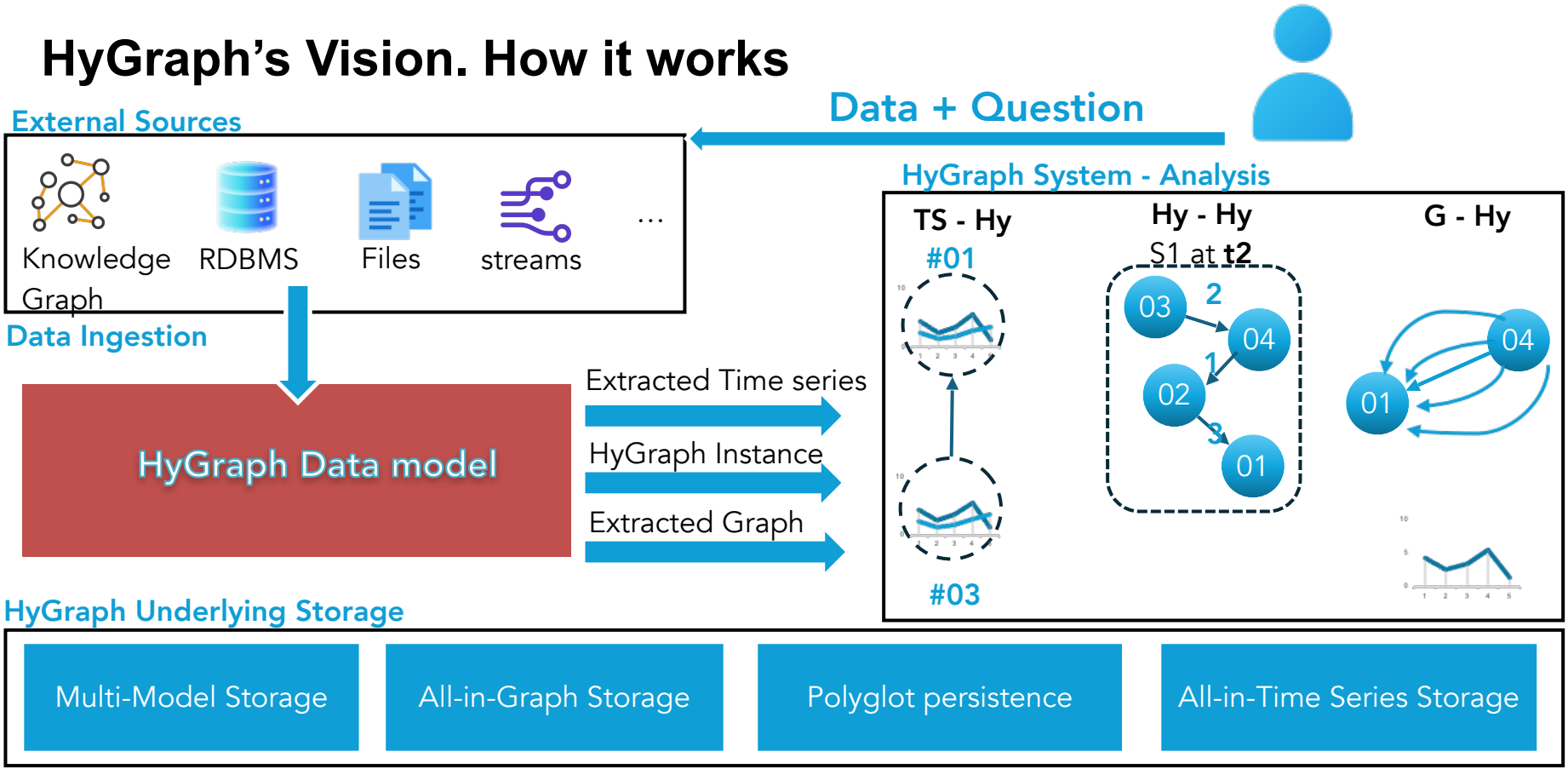

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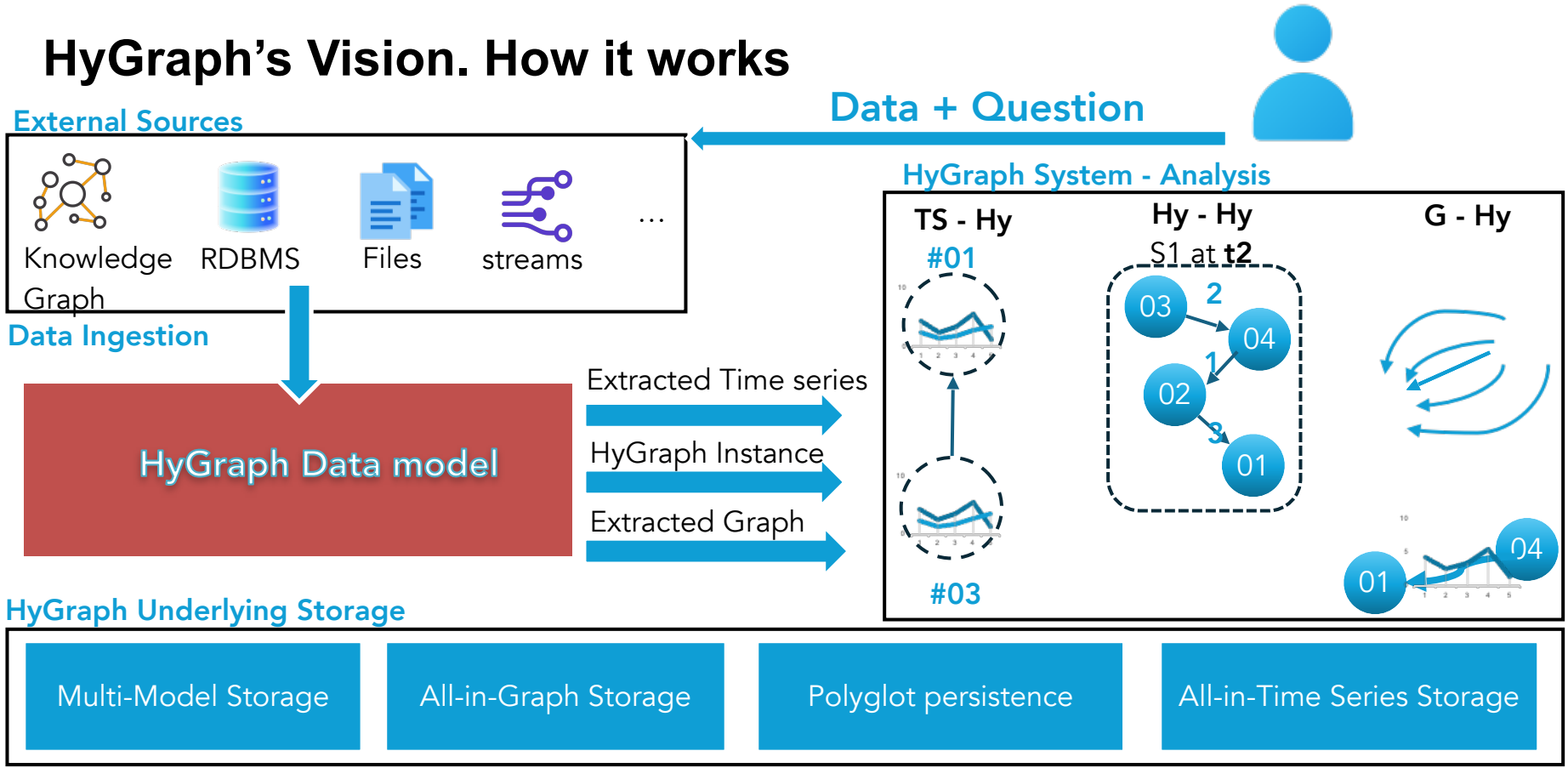

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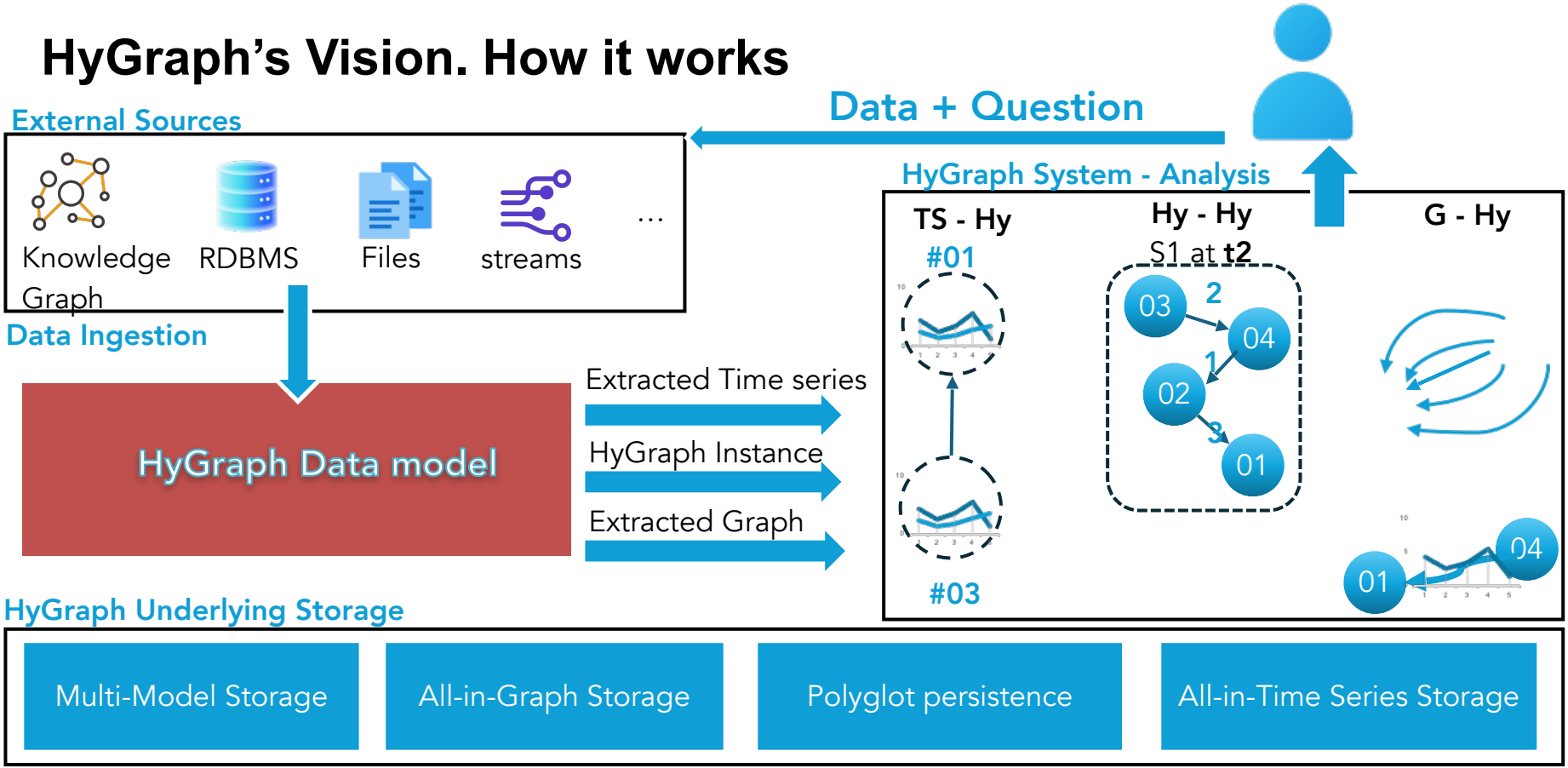
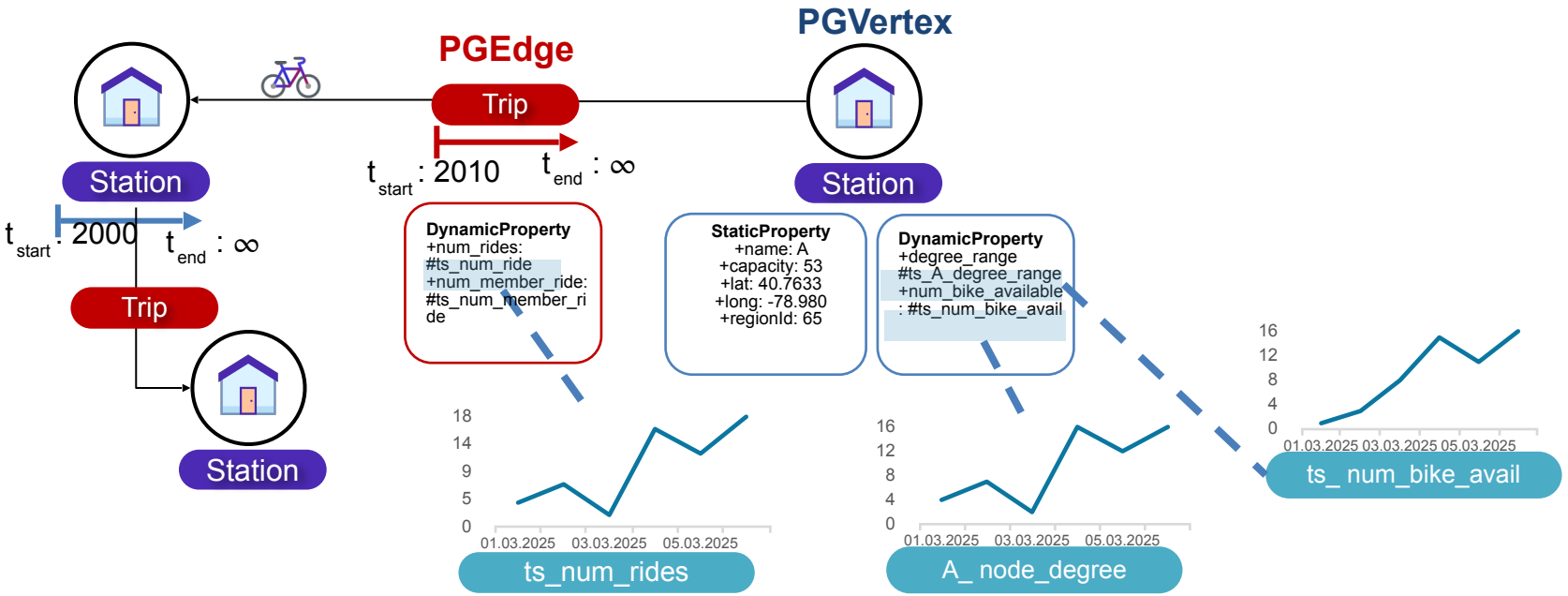


HyGraph Operators (selection)

- Data Import & Export
  - Ingesting hybrid / single data into HyGraph
  - Extracting time series / graphs from HyGraphs
- Hybrid Pattern Matching
  - Querying both graph structures and time-series patterns in unified way
- Generating time-series data from evolving graph metrics
  - E.g., node degree evolution, clustering evolution
- Generating a graph from similar time series patterns

Using HyGraph for Bike Sharing use case

- Calculate node degree over time and store it as a property
- Calculate similarity between time series and create relationships



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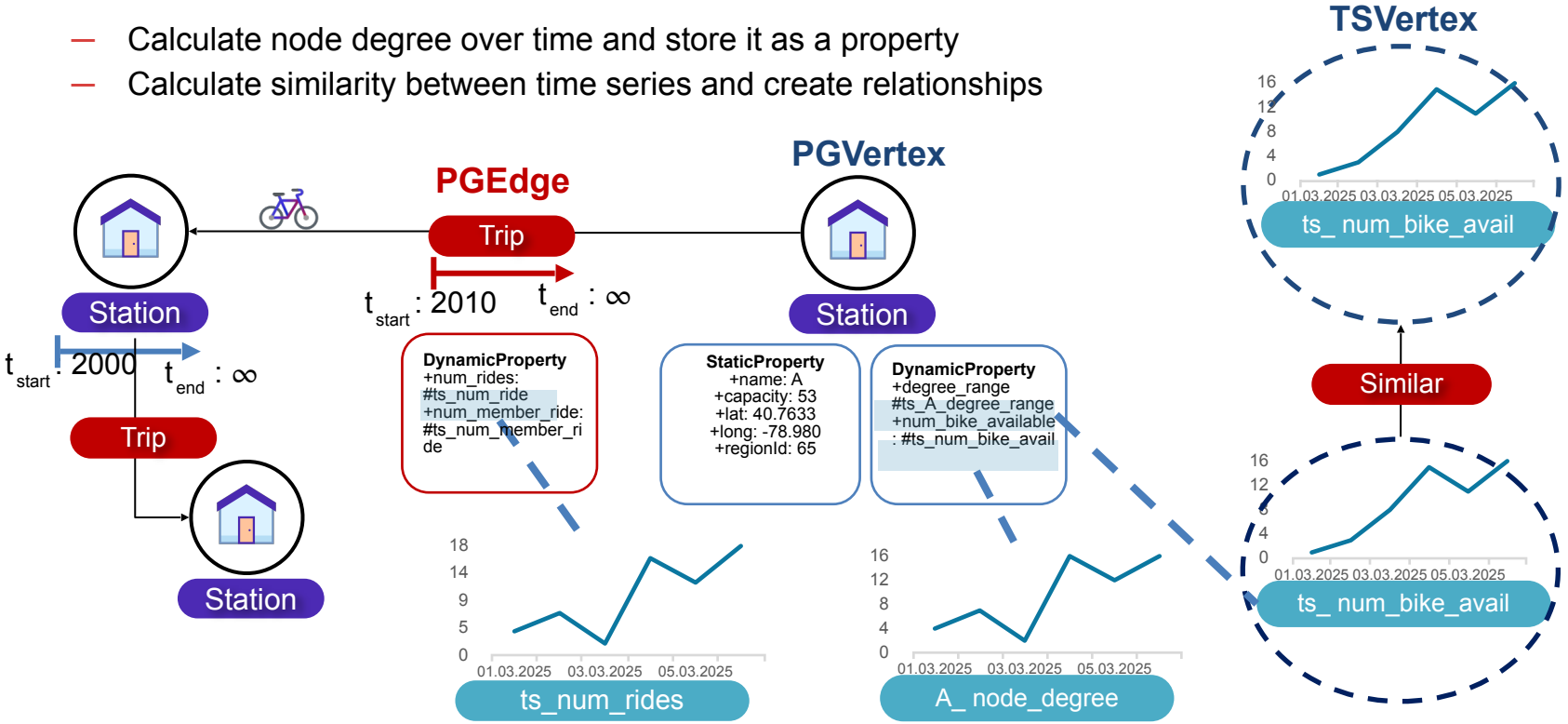

Preliminary Work & Open Challenges

HyGraph open source python Library https://pypi.org/project/hygraph-core/

- Handling Graph and Time series storage and processing in-memory
- Libraries: NetworkX (graph operations), Xarray (for time series data)

Open Challenges:

✓ Extending the hybrid analytics possibilities,

✓ Hybrid learning models over structural and temporal features,

✓ Scalable storage and indexing of hybrid operators

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HyGraph

Thanks for your attention !

Contact us to collaborate or to suggest a use case

Visit our website !

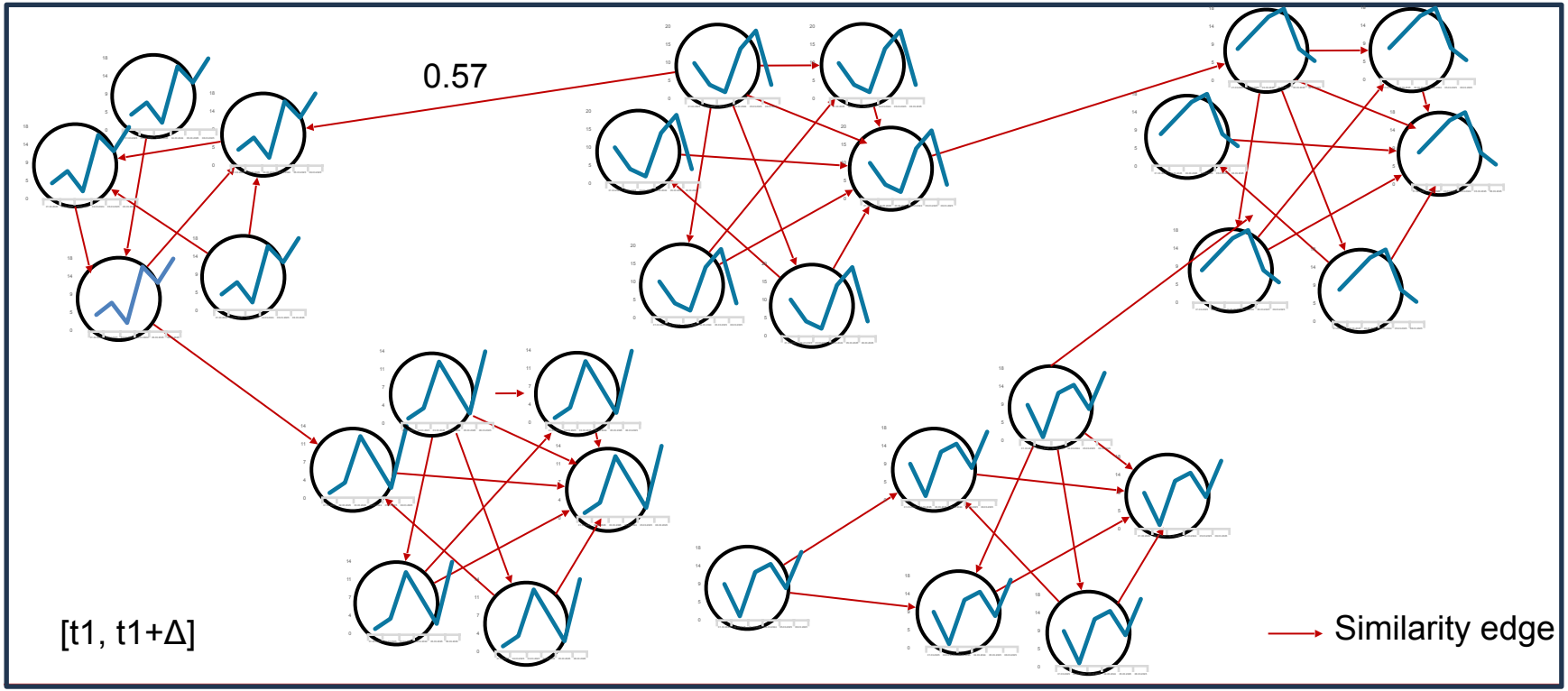
https://hygraph.net/

Comparing between All-in-Graph and Polyglot approach « TimeTravelDB »

	Neo4j	TTDB
QUERIES	MRT(s)	MRS
Q1	0.0034	4.33
Q2	41.47	7.02
Q3	56.09	20.48
Q4	31109	71.86
Q5	73814	62.85
Q6	73446	64.95
Q7	48299	48.39
Q8	54494	48.61

Example: Extracting Time series for an evolving Subgraph

Similar bike stations are grouped in the same Subgraph



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