Pattern Matching on Event Streams & Time Series & …

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SCALABLE DATA MANAGEMENT FOR FUTURE HARDWARE

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Overview of This Talk

- Introduction to Event Processing

- Introduction to (Event) Pattern Matching
- Highlight Features of current state-of-the-art
- Interval-based Pattern Matching Developed @ UMR
- Group Patterns

- Brief Outlook: Pattern Matching on Property Graphs

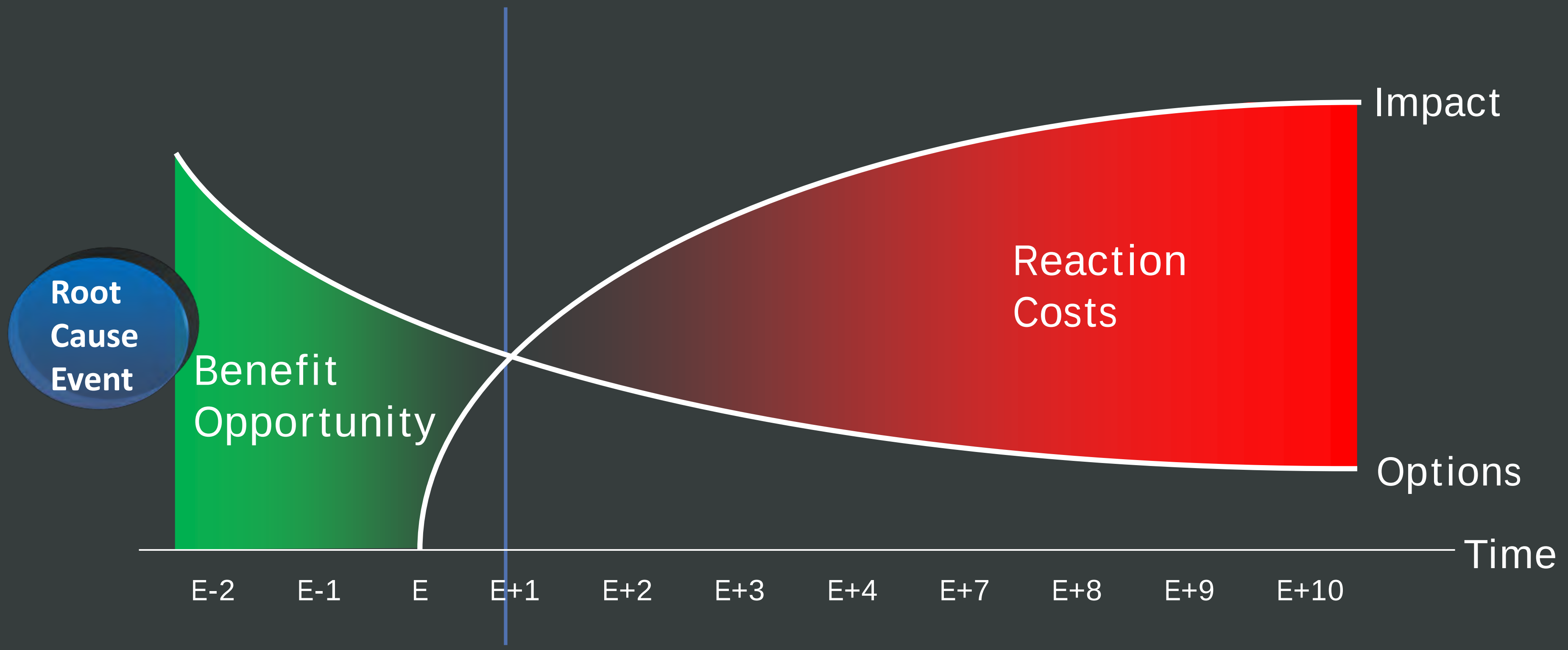
Introduction to Event Processing

1. Motivation

- **reactive monitoring of time-critical business processes**

- **predictions about the near future and recommendations for actions**

Situations of Interest



Many application domains

- Algorithmic trading
- Logistics
- Traffic management
- Internet of Things & Industry 4.0
- System Monitoring & Security

Example: Traffic Management

- Data from Sensors

  `HighwayStream( lane, speed, length, timestamp )`

- Continuous Flow ➔ Data Stream
  - variable data rates
  - time and space as default dimensions
- Queries
  - continuously processed

"At which positions of the highway was the average speed below 30 km/h within the last 15 minutes?"

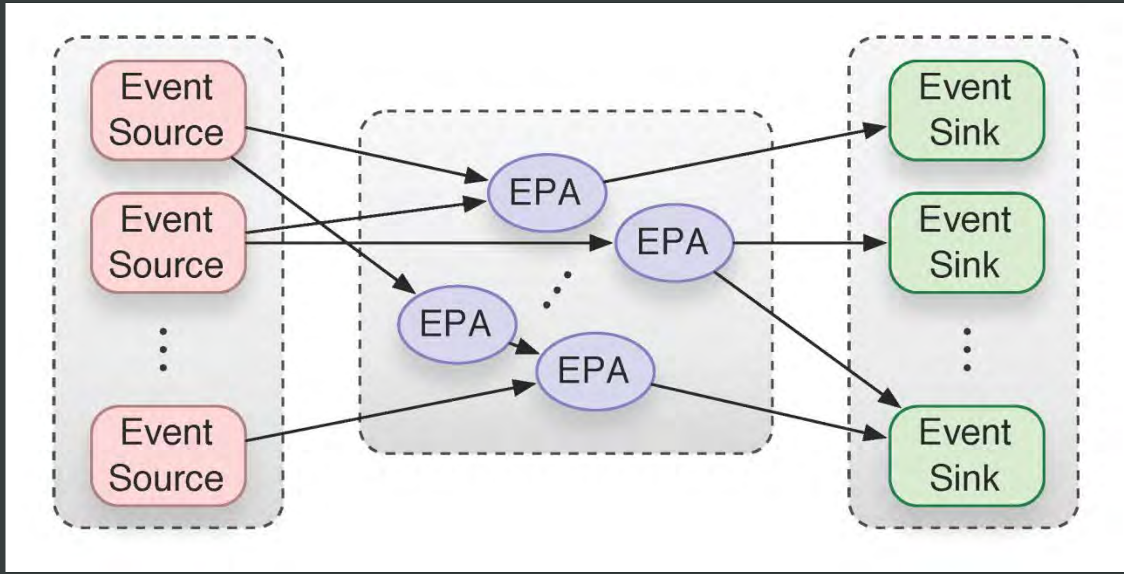
What is an Event?

- Basic events (aka temporal data item): (o, p, t)
  - Object o
  - Property p
  - Time point or a time interval t

- Derived events (aka complex events)

- Event stream
  - Temporally ordered sequence of events with the same schema received from an active event source

Basic Idea of Event Processing



- Event Sources
  - Continuous production of events
- Event Processing Agents (EPAs)
  - Processing building blocks: Consume input events & process them & deliver output events
- Event Sinks
  - Consumers of events

Comparison

Time Series Database Systems

- Data items are persistent
  - Time Series
- Queries are ephemeral
  - Throughput optimization

Event Processing Systems

- Data items are ephemeral
  - Event Streams
- Queries are persistent
  - Latency optimization

- Applications need both systems working hand in hand
  - COMMONITIES
    - Data Model
    - Query Language

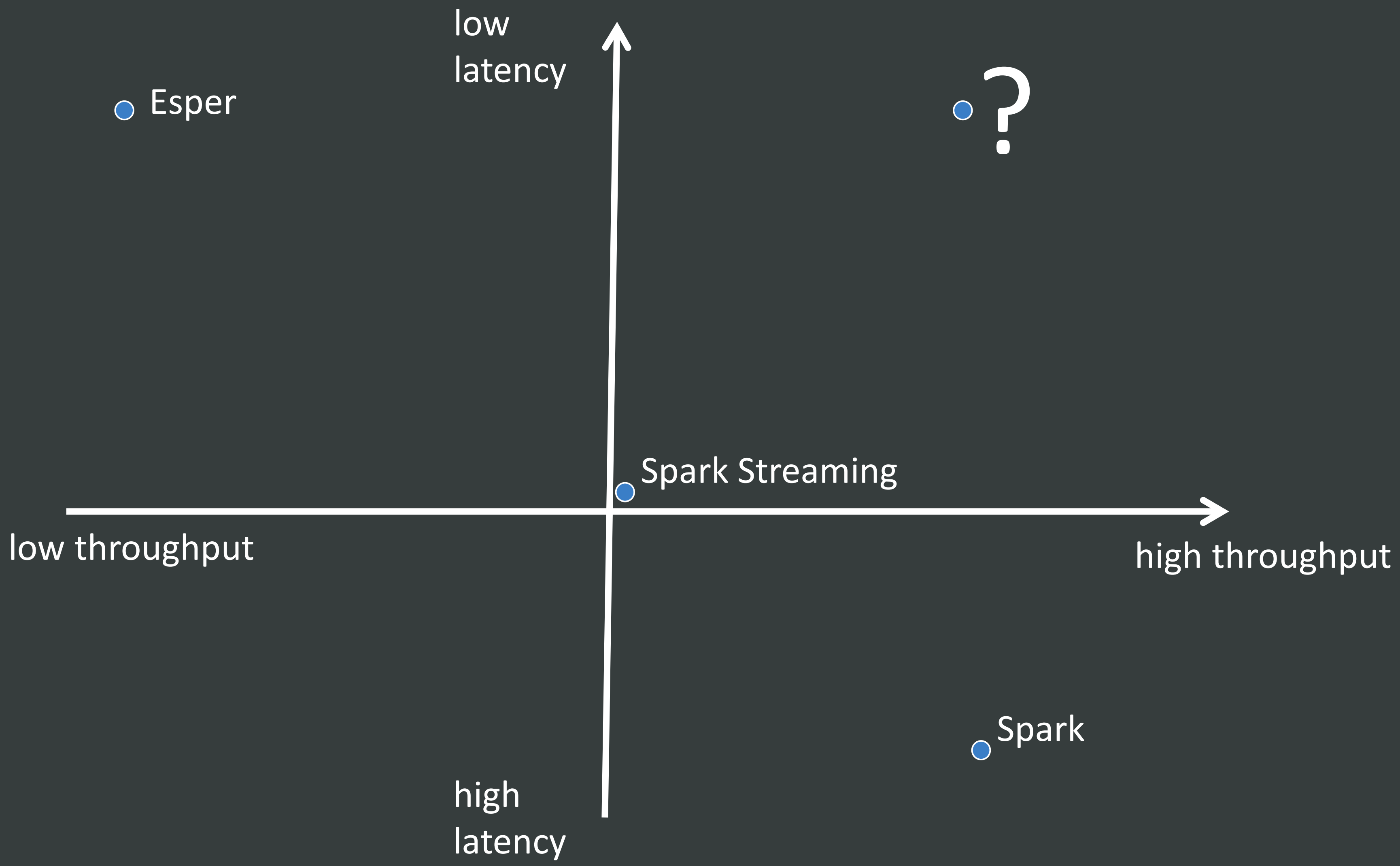
Problems and Issues

- Performance
  - High Throughput vs. Low Latency
- Event Store (= Time Series Database)
  - Persistent management of very fast arriving events
- Functionality
  - Powerful pattern matching
  - Spatial processing

Problems and Issues

- Performance
  - High Throughput vs. Low Latency
- Event Store
  - Persistent Management of Events
- Functionality
  - Powerful pattern matching
  - Spatial and graph processing

The Performance Issue of CEP



The Persistence Issue of Event Processing

- Event processing systems are in-memory only.
  - Volatile Data and Persistent Queries

- Applications require persistence of events.
  - Analysis of historical data → Anomaly Patterns
  - Revision and reproducibility

- Special Requirements
  - Extremely high input rates (millions of events/s)
  - Time-based queries on massive databases

- **Are standard DBMS or NoSQL systems suitable?**

The Functionality Issue

- Pattern Matching is the Core Operator for Event Processing
  - Example of an alarm pattern

    Detect a sharp increase in temperature together with sufficiently large amount of smoke within a short period of time.

  - Example of an aggressive driver pattern (see AAA)

    A sharp acceleration followed by hard braking, both accompanied by a period of speeding.

Selection of Literature

- Luckham, D. (2002). *The power of events* (Vol. 204). Reading: Addison-Wesley.
- Babcock, B., Babu, S., Datar, M., Motwani, R., & Widom, J. (2002, June). Models and issues in data stream systems. In *Proceedings of the twenty-first ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems* (pp. 1-16). ACM.
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- Anicic, D., Fodor, P., Rudolph, S., & Stojanovic, N. (2011, March). EP-SPARQL: a unified language for event processing and stream reasoning. In *Proceedings of the 20th international conference on World wide web* (pp. 635-644). ACM.
- Cugola, G., & Margara, A. (2012). Processing flows of information: From data stream to complex event processing. *ACM Computing Surveys (CSUR)*, *44*(3), 15.

Pattern Matching: Introduction

Pattern Matching

- Process a stream of data and find a specific pattern within the stream
  - Basically a sequence of conditions mapped to a subsequence of the input stream

- Example
  - Find a sequence of temperature sensor events for which the following holds:
    - The first event provides a temperature below 50°
    - The subsequent events deliver a monotonically increasing temperature
    - Finally, the temperature raises above 90°

- Difference to traditional relational data processing
  - (temporal) order is important

Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Pattern: $\overrightarrow{\text{AB[...]BC}}$

Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Filter

Pattern: AB[…]BC

Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Pattern: $\overrightarrow{AB[\ldots]BC}$

Aggregation

Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Pattern: AB[…]BC

Join

Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Pattern: AB[…]BC

Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Pattern: AB[...]BC

Pattern Matching - Example

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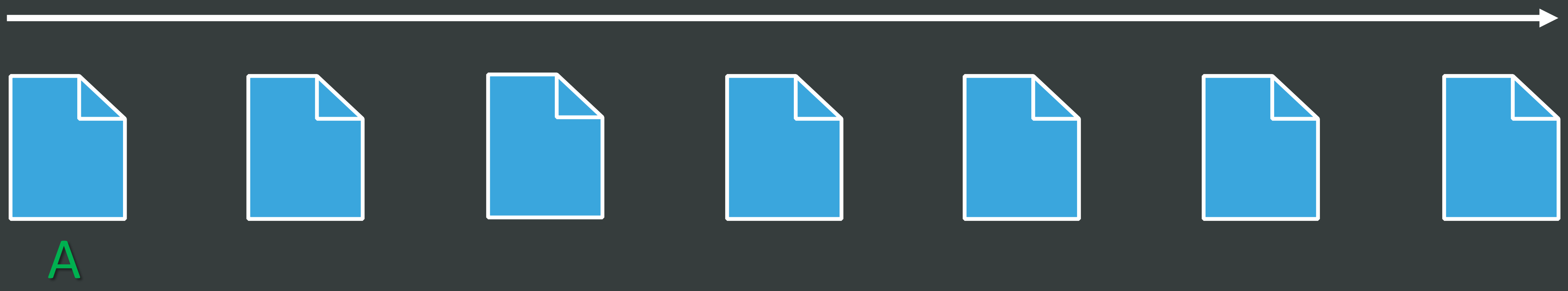
Pattern: $\overrightarrow{\text{AB[...]BC}}$



Pattern Matching - Example

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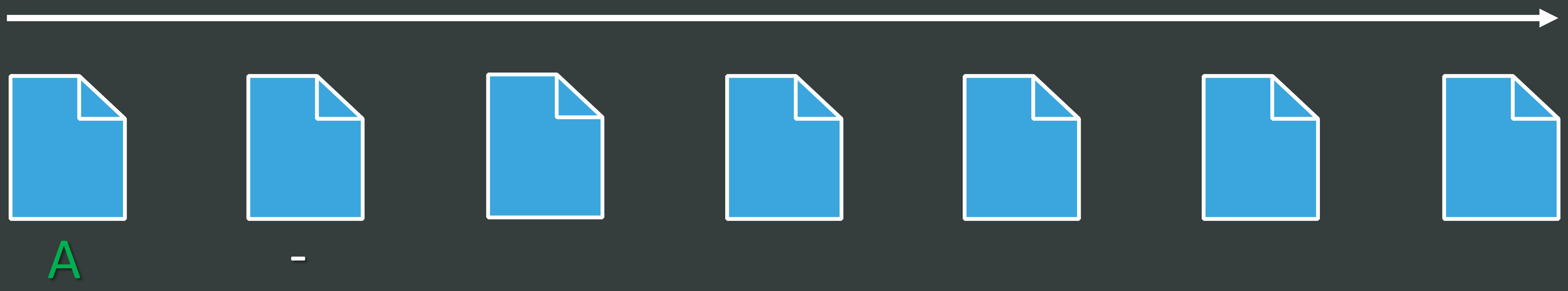
Pattern: AB[...]BC



Pattern Matching - Example

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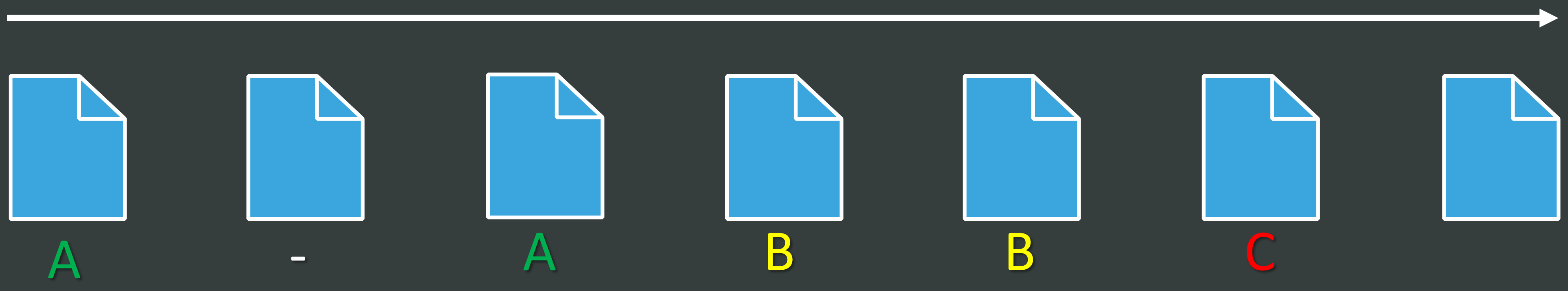


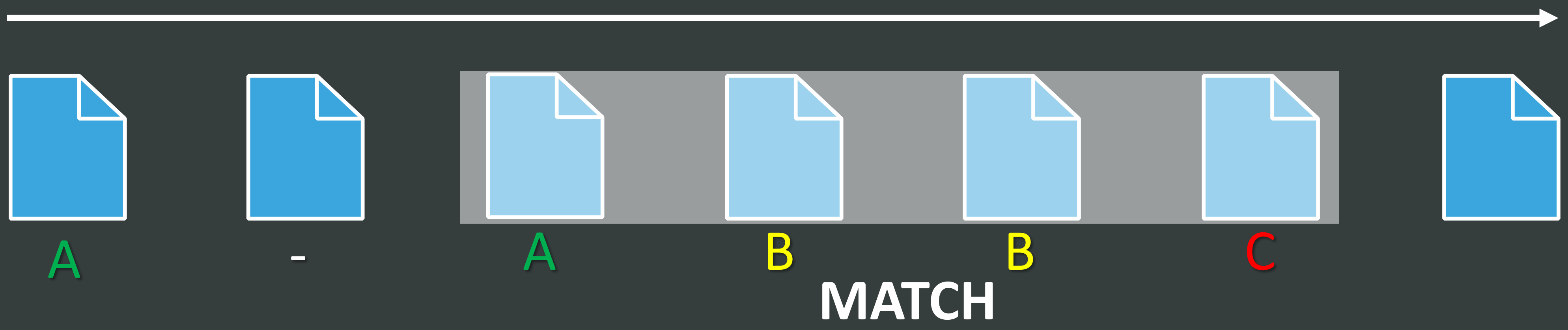
Pattern Matching - Example

A: value < 50°

B: value > previous value

C: value >= 90°

Pattern: AB[...]BC



MATCH RECOGNIZE

STATE-OF-THE-ART PATTERN MATCHING

Introduction

- Row based pattern matching language supporting
  - Aggregations
  - Dependencies between pattern variables and arbitrary rows
  - Fine grained control of how, how many, and when results are delivered

- SQL:2016 Standard

- (Partially) implemented in a few database systems and event systems
  - Oracle (since 12c)
  - Esper
  - Apache Flink

Example

Find a steadily increasing temperature, eventually reaching a **value above a threshold**

```
SELECT *
FROM Sensors MATCH_RECOGNIZE (
     PARTITION BY SENSOR_ID
     MEASURES  FIRST(A.TIME) AS START,
               B.TIME AS END
     PATTERN A+ B
     DEFINE
       A AS A.TEMP > PREV(A.TEMP)
       B AS B.TEMP > 90
)
```

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
    [PARTITION BY …]
    [ORDER BY …]
    MEASURES  …
    [ONE|ALL] ROW PER MATCH
    AFTER MATCH SKIP TO …
    PATTERN …
    DEFINE …
)
```

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
      [PARTITION BY …]
      [ORDER BY …]
      MEASURES  …
      [ONE|ALL] ROW PER MATCH
      AFTER MATCH SKIP TO …
      PATTERN …
      DEFINE …
)
```

Source relation/ event stream

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
     [PARTITION BY …]
     [ORDER BY …]
     MEASURES  …
     [ONE|ALL] ROW PER MATCH
     AFTER MATCH SKIP TO …
     PATTERN …
     DEFINE …
)
```

Variable definitions

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
    [PARTITION BY …]
    [ORDER BY …]
    MEASURES  …
    [ONE|ALL] ROW PER MATCH
    AFTER MATCH SKIP TO …
    PATTERN …
    DEFINE …
)
```

Pattern definition

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
    [PARTITION BY …]
    [ORDER BY …]
    MEASURES  …
    [ONE|ALL] ROW PER MATCH
    AFTER MATCH SKIP TO …
    PATTERN …
    DEFINE …
)
```

Output definition

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
    [PARTITION BY …]
    [ORDER BY …]
    MEASURES  …
    [ONE|ALL] ROW PER MATCH
    AFTER MATCH SKIP TO …
    PATTERN …
    DEFINE …
)
```

Optional partitioning/ordering
- Matchig is performed separately on each partition
- Data is reordered accordingly

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
       [PARTITION BY …]
       [ORDER BY …]
       MEASURES  …
       [ONE|ALL] ROW PER MATCH
       AFTER MATCH SKIP TO …
       PATTERN …
       DEFINE …
)
```

Output
- only one row per successful match or
- all rows that participated

Basic Match Recognize Syntax

```
SELECT …
FROM … MATCH_RECOGNIZE (
      [PARTITION BY …]
      [ORDER BY …]
      MEASURES  …
      [ONE|ALL] ROW PER MATCH
      AFTER MATCH SKIP TO …
      PATTERN …
      DEFINE …
)
```

Where to continue processing after a match was found?

Match Recognize Details – Pattern Definition

- Patterns are **regular expressions** over pattern variables
  - Zero or one occurrence: A?
  - Kleene: A*/ A+
  - Quantifies: A{n,m}, A{n,}, A{,m}
  - Alternatives: A|B
  - Anchors: Before first event (^), after last event ($) of a partition
- Examples:
  - `A B* C          // A followed by zero or more Bs, followed by C`
  - `A (B|C)+ D      // A followed by at least 1 B or C, followed by D`
  - `A B{3,} C       // A followed by at least 3 Bs, followed by C`
  - `^A+$            // The entire partition must satisfy A`

Match Recognize Details – Variable Definitions

- Variables
  - Building blocks for the pattern definition
  - Representation of user defined conditions
- Basic Syntax: `DEFINE <NAME> AS <CONDITION>`
  - Condition consists of Boolean expressions and the following PM specific constructs:
    - `PREV`, `NEXT`
      - refer to rows (events) that occur before/after the currently processed row
      - operate on physical rows, not restricted to pattern variables
    - `FIRST`, `LAST`
      - navigate rows that were mapped to a pattern variable
      - operate on logical rows, restricted to pattern variables
    - Aggregates
      - Access to *running* aggregates over a specific pattern variable

Variable Definitions with PREV and NEXT

- Access rows/events by physical relative offset
- `A AS A.temp > PREV(A.temp)                    // refer to previous row`
- `A AS A.temp > PREV(A.temp, 50)                // move back 50 events`
- `A AS PREV(A.temp * A.accuracy) > 90           // refer to multiple columns`
- ```
  A AS A.temp > 2 * ( PREV (A.temp, 2)      // find outlier (> than twice
                    + PREV (A.temp 1)       // the average of its four
                    + NEXT (A.temp, 1)      // neighbors)
                    + NEXT (A.temp, 2)) / 4
  ```
- ```
  A AS A.temp > PREV(B.temp)                // refer to another variable:
                                            // previous row of the last
                                            // row mapped to B
  ```

Variable Definitions with FIRST and LAST

- Access rows with logical offset based on pattern variable
- ```
  DEFINE A AS A.TEMP > 90
         B AS B.TEMP < LAST(A.TEMP)    // Refer to the last
                                       // occurrence of A
  ```
- ```
  DEFINE A AS A.TEMP > 90
         B AS B.TEMP < LAST(A.TEMP,20)  // with offset 20
  ```

Example

- **Event Stream**

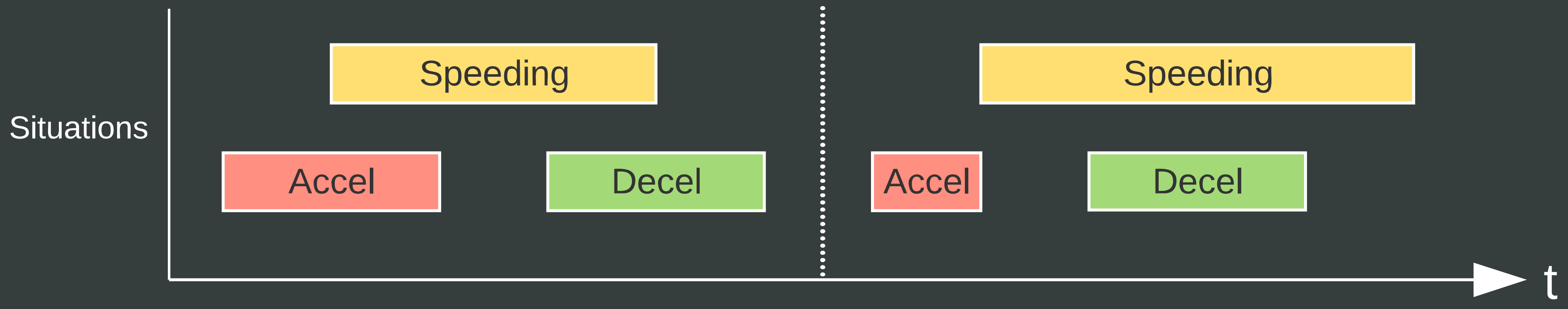
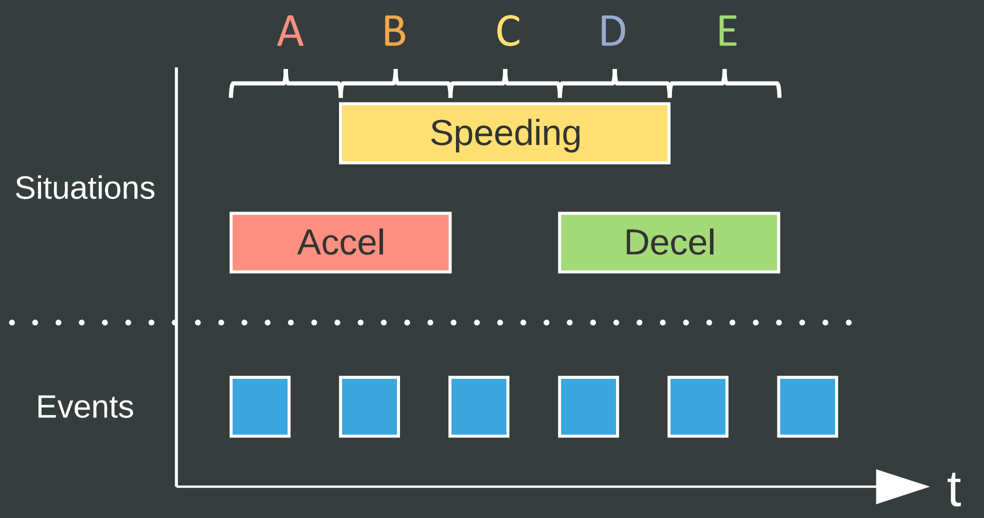
Record sequence	Value	Variable Mapping
R1	10	A
R2	20	B
R3	30	A
R4	40	C
R5	50	A

- FIRST (A.Price) = FIRST (A.Price, 0) = LAST (A.Price, 2) = 10
- FIRST (A.Price, 1) = LAST (A.Price, 1) = 30
- FIRST (A.Price, 2) = LAST (A.Price, 0) = LAST (A.Price) = 50
- FIRST (A.Price, 3) is null, LAST (A.Price, 3) is null

Variable Definitions with Aggregates

- Define Variable based on running aggregates

- `DEFINE A AS A.TEMP > AVG(A.TEMP)          // self reference`

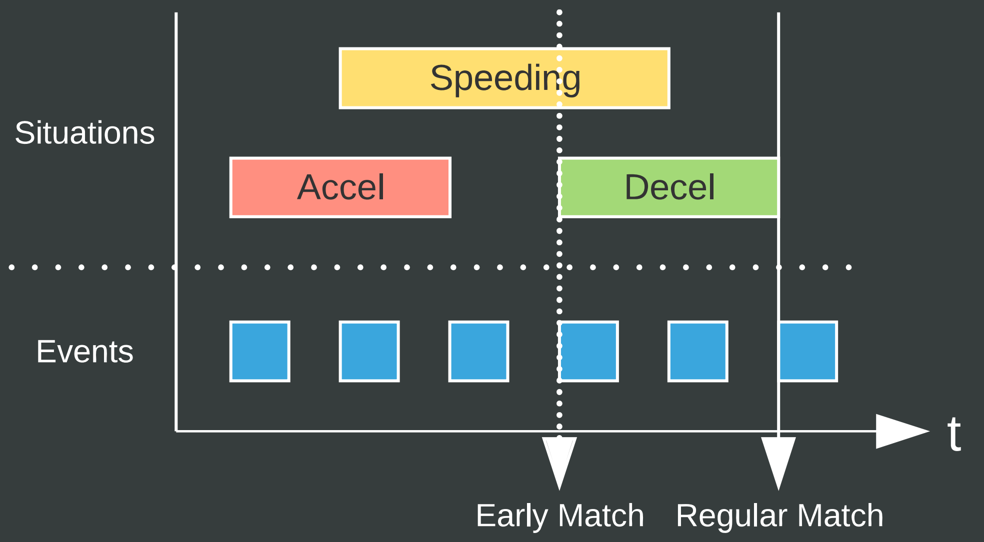
- ```
  DEFINE A AS true
         B AS B.TEMP >= 2*AVG(A.TEMP)     // refer to another
                                          // variable A
  ```
  ```

Match Recognize Details – Output Definition

- Output defined via MEASURES clause
    - access to defined pattern variables
    - Basic syntax: `<EXPRESSION> AS <NAME>`

- Expressions refer to specific values via
    - FIRST/LAST expressions
    - Aggregates over attributes of a pattern variable

- Expressions can be *running* or *final*
  - If the user specifies to output all rows contributing to a match
    - running means: Use the values seen so far
    - final means: Always use the values obtained after processing the last row

Match Recognize Details – Output Definition

```
MEASURES FIRST(A.TIME) AS START,
         B.TIME AS END,
         AVG(A.TEMP) as AVG_TMP
PATTERN  A+ B
DEFINE   A AS A.TEMP > PREV(A.TEMP)
         B AS B.TEMP > 90
```

Match Recognize Details – Output Definition

```
MEASURES FIRST(A.TIME) AS START,
         B.TIME AS END,
          AVG(A.TEMP) as AVG_TMP
PATTERN  A+ (B|C)
DEFINE   A AS A.TEMP > PREV(A.TEMP)
         B AS B.TEMP > 90
         C AS C.TEMP < FIRST(A.TEMP)
```

B.TIME is undefined, if
the pattern ended with C

Match Recognize Details – Output Definition

```
MEASURES FIRST(A.TIME) AS START,
         COALESCE(B.TIME,C.TIME) AS END,
          AVG(A.TEMP) as AVG_TMP
PATTERN  A+ (B|C)
DEFINE   A AS A.TEMP > PREV(A.TEMP)
         B AS B.TEMP > 90
         C AS C.TEMP < FIRST(A.TEMP)
```

Use first non-null value instead

Match Recognize Details – Continue Search

- Position to start looking for the next match after a successful match:
  - `AFTER MATCH SKIP TO NEXT ROW`
    - Resume pattern matching at the row after the first row of the current match.
  - `AFTER MATCH SKIP PAST LAST ROW` (Default)
    - Resume pattern matching at the next row after the last row of the current match.
  - AFTER MATCH SKIP TO FIRST <pattern_variable>
    - Resume pattern matching at the first row that is mapped to the pattern variable.
  - AFTER MATCH SKIP TO LAST <pattern_variable>
    - Resume pattern matching at the last row that is mapped to the pattern variable.

Another Example

- Find flickering alarms
- SELECT * FROM ALARMS MATCH_RECOGNIZE(

```
    PARTITION BY ALARM_ID
    ORDER BY TIME
    AFTER MATCH SKIP TO FIRST B
    MEASURES FIRST(A.ALARM_ID) AS ID,
             FIRST(A.TIME) AS BEGIN,
             LAST(B.TIME) AS END,
    PATTERN (A+B+){50,}
    DEFINE A AS A.alarm = true,
           B AS B.alarm = false AND B.time – FIRST(A.TIME) <= 5 min
)
```

Summary – Match Recognize

- Pattern definitions via regular expression over pattern variables

- Complex variable- and result-definitions via:
  - Aggregates
  - Physical offsets (PREV,NEXT)
  - Logical offsets (FIRST,LAST)

- Control output via:
  - Resume options (AFTER MATCH …)
  - ALL ROWS/ONE ROW

- Not discussed so far: Window-Clause
  - Define a time window in which the pattern must occur completely

Literature

- Agrawal, J., Diao, Y., Gyllstrom, D., & Immerman, N. (2008, June). Efficient pattern matching over event streams. In *Proceedings of the 2008 ACM SIGMOD international conference on Management of data* (pp. 147-160). ACM.
- Mei, Y., & Madden, S. (2009, June). Zstream: a cost-based query processor for adaptively detecting composite events. In *Proceedings of the 2009 ACM SIGMOD International Conference on Management of data* (pp. 193-206). ACM.
- Michels, J., Hare, K., Kulkarni, K., Zuzarte, C., Liu, Z. H., Hammerschmidt, B., & Zemke, F. (2018). The New and Improved SQL: 2016 Standard. *ACM SIGMOD Record*, *47*(2), 51-60.
- SO/IEC TR 19075-5:2016, Information technology —Database languages — SQL Technical Reports —Part5: Row Pattern Recognition in SQL, http://standards.iso.org/ittf/PubliclyAvailableStandards/

Complex Temporal Pattern Matching

Motivation

- Sequential Patterns are limited to before/after/at the same time relationships

- Many real-world applications require the definition of complex temporal relationships between **situations**
  - Running Example: Traffic monitoring

- Cumbersome/impossible to express with sequential patterns
  - Queries are hard to understand
  - Evaluation performance is poor

Example: Detect Aggressively Driving Cars

- Input: sensor data from connected cars
  - ID, position, speed, acceleration, etc.
- Indicators for aggressive driving according to AAA
  - “[…] suddenly changing speeds” and “Driving […] in excess of posted speed limit”
- Query: „A sharp acceleration followed by hard braking, both accompanied by a period of speeding”



Option 1: Raw Events + Pattern Matching

- Process raw event stream
  - Infinite sequence of timestamped relational tuples
- Detection of sequential patterns
  - Pattern expressed via regular expressions or equivalent
  - Poor evaluation performance
  - Awkward query definitions
    - ```
      FROM CARS PARTITION BY CAR_ID
      PATTERN A+ B+ C+ D+ E+
      WHERE A.SPEED <= 75 mph
      AND A.ACCEL > 8 m/s²
      AND B.SPEED > 75 mph
      AND B.ACCEL > 8 m/s²
      AND C.SPEED > 75 mph
      AND C.ACCEL >= -9 m/s²
      AND C.ACCEL <= 8 m/s²
      AND D.SPEED > 75 mph
      AND D.ACCEL < -9 m/s²
      ```


      ```

Option 2: Interval Based Systems

- Process streams of interval events
  - Infinite sequence of relational tuples associated with a time interval
- Pattern stated as interval endpoint order
  - $A.start < S.start < A.end < D.start < \ \ldots$
- Intervals created externally
  - Visible to the system after interval ended

    ➔ No early results

    ➔ No optimization opportunities
- Poorly supported by existing systems



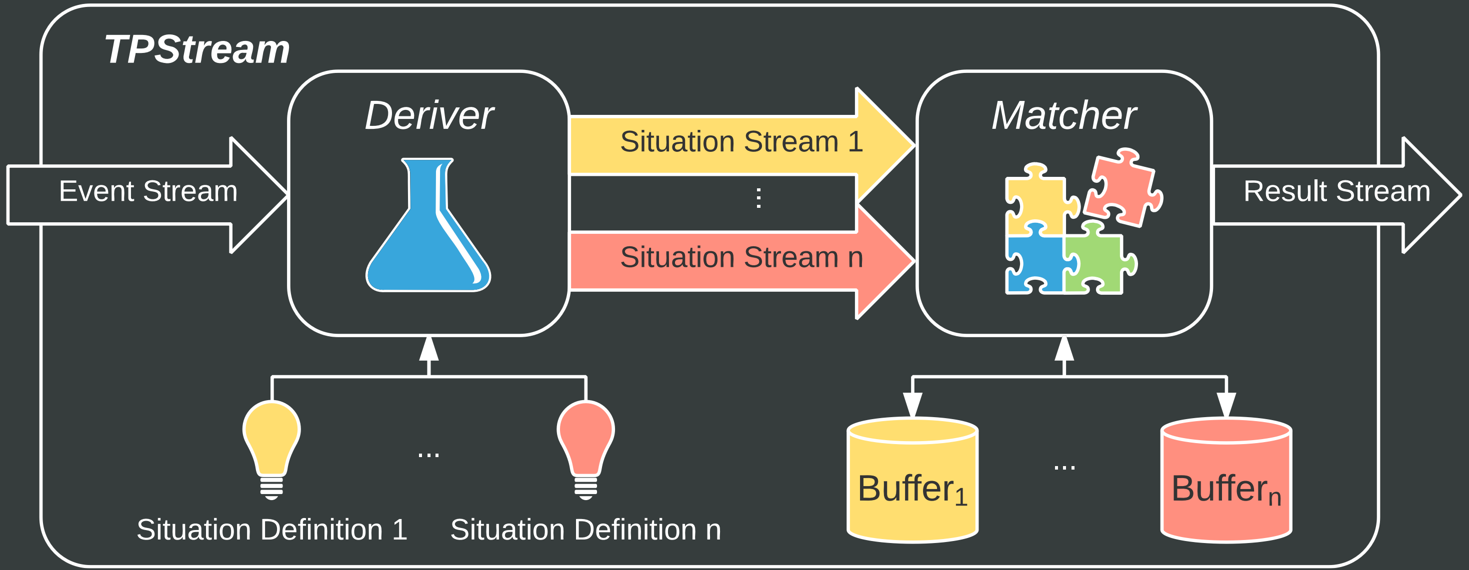
Requirements for Temporal Pattern Matching

- Easily readable queries
- Compatible with event processing systems
  - Process raw event streams
- Early result detection (low latency)
- Efficient query processing

```
FROM CARS PARTITION BY CAR_ID
DEFINE A AS ACCEL > 8 m/s²,
       B AS SPEED > 75 mph,
       C AS ACCEL < -9 m/s²
PATTERN A OVERLAPS B AND
        B OVERLAPS C
```

TPStream*: Basic Ideas

- Input and Output are event streams
- Temporal patterns as binary constraints using Allen's interval algebra
  - E.g. Acceleration *overlaps* Speeding
- Tight coupling of derivation and matching
  - Early results



*M. Körber, N. Glombiewski, B. Seeger: TPStream: Low-Latency and High-Throughput Temporal Pattern Matching on Event Streams, will appear in Distributed and Parallel Databases

TPStream: Basic Ideas

- Input and Output are event streams
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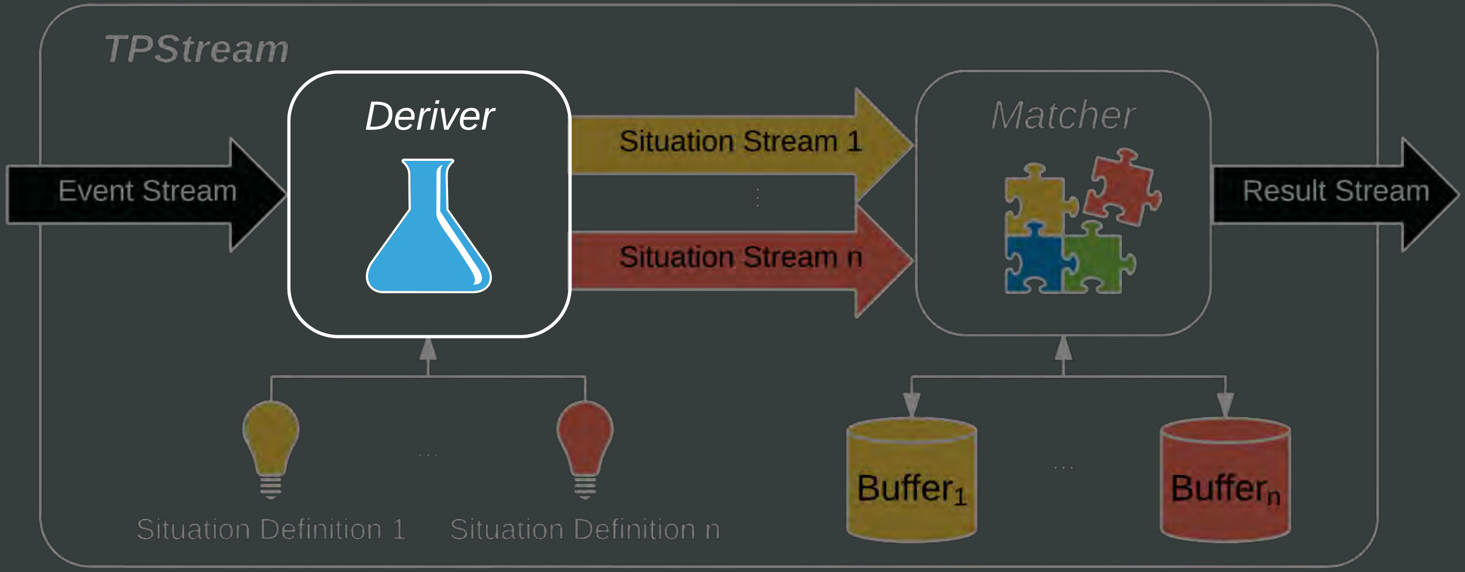


Deriving Situations

- **Situation**: A period of time for which a set of conditions holds true
  - Summarization of a continuous subsequence of events
- Defined via
  - φ: Predicate, e.g. $speed\ >\ 75\ mph$
    - Identify continuous subsequences
  - γ: Set of aggregates, e.g. $avg(speed), \max(acceleration)$
    - Summarize events of subsequence
  - Δ: Optional duration constraints, e.g. $5s\ <\ duration\ <\ 2\text{min}$
    - Restrict situations of interest
- Derived on the fly from incoming events

Deriving Situations - Example

Speeding:
$\varphi: speed > 75mph$
$\gamma: avg(speed)$

Acceleration:
$\varphi: accel > 8m/s^2$
$\gamma: max(accel)$

Deceleration:
$\varphi: accel < -9m/s^2$
$\gamma: min(accel)$

t

Events:

Speed: 70 mph
Accel: 7 m/s²
…
Timestamp: 1

Deriving Situations - Example

Speeding:
$\varphi: speed > 75mph$
$\gamma: avg(speed)$

Acceleration:
$\varphi: accel > 8m/s^2$
$\gamma: max(accel)$

max(accel): 9 m/s^2
Validity: [2,*)

Deceleration:
$\varphi: accel < -9m/s^2$
$\gamma: min(accel)$

t

Events:

Speed: 72 mph
Accel: 9 m/s^2
…
Timestamp: 2

Deriving Situations - Example

Speeding:
$\varphi: speed > 75mph$
$\gamma: avg(speed)$

avg(speed): 76 mph
Validity: [3,*)

Acceleration:
$\varphi: accel > 8m/s^2$
$\gamma: max(accel)$

max(accel): 10 m/s^2
Validity: [2,*)

Deceleration:
$\varphi: accel < -9m/s^2$
$\gamma: min(accel)$

t

Events:

Speed: 76 mph
Accel: 10 m/s^2
…
Timestamp: 3

Deriving Situations - Example

Speeding:
$\varphi: speed > 75mph$
$\gamma: avg(speed)$

avg(speed): 77 mph
Validity: [3,*)

Acceleration:
$\varphi: accel > 8m/s^2$
$\gamma: max(accel)$

max(accel): 10 m/s^2
Validity: [2,4)

Deceleration:
$\varphi: accel < -9m/s^2$
$\gamma: min(accel)$

t

Events:

Speed: 78 mph
Accel: 5 m/s^2
…
Timestamp: 4

Deriving Situations - Example

Speeding:
$\varphi: speed > 75mph$
$\gamma: avg(speed)$

avg(speed): 76,6 mph
Validity: [3,*)

Acceleration:
$\varphi: accel > 8m/s^2$
$\gamma: max(accel)$

max(accel): 10 m/s²
Validity: [2,4)

Deceleration:
$\varphi: accel < -9m/s^2$
$\gamma: min(accel)$

min(accel): -10 m/s²
Validity: [5,*)

t

Events:

Speed: 76 mph
Accel: -10 m/s²
…
Timestamp: 5

Deriving Situations - Example

Speeding:
$\varphi: speed > 75mph$
$\gamma: avg(speed)$

avg(speed): 76,6 mph
Validity: [3,6)

Acceleration:
$\varphi: accel > 8m/s^2$
$\gamma: max(accel)$

max(accel): 10 m/s²
Validity: [2,4)

Deceleration:
$\varphi: accel < -9m/s^2$
$\gamma: min(accel)$

min(accel): -11 m/s²
Validity: [5,*)

t

Events:

Speed: 72 mph
Accel: -11 m/s²
…
Timestamp: 6

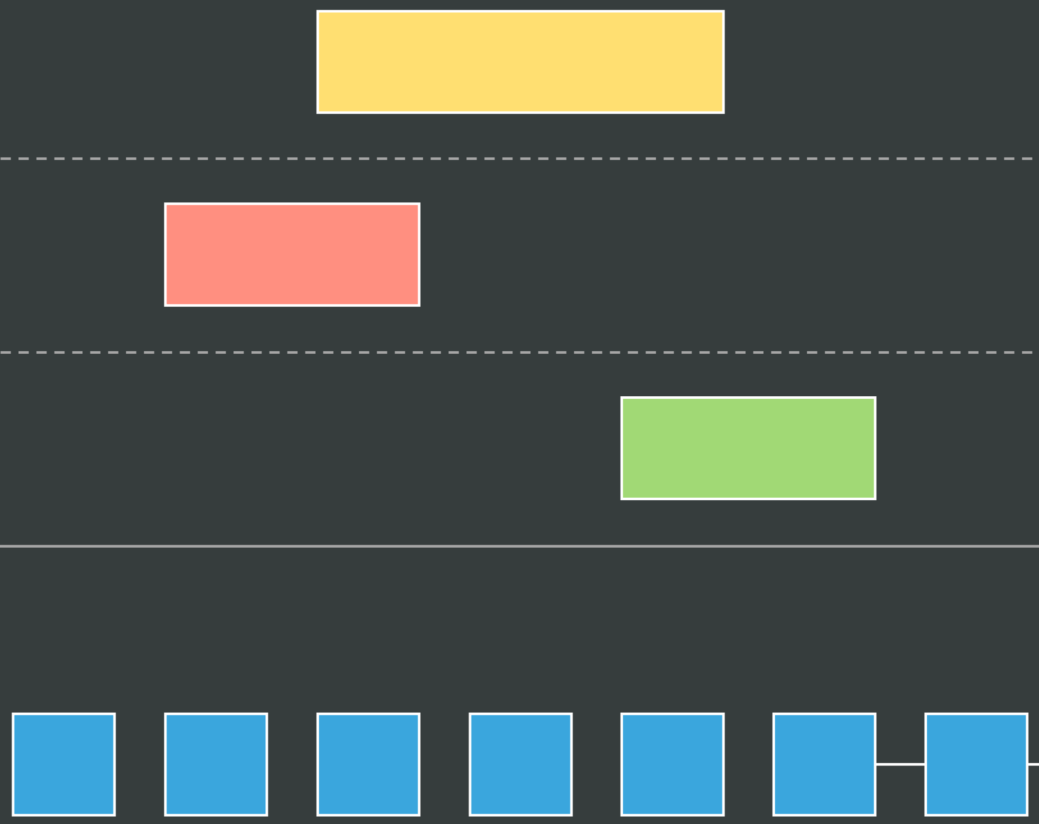
Deriving Situations - Example

Speeding:
$\varphi: speed > 75mph$
$\gamma: avg(speed)$

Acceleration:
$\varphi: accel > 8m/s^2$
$\gamma: max(accel)$

Deceleration:
$\varphi: accel < -9m/s^2$
$\gamma: min(accel)$

Events:



avg(speed): 76,6 mph
Validity: [3,6)

max(accel): 10 m/s²
Validity: [2,4)

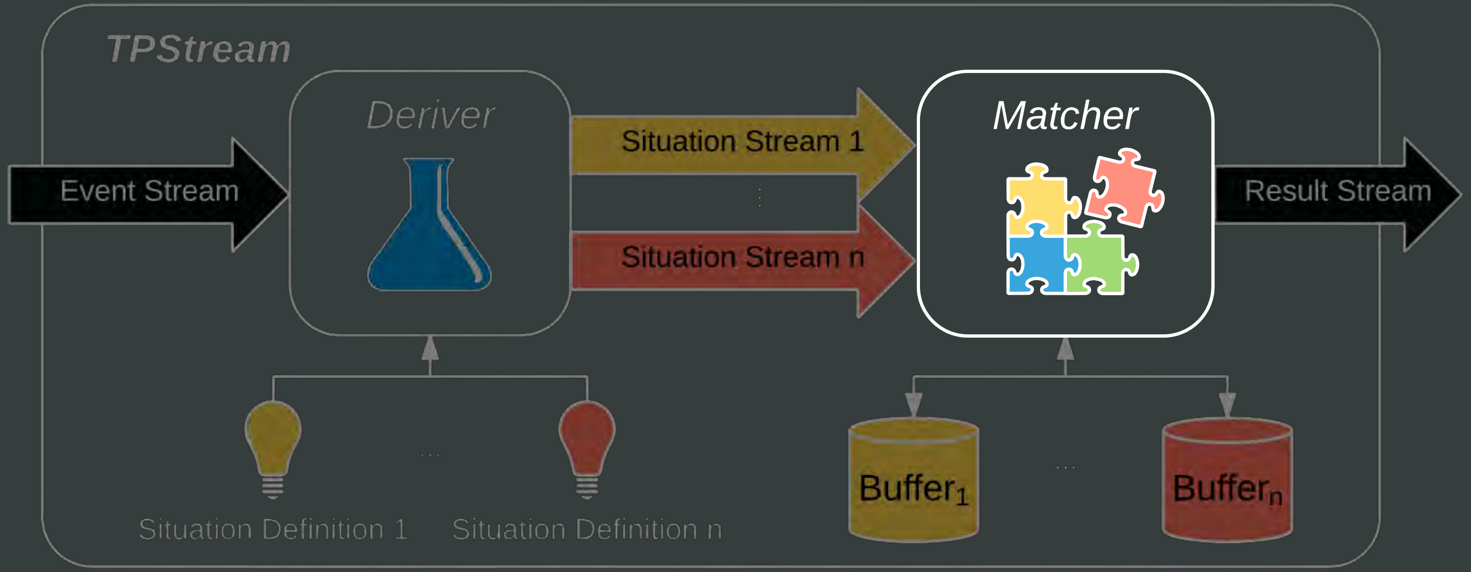
min(accel): -11 m/s²
Validity: [5,7)

t

Speed: 68 mph
Accel: -5 m/s²
…
Timestamp: 7

TPStream: Basic Ideas

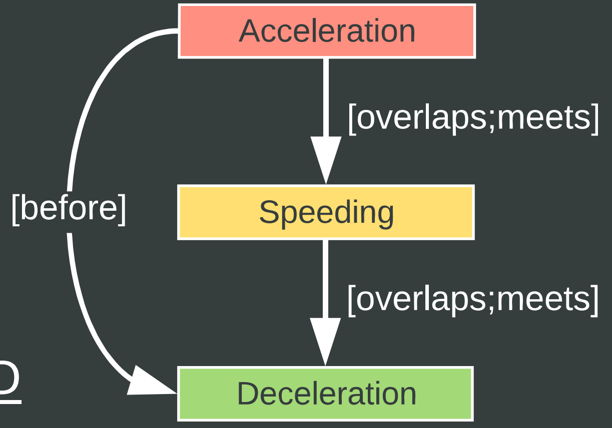
- Input and Output are event streams
- Temporal patterns as binary constraints using Allen's interval algebra
  - E.g. Acceleration *overlaps* Speeding
- Tight coupling of derivation and matching
  - Early results



Temporal Pattern

- Temporal Relation
  - Basic building block of a pattern
  - Based on Allen‘s interval algebra
  - Example: Acceleration *overlaps* Speeding
- Temporal Constraint
  - Disjunction of temporal relations
  - Definition of alternatives
  - Example: Acceleration *overlaps* OR *meets* Speeding
- Temporal Pattern
  - Conjunction of temporal constraints
  - Additional time window
  - Example: (Acceleration *overlaps* OR *meets* Speeding) AND
    (Speeding *overlaps* OR *contains* Deceleration) AND
    (Acceleration before Deceleration)

Relation	Equivalent	Visualization
A before B	B after A	
A starts B	B started-by A	
A meets B	B met-by A	
A overlaps B	B overlapped-by A	
A during B	B contains A	
A finishes B	B finished-by A	
A equals B		



Low Latency Matching (1)

- Revisit definitions of Allen‘s interval relations:

<table>
<tr><th>Relation (R)</th><th>Definition</th><th>$t_d(R)$</th><th>Prefix-Group (G)</th><th>$t_d(G)$</th></tr>
<tr><td>A overlaps B</td><td>A.ts < B.ts < A.te < B.te</td><td>A.te</td><td rowspan="3">A.ts < B.ts</td><td rowspan="3">B.ts</td></tr>
<tr><td>A finishes B</td><td>A.ts < B.ts < A.te = B.te</td><td>A.te = B.te</td></tr>
<tr><td>A contains B</td><td>A.ts < B.ts < B.te < A.te</td><td>B.te</td></tr>
<tr><td colspan="5">…</td></tr>
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- Each temporal relation can be detected/validated at $t_3\left(t_d(R)\right)$
  - Example : t_d(A overlaps B) $=$ A.te
  - We know A.ts < B.ts and B will definitely end at a later point in time

Low Latency Matching (1)

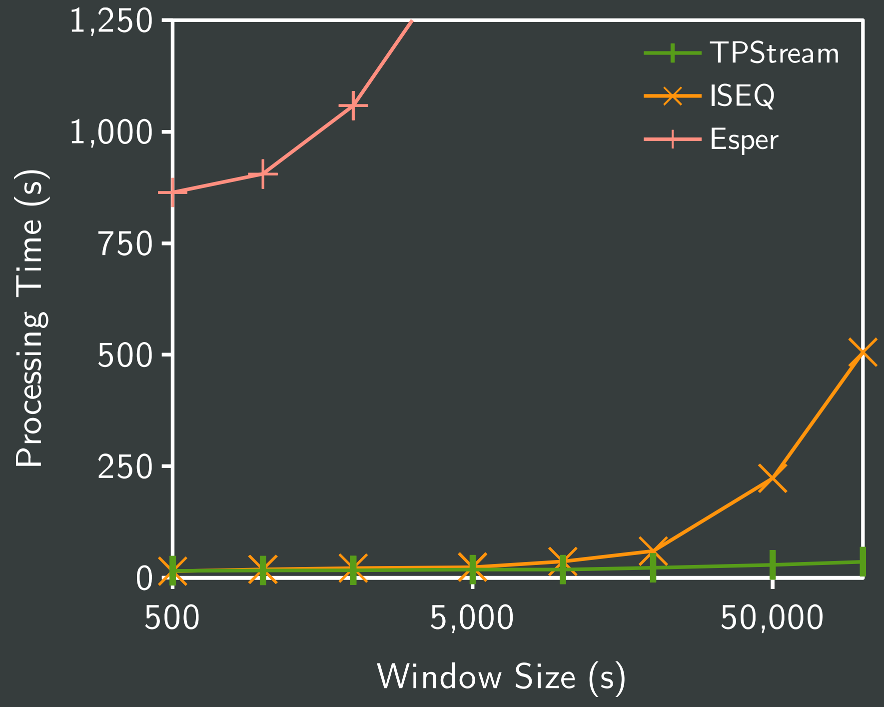
- Revisit definitions of Allen's interval relations:

Relation (R)	Definition	t_d(R)	Prefix-Group (G)	t_d(G)
A overlaps B	$\boxed{\text{A.ts} < \text{B.ts}}$ < A.te < B.te	A.te	A.ts < B.ts	B.ts
A finishes B	$\boxed{\text{A.ts} < \text{B.ts}}$ < A.te = B.te	A.te = B.te		
A contains B	$\boxed{\text{A.ts} < \text{B.ts}}$ < B.te < A.te	B.te		
…				

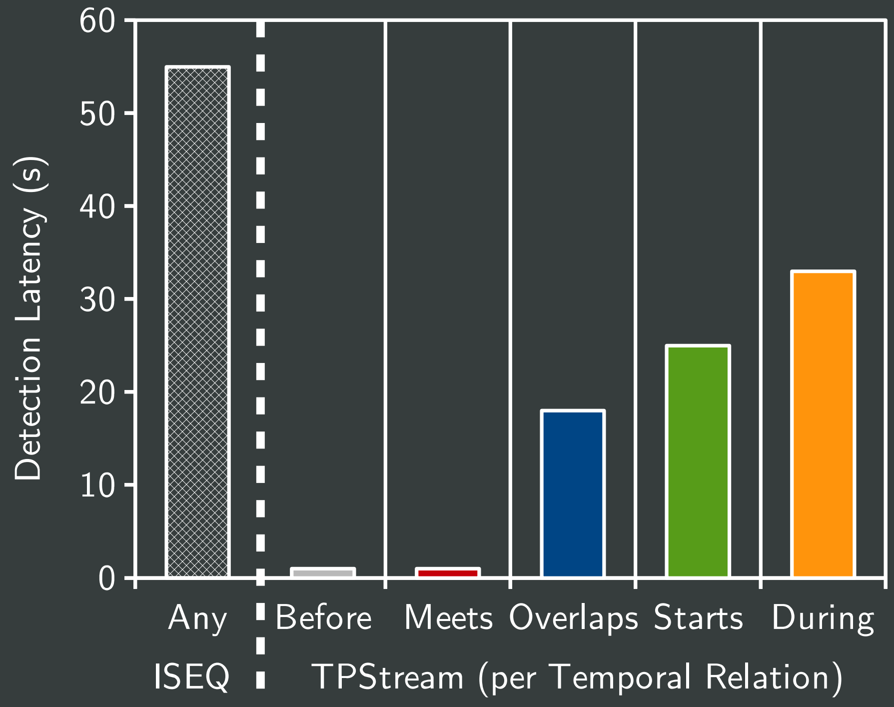
- Each temporal relation can be detected/validated at t_3 $\left(t_d(R)\right)$
  - Example : t_d(A overlaps B) $=$ A.te
  - We know A.ts < B.ts and B will definitely end at a later point in time
- Prefix groups allow detection/validation at t_2 $\left(\ t_d(G)\right)$
  - Example: t_d(A *overlaps* <u>OR</u> *finishes* <u>OR</u> *contains* B) $=$ B.ts
  - Ordering of A.te and B.te does not matter

Experimental Results

- Query with 3 situations
  - A before B AND B overlaps C
- Synthetic data (300M events)
- Varying window size



- Detection latency per temporal relation
- 2 situation streams
- 55s average duration
- Application time (event timestamps)



Group Patterns

Group Patterns I

- Detect groups of objects with similar behavior over time
  - Similarity often refers to the spatial position of (moving) objects

- Two kinds of basic patterns
  - Concurrency: Find all birds currently flying in south direction
  - Mutual relationship: Find a group of gazelles heading towards a specific location
- Complex patterns are composed of temporal relationships instances of simple patterns

- Assumptions
  - Every event has at least the following attributes
    - unique object ID
    - attribute to be analyzed (e.g., position)
    - timestamp

Basic Group Patterns

- Generate snapshots of the objects at given points in time

- Concurrency
  - Evaluate the predicate for every object on each snapshot
  - **All objects satisfying the predicate** form a group
  - Time intervals describe the lifetime of a group

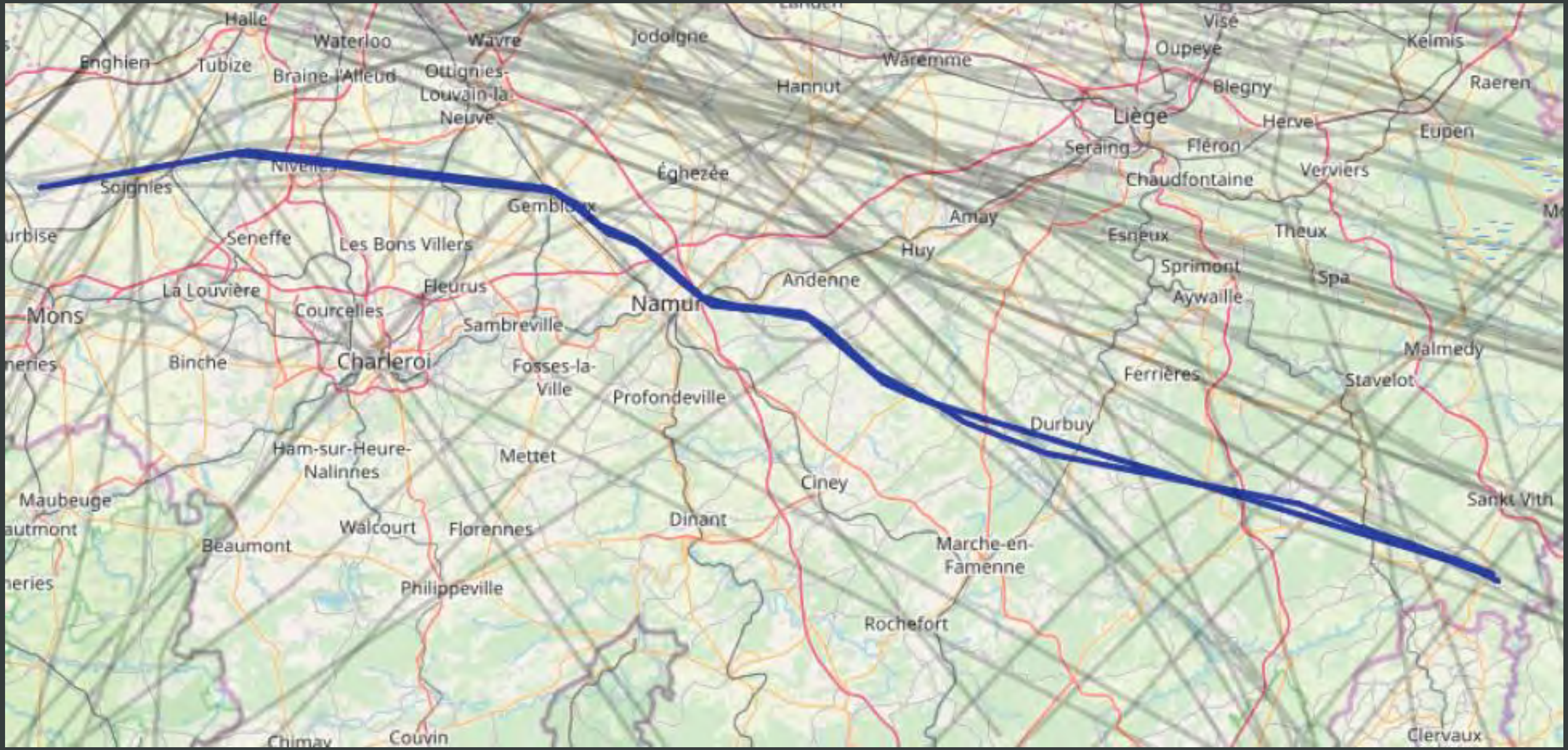
- Mutual relationship
  - Evaluate predicates for all pairs of objects on each snapshot (e.g. distance between)
    - **Generation of a graph** with an edge if two objects fulfill the predicate
  - Connected components inside the graph form groups
  - Time intervals describe the lifetime of a group

Complex Group Patterns with TPStream

- Complex patterns
  - Combination of simple patterns using TPStream
- Challenges
  - Keep track of group development (leaves, joins, splits, merges)
  - Efficient computation
- Example: Find a group of gazelles heading towards a specific location
  - Predicate: First derivative of the distance < 0
    - Distance shrinks
  - Find a connected component inside the graph
    - Distance between all members of the subgraph shrinks

Example

- Find planes that are moving close to each other over a certain distance
  - What is the meaning of proximity?
  - What is the minimum distance?



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Discussion