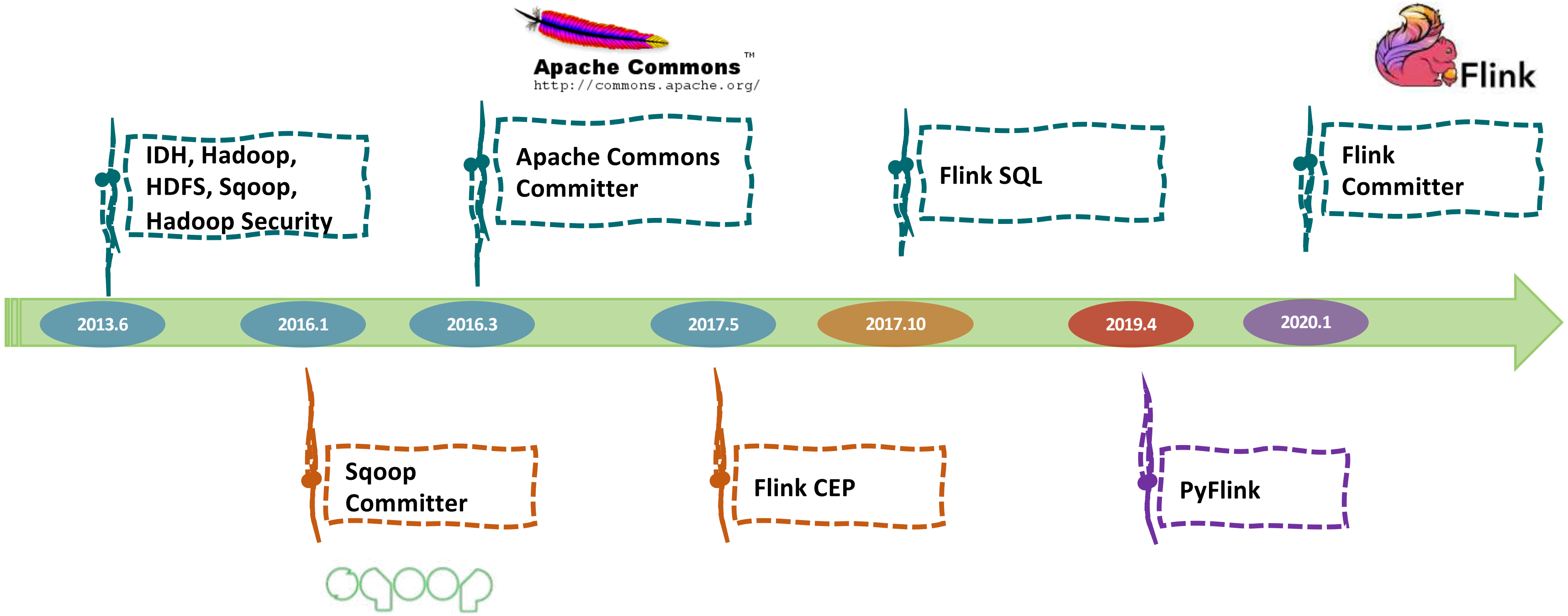
Geospatial Situation Detection through FlinkCEP @Uber

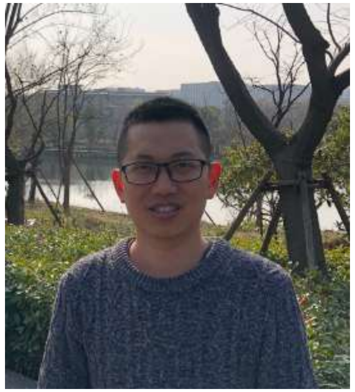
使用Flink CEP进行地理情形检测的实践

Niel Hu
Engineer | Uber
niel.hu@uber.com

付典
Flink Committer | Alibaba
dian0511.fu@gmail.com

About Me


IDH, Hadoop, HDFS, Sqoop, Hadoop Security
Apache Commons
http://commons.apache.org/
Apache Commons Committer
Flink SQL
Flink
Flink Committer
2013.6
2016.1
2016.3
2017.5
2017.10
2019.4
2020.1
Sqoop Committer
Flink CEP
PyFlink



付典

Outline 概述

- Marketplace
- Observability Problem
- Large-Scale Clustering
- Situation Detection through Pattern Matching
- Tips, Tricks and Lessons Learned

Marketplace

可观测性问题

大规模聚类

通过模式匹配(CEP)进行趋势检测

经验与教训

Marketplace

- Modeling the physical world
- Global Logistics Network
- Real-Time Decision Engine

- 为物理世界建模
- 全球物流网络
- 实时决策引擎

Marketplace

Driver Positioning

Forecasting

司机位置预测

Dynamic Pricing

Fares

动态定价

Intelligent Dispatch

Driver / Rider Pricing

智能调度

Marketplace Health

Marketplace Platform & Data

市场健康
平台和数据

Observability Problem 可观察性问题

Photo: Jessica Christian / The Chronicle

Scaling Observability 可伸缩的可观察性

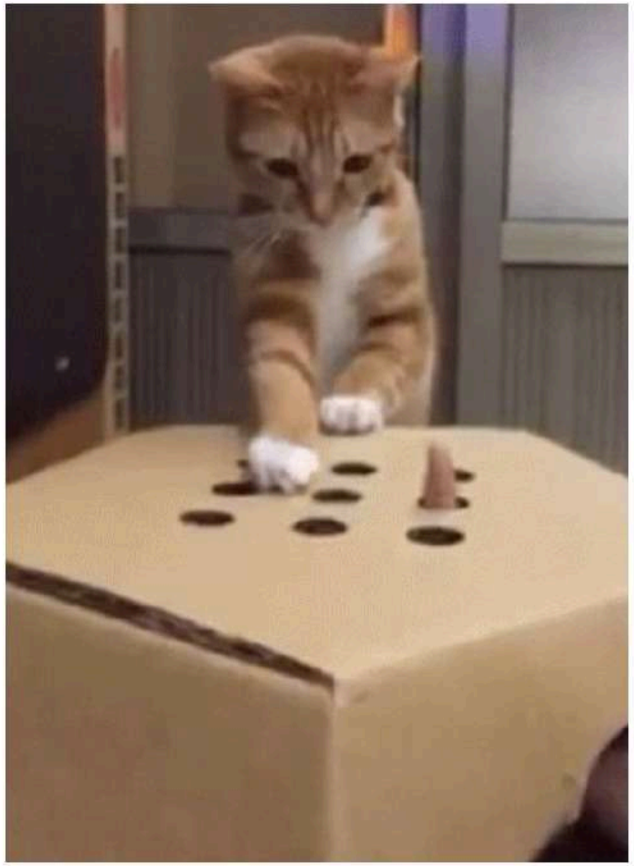
- 700+ Cities
- Local Heterogeneity
- Space and Time Dimensions
- Real-Time Constraints

700多个城市

局部异构

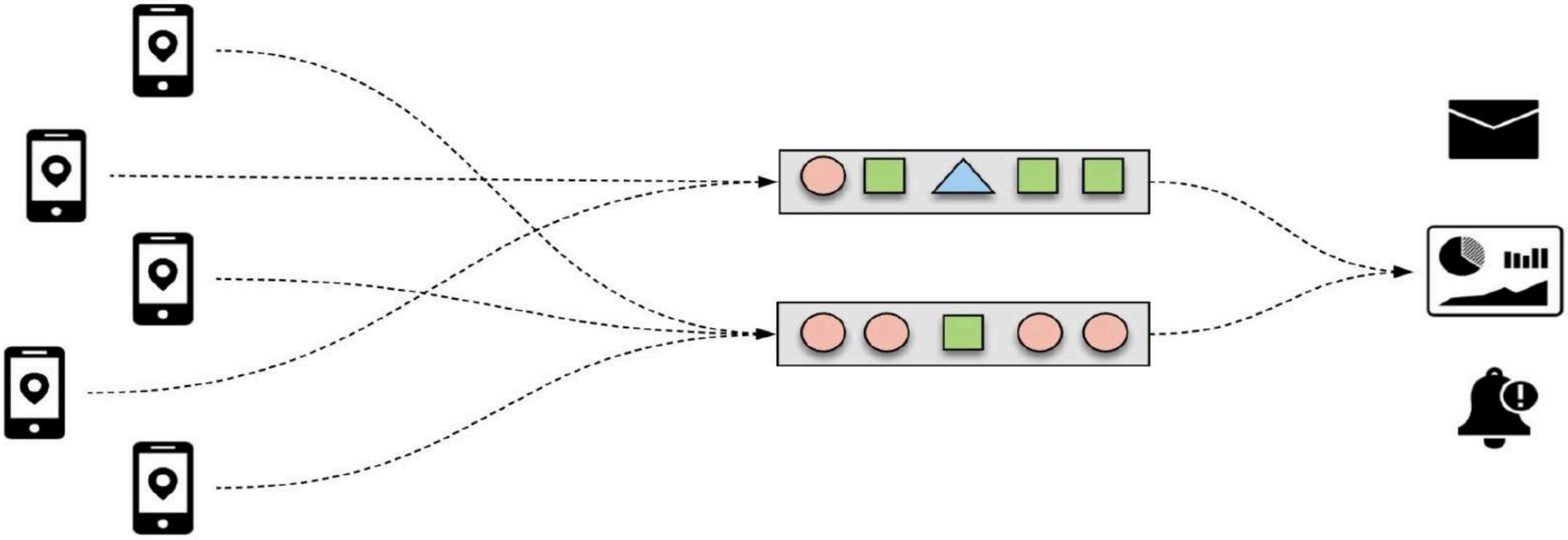
空间和时间维度

实时性约束



Source: Giphy
[https://giphy.com/gifs/FmNXeuoadNTpe]

Problem 所要解决的问题



EDGE
手机等终端设备

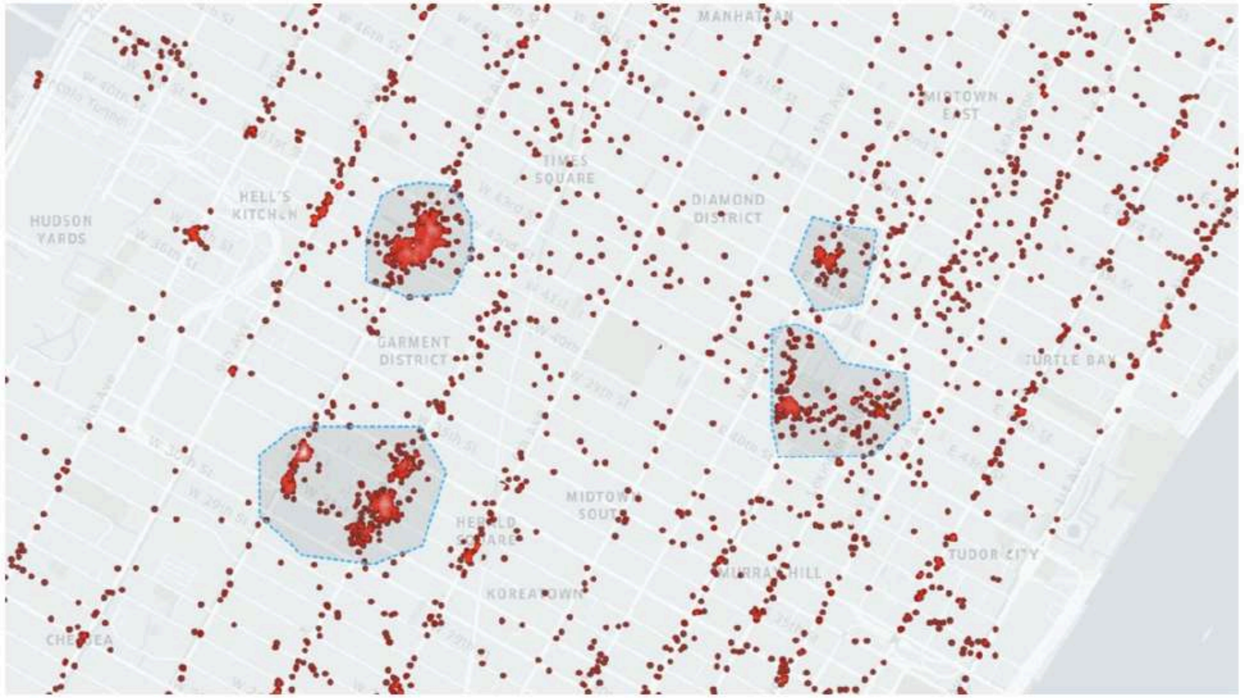
ZOOM IN
缩小问题空间

PATTERN MATCH
模式匹配（CEP）

OBSERVER
仪表盘或者Email报警

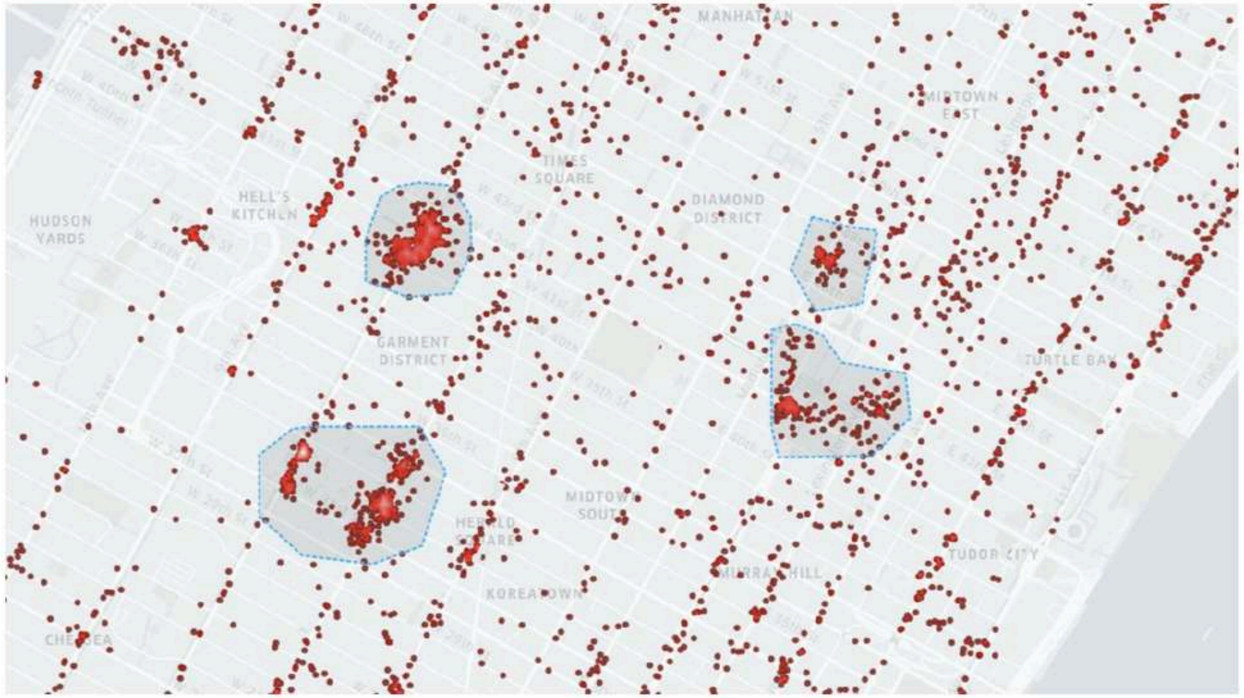
Detecting the Region 识别热点区域

- Similar Characteristics 相似的特性
- Connected Region 连通区域
- Arbitrary Shape 任意形状
- Cheap in Computation 计算代价低



Detecting the Region through clustering 通过聚类识别热点区域

- K-means ? K-均值
- Density-based clustering ? 基于密度的聚类



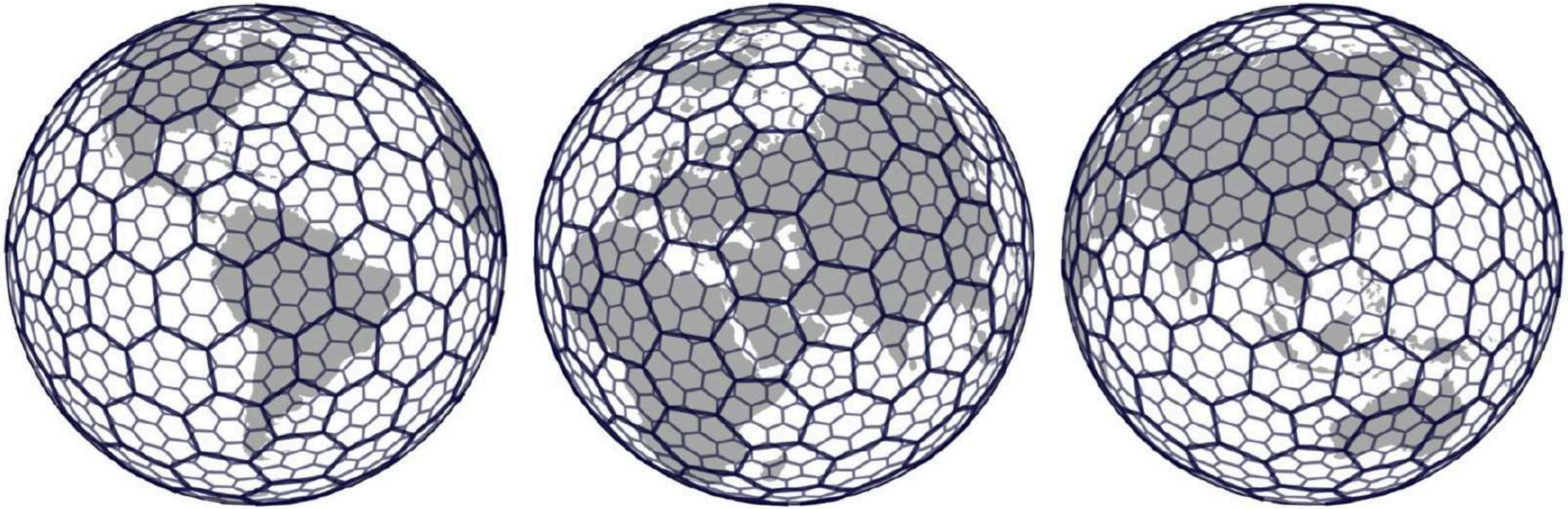
聚类算法的问题

- 不能实时处理
- 数据规模比较大时，计算代价也比较大

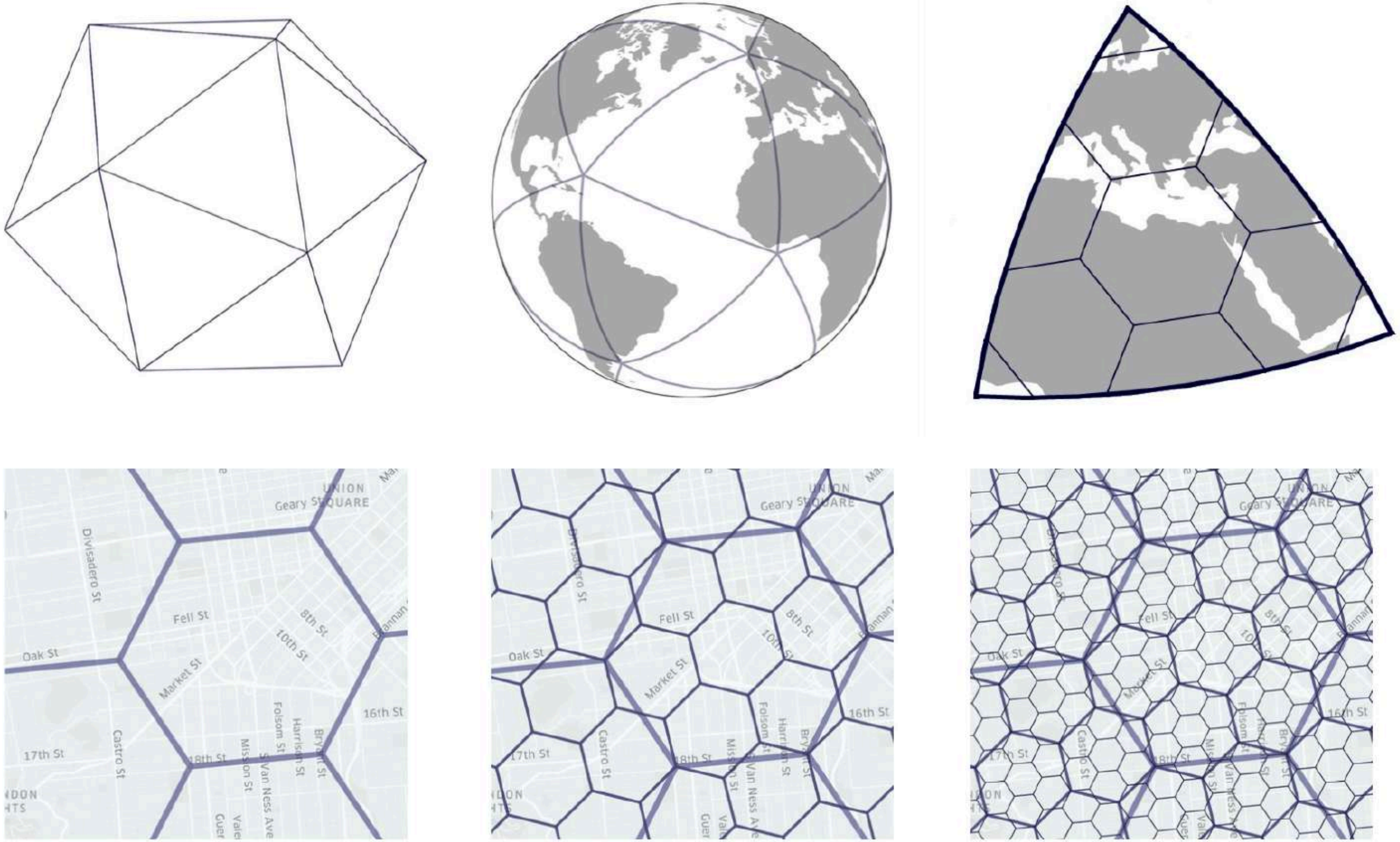
How can we do better ?

是否有其他解决方案?

H3 : Hexagonify the World !　将世界六边形化

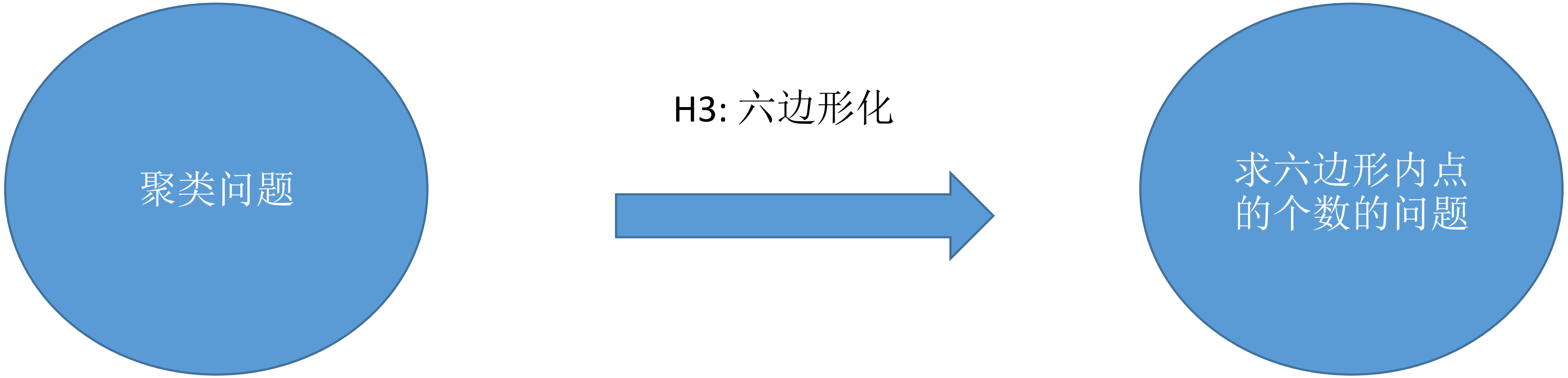


https://h3geo.org/#/



Credited to Nick Rabinowitz

检测热点区域



Low-Latency Clustering on Streams 流上的低延迟聚类

Junior, M.R., Souza, B.J., & Endler, M. (2019). DG2CEP: a near real-time on-line algorithm for detecting spatial clusters large data streams through complex event processing. *Journal of Internet Services and Applications, 10*, 1-28.

通过CEP进行空间聚类的一种近实时算法

Roriz Junior *et al. Journal of Internet Services and Applications* (2019) 10:8
https://doi.org/10.1186/s13174-019-0107-x

Journal of Internet Services and Applications

RESEARCH Open Access

DG2CEP: a near real-time on-line algorithm for detecting spatial clusters large data streams through complex event processing

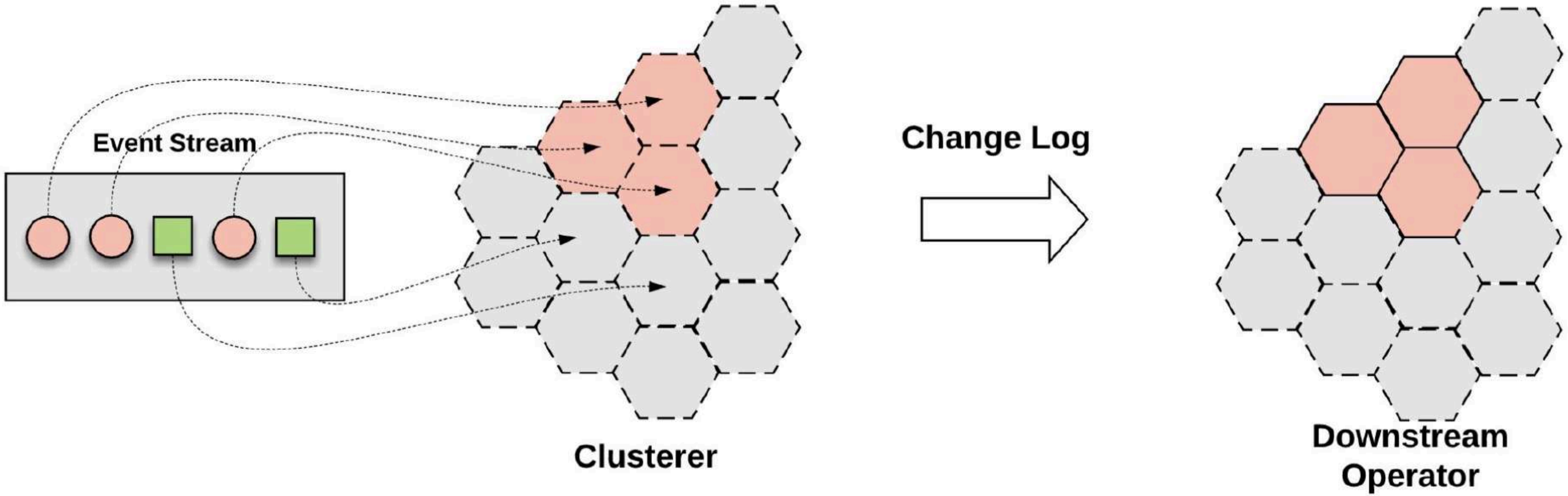
Marcos Roriz Junior[1,2*], Bruno Olivieri[2] and Markus Endler[2]

Abstract

Spatial concentrations (or spatial clusters) of moving objects, such as vehicles and humans, is a mobility pattern that is relevant to many applications. Fast detection of this pattern and its evolution, e.g., if the cluster is shrinking or growing, is useful in numerous scenarios, such as detecting the formation of traffic jams or detecting a fast dispersion of people in a music concert. On-Line detection of this pattern is a challenging task because it requires algorithms that are capable of continuously and efficiently processing the high volume of position updates in a timely manner. Currently, the majority of approaches for spatial cluster detection operate in batch mode, where moving objects location updates are recorded during time periods of a certain length and then batch-processed by an external routine, thus delaying the result of the cluster detection until the end of the time period. Further, they extensively use spatial data structures and operators, which can be troublesome to maintain or parallelize in on-line scenarios. To address these issues, in this paper we propose DG2CEP, a parallel algorithm that combines the well-known density-based clustering algorithm DBSCAN with the data stream processing paradigm Complex Event Processing (CEP) to achieve continuous and timely detection of spatial clusters. Our experiments with real-world data streams indicate that DG2CEP is able to detect the formation and dispersion of clusters with small latency while having higher similarity to DBSCAN than batch-based approaches.

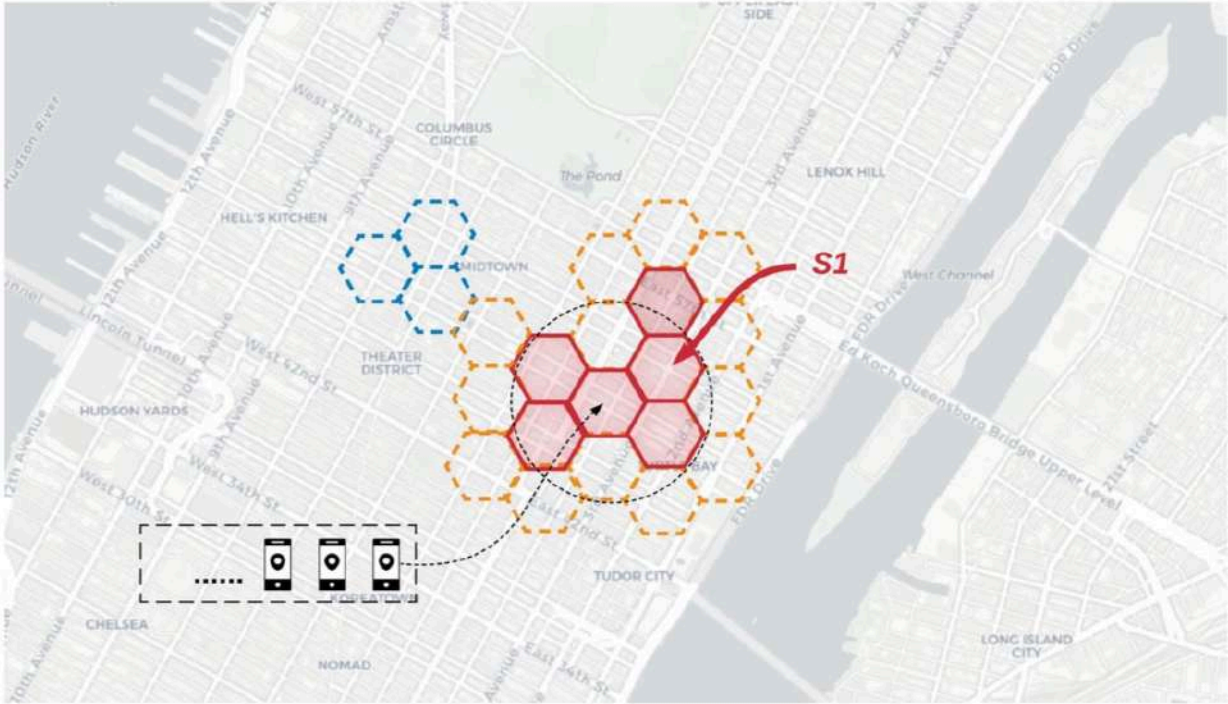
Keywords: Spatial stream clustering, On-line clustering, Real-time clustering, Mobility patterns, Complex event processing, Smart city

Low-Latency Clustering on Streams 流上的低延迟聚类



Clustering on streaming data 流式数据的聚类

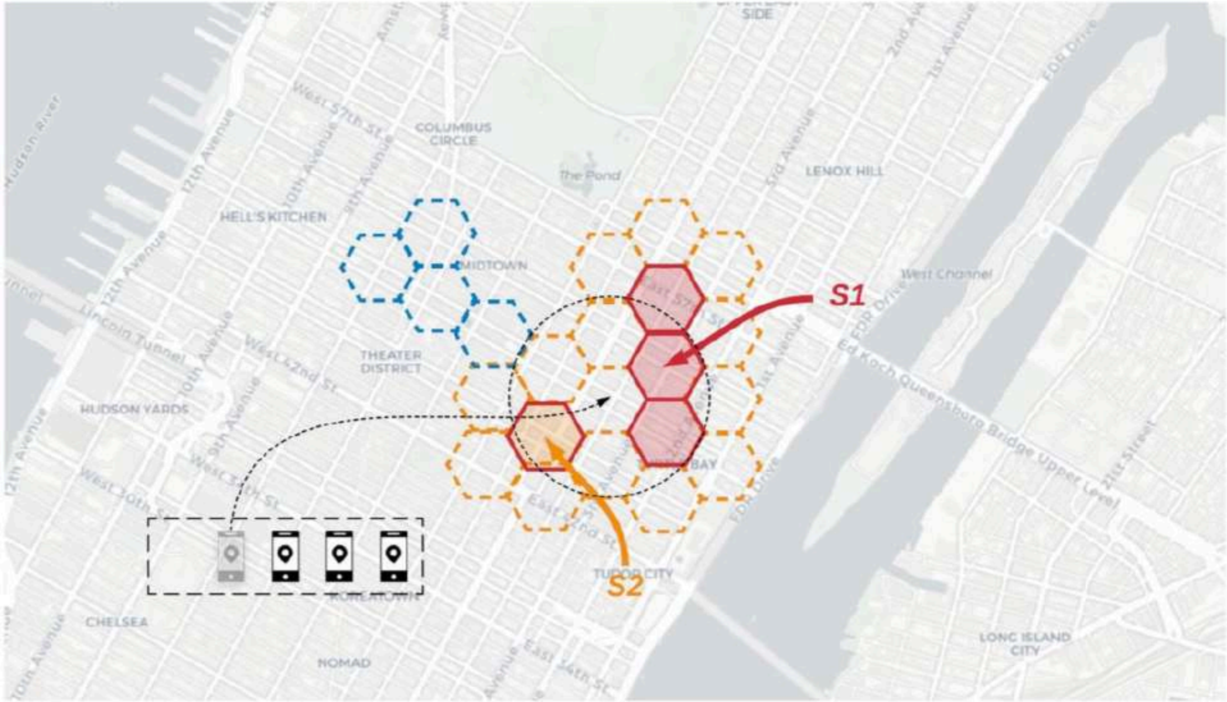
- Create 创建
- Update 更新
- Merge (expensive!) 合并



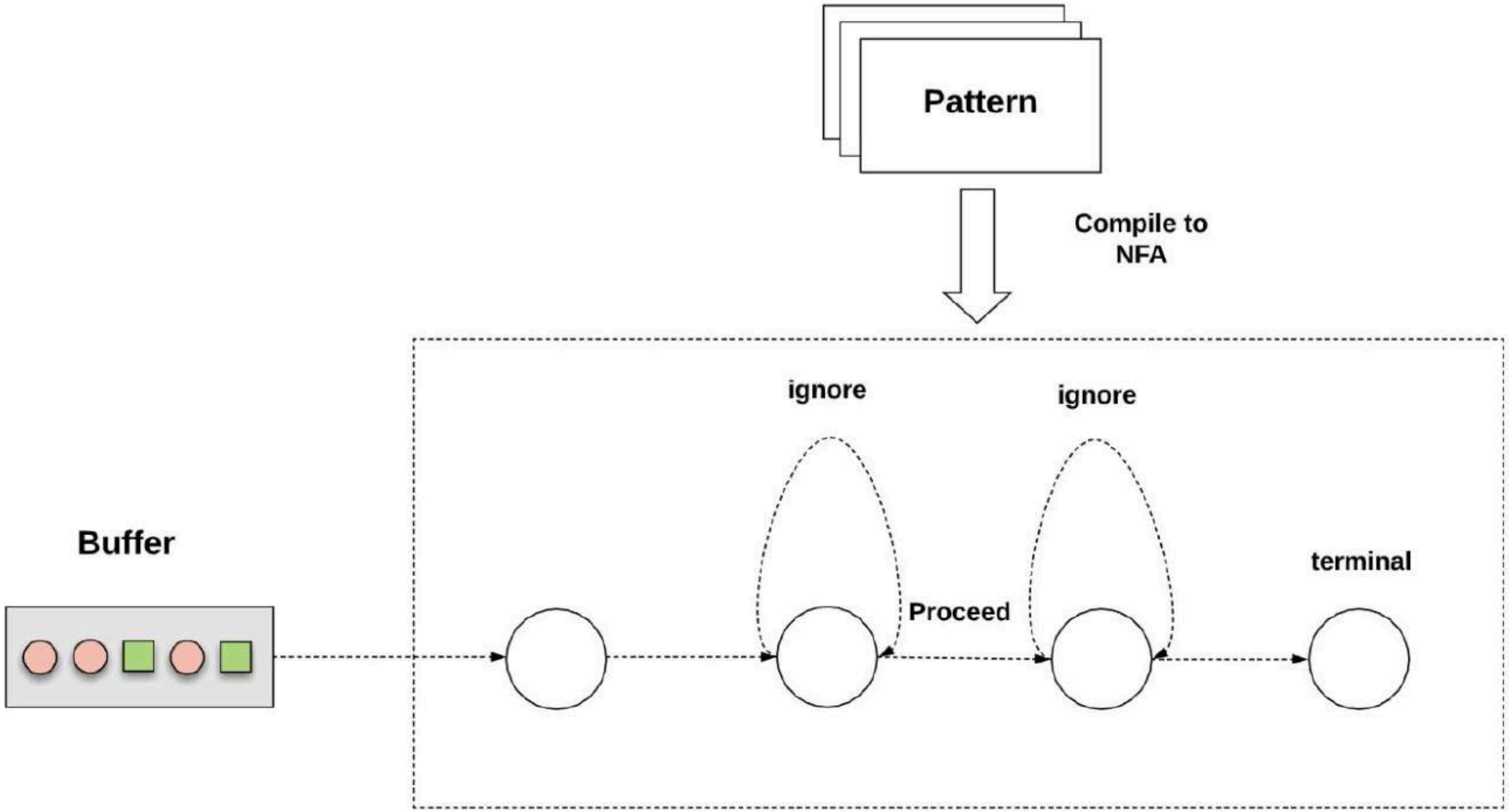
Clustering on streaming data

流式数据的聚类

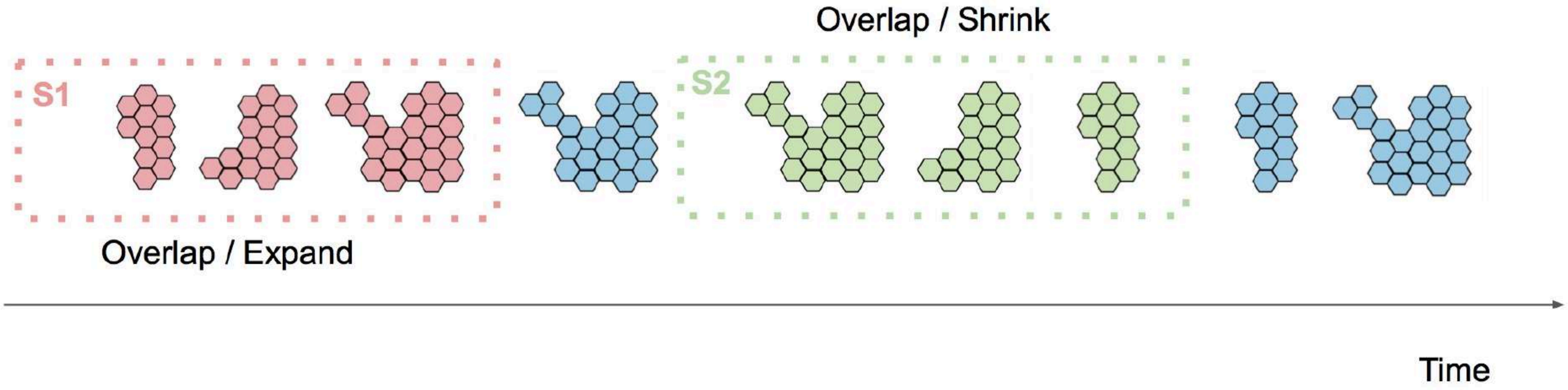
- Disperse 分散
- Split (expensive!) 切分



Complex Event Processing 复杂事件处理



CEP : Cluster as Primitive 复杂事件处理：聚类作为基本单元

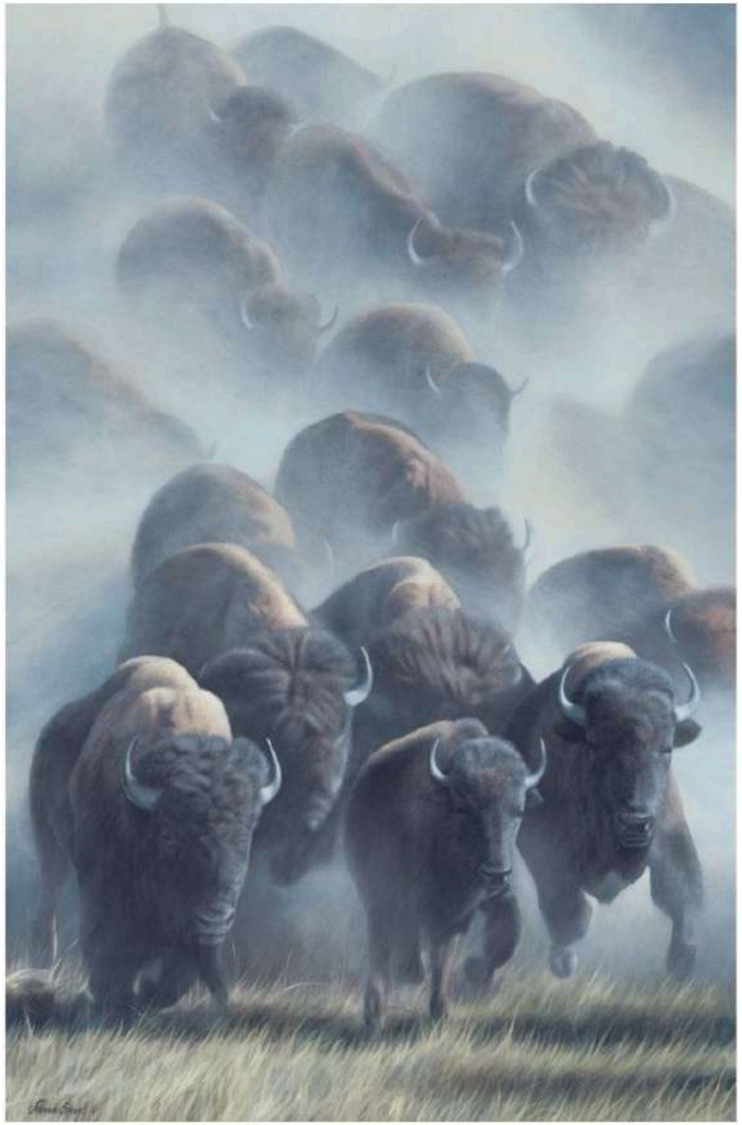


Tips, Tricks and Lessons learned

经验与教训

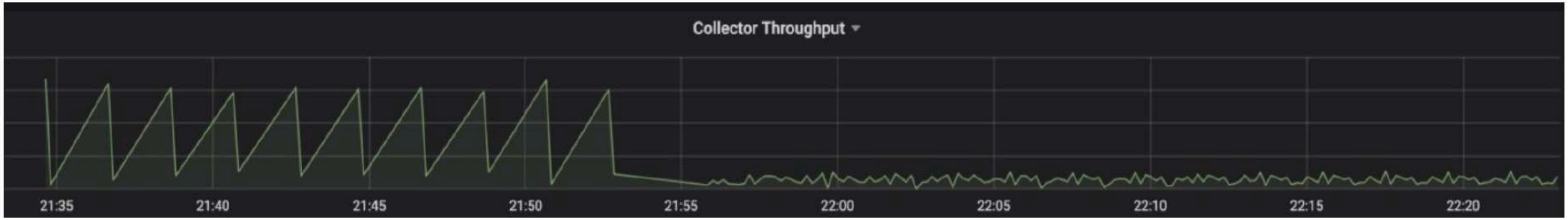
Staggering Window 交错窗口

- *Thundering Herd* Workload 惊群效应
- Low utilization of compute resource 计算资源利用率低
- Massive Fan-Out 大量的换出



Staggering Window 交错窗口

FLINK-12855



CEP使用过程中的常见问题

- 问题1：source并发为1的时候，有输出，source并发改大之后，没有输出

　常见原因：event time情况下，CEP依赖watermark触发，当有多个source节点时，如果某些source节点没有数据，watermark不增长，导致CEP规则不触发

- 问题2：测试数据中，明明有满足规则的事件，但是没有输出

　常见原因： event time情况下，迟到数据会被CEP节点丢弃，所以如果乱序比较严重，可能会导致大量迟到数据的产生，由于某些事件被当成迟到数据丢弃了，导致规则不触发

- 问题3: 规则不要太复杂

Thank you !

niel.hu@uber.com

https://www.linkedin.com/in/tenghu/