MSH

MySmartHome AG

Our Big Data Architecture | Adding value to IoT streaming data

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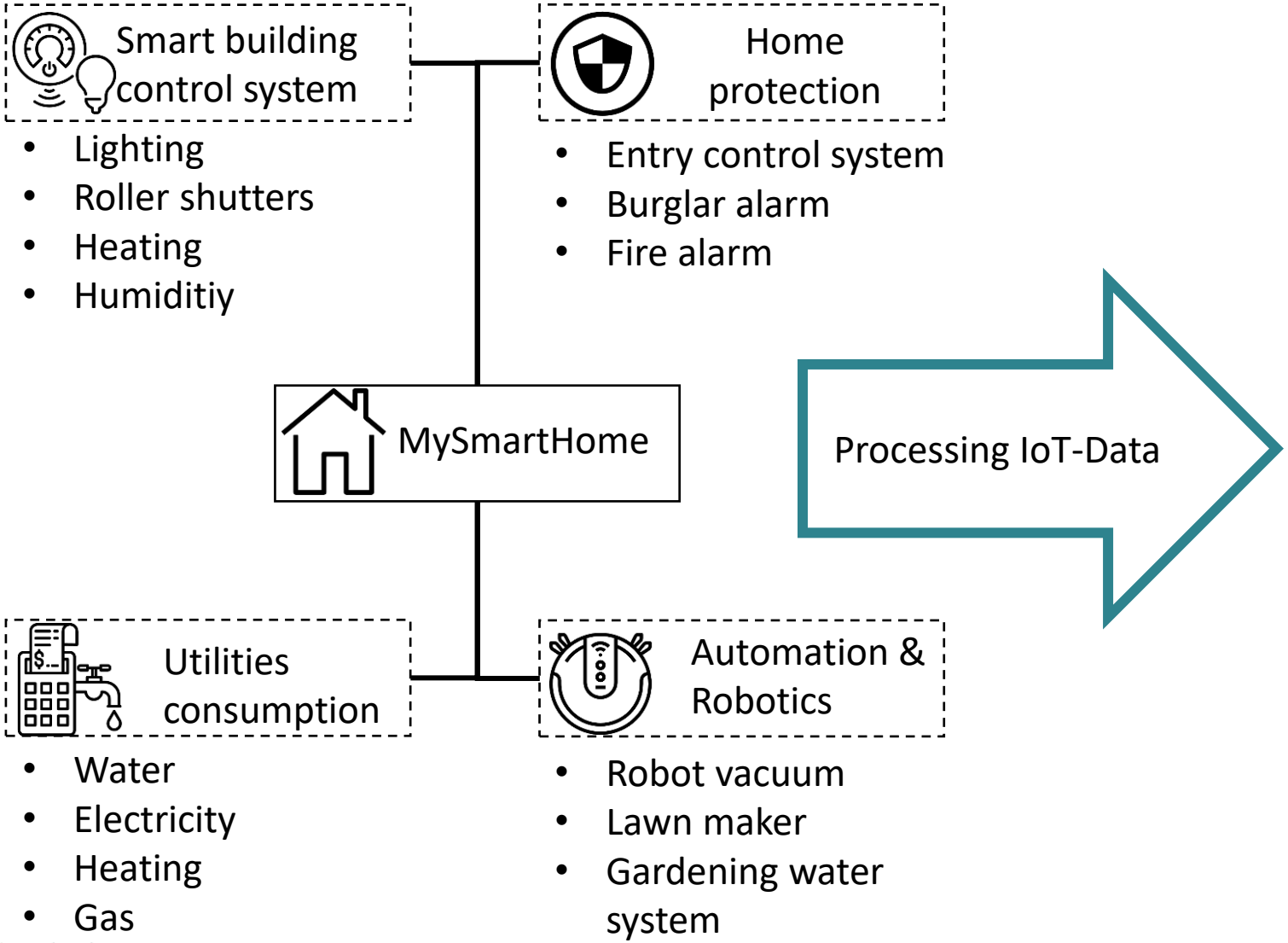
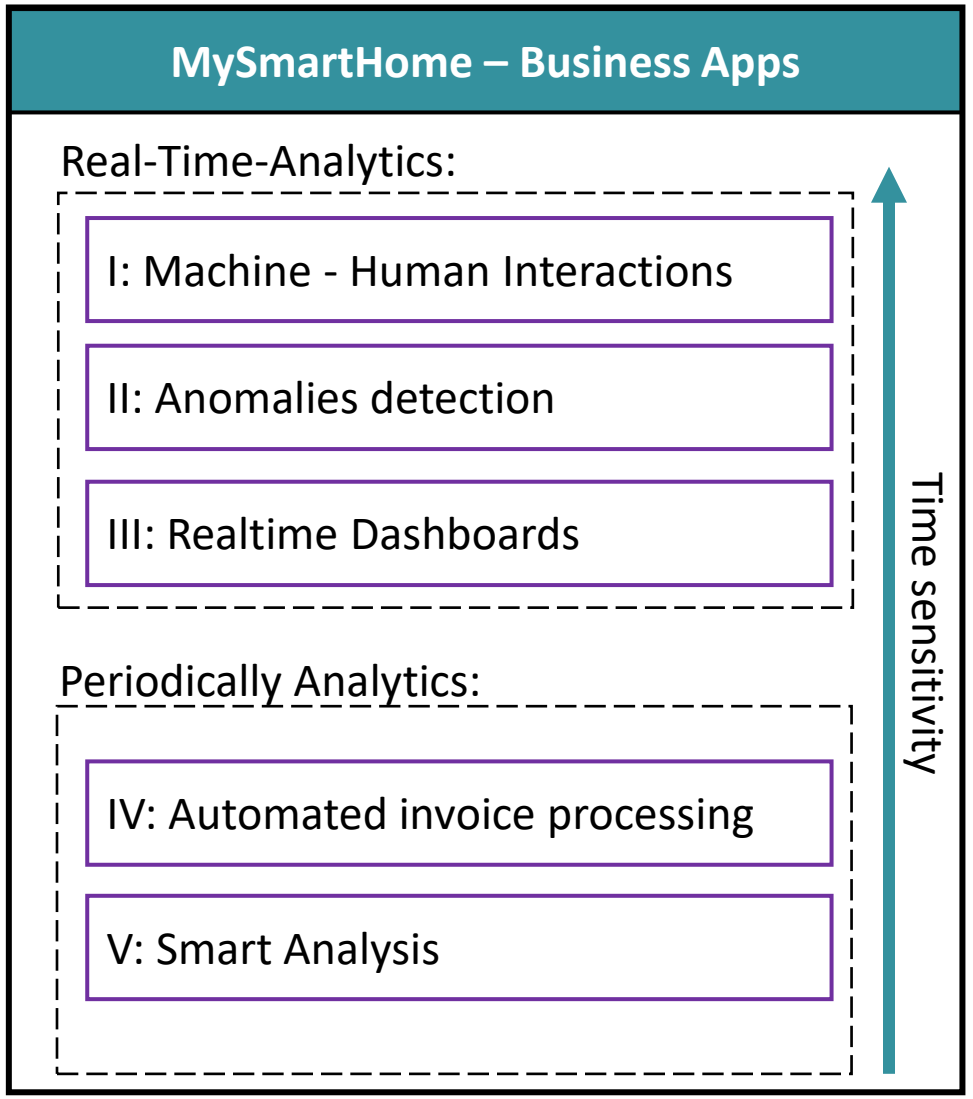
Agenda

1. Our Mission - How to add value to smart home IoT-data?
2. Core requirements of big data processing systems
3. Stream versus Batch processing of big data
4. MSH - Our big data architecture
5. Conclusion

Save peoples time by minimizing their manually daily chores by the means of IoT devices and big data technology.

Our Mission - How to add value to smart home IoT-data?





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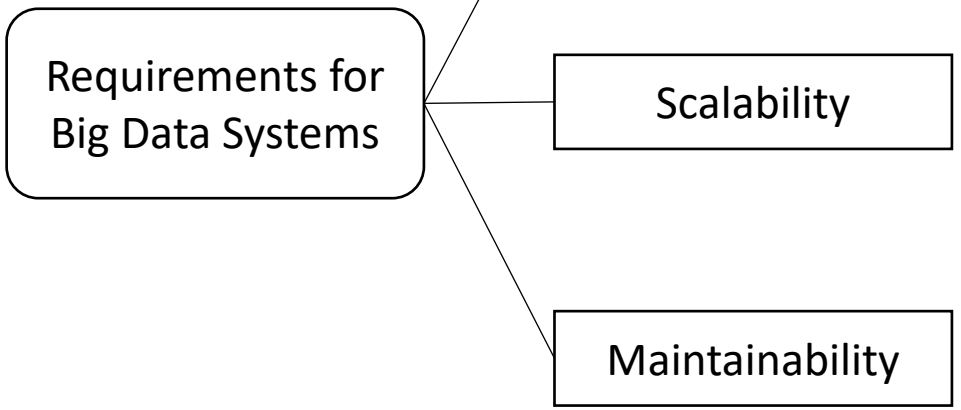
Core requirements of big data processing systems

Reliability, scalability and maintainability



- The System should perform the correct function at the desired level of performance by preventing faults (hardware, software or human errors) causing failures & downtimes
- How to add resources to cope with increasing data volume, traffic volume or complexity while keeping the performance?
- Maintain the functionalities in the most efficient way while being prepared for updates (operability, simplicity & evolvability).

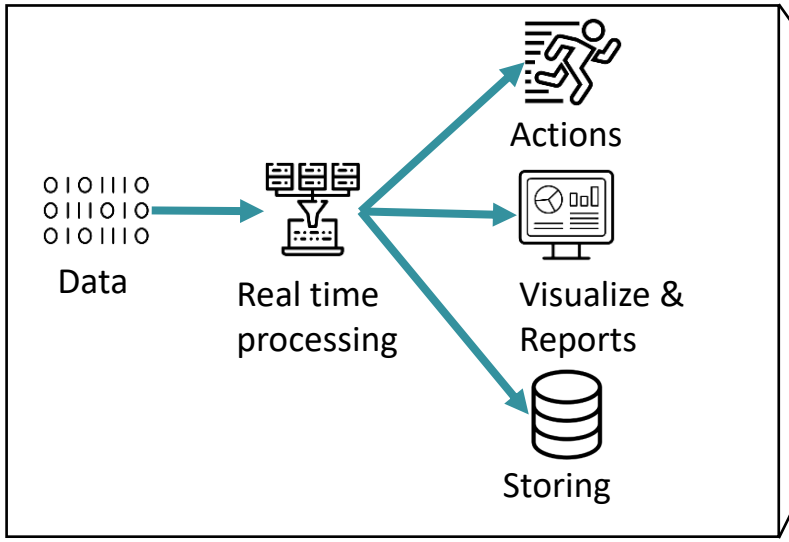
Focus on:

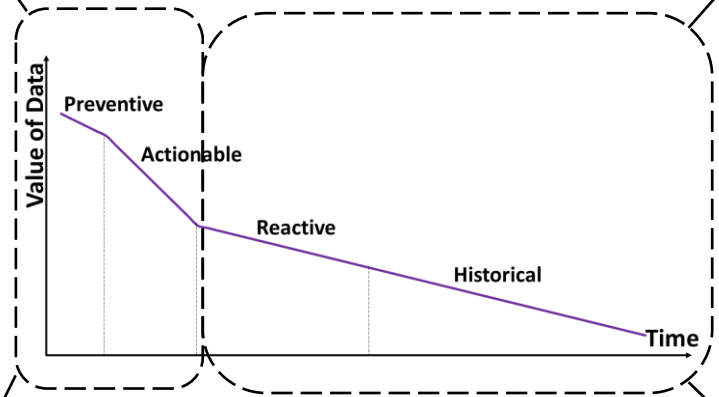
Optimized for availability, high throughput and low latency

See Kleppmann (2017), Marz (2015)

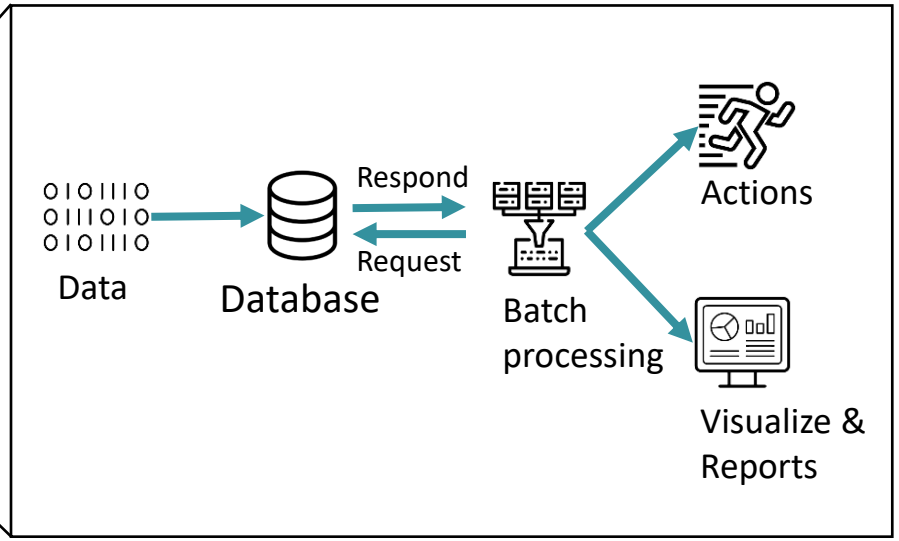
Stream versus Batch processing of big data

Stream processing:





Batch processing:



- Low latency
- Up to date data
- Expensive
- Higher complexity
- Normally less complex analysis

Use Cases:

- Machine - Human Interactions
- Anomalies detection
- Realtime Dashboards

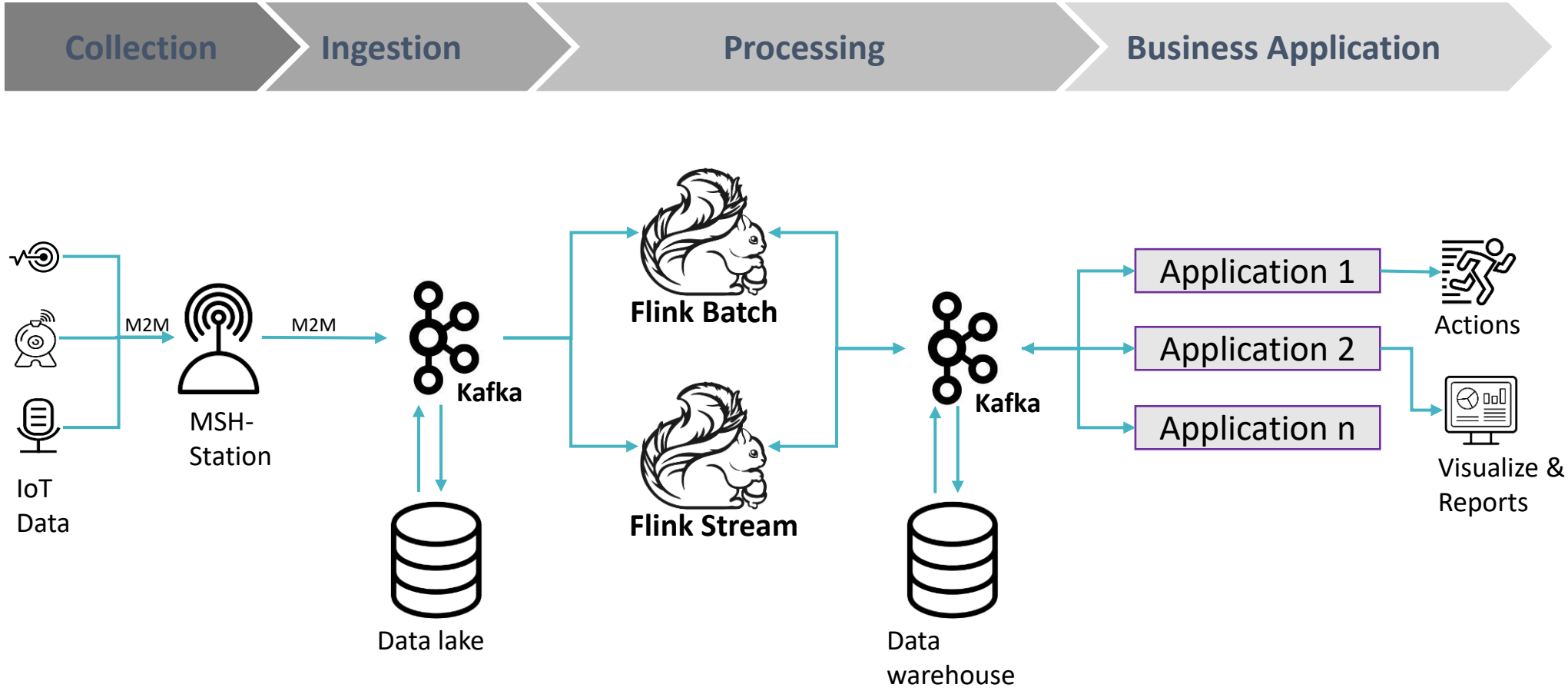
- Large batches of data
- Complex analytics & independency
- Efficient, cost effective
- High latency

Use Cases:

- Automated invoice processing
- Smart Analysis

See: Gualtiri (2016)

MSH - Our big data architecture



See Gupta (2020), Akanbi (2020), Nasiri (2019), Dendane (2019), Cheng (2018)

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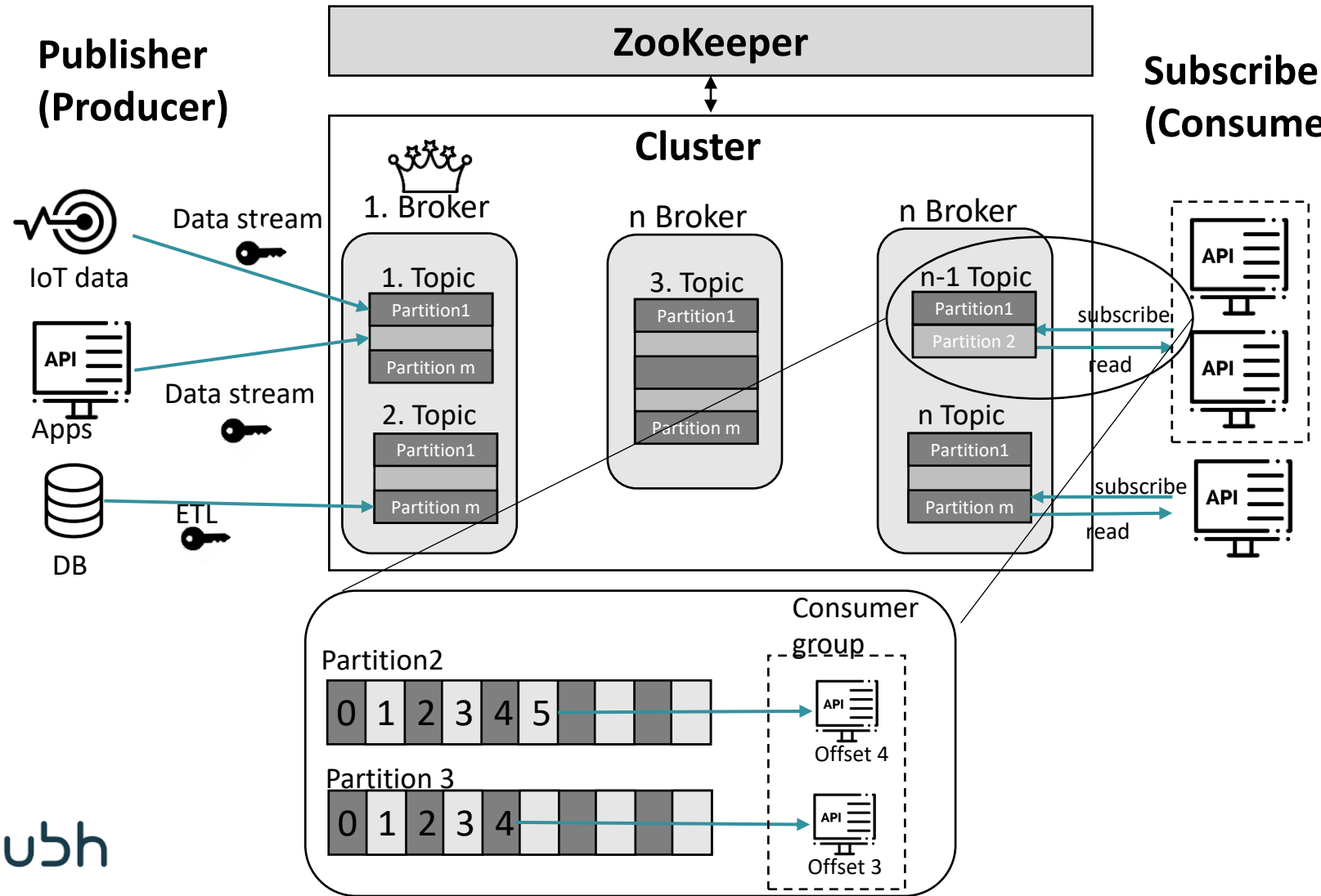
Kafka | Pub/Sub messaging system with distributed immutable commit log



Reliability guaranties:

- Guaranties the order in a partition
- At-least once messages guarantee

Scalability:

- Highly scalable (horizontal)

Maintainability:

- Highly configurable +retention
- Reduces integration complexity
- Fault tolerant
- Multiple producers/ consumers

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- ETL & Big Data ingestion
- High Throughput
- Fairly low latency

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- Training
- Not for real low latency

See Müller-Kett (2020); Finematics(2019)

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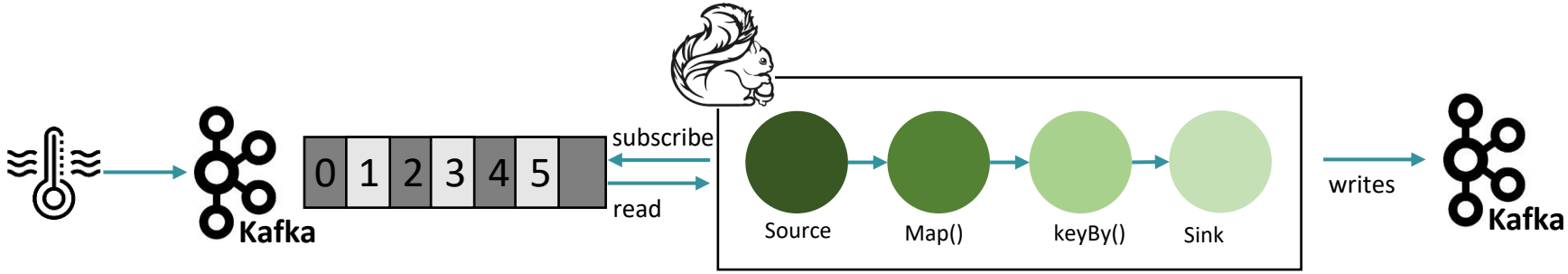
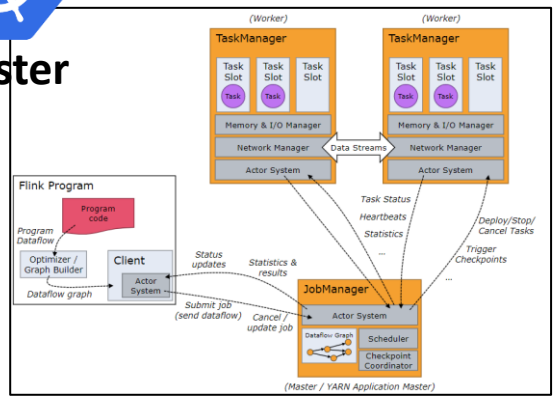
Flink | Distributed processing engine for stateful computations over (un-) & bounded data streams

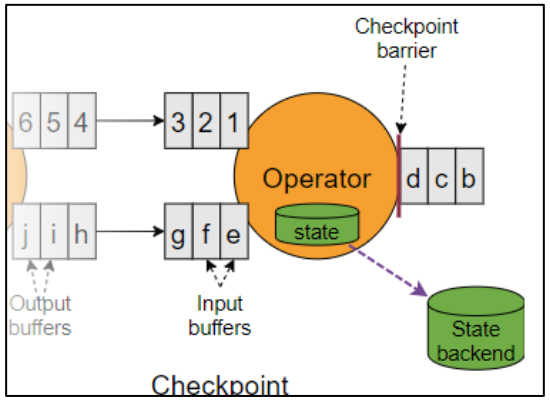


Cluster

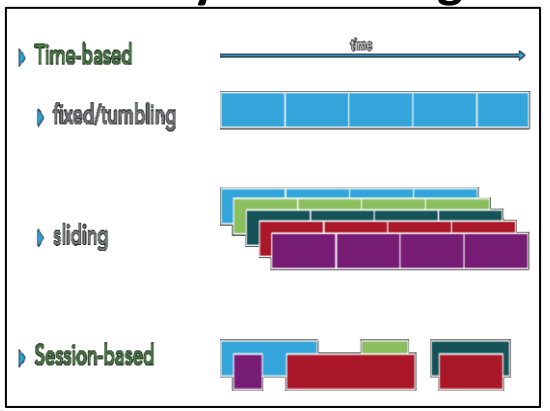
Distributed



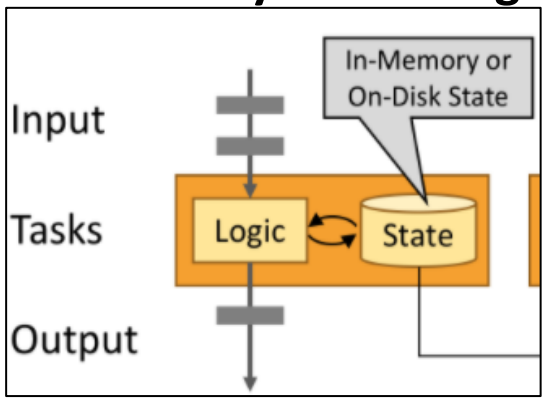
Stateful Processing



Timely Processing



In-Memory Processing



- Scalability:
  - Horizontal scaling
  - High throughput
- Reliability:
  - Exactly once guarantee
  - Fault tolerant
- Enabling stream processing
- Low latency

See Flink (1-3), Waski (2016), Sakr (2020)

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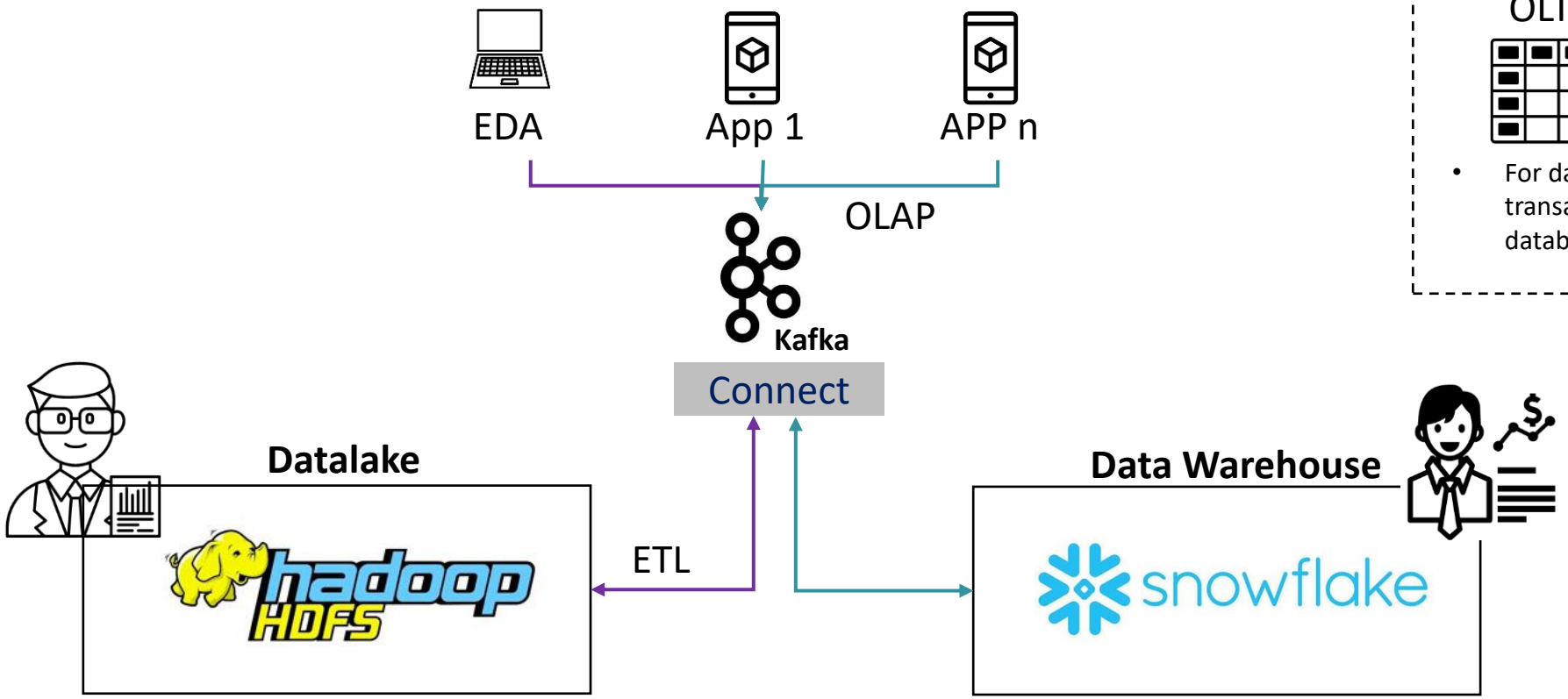
MSH - Our big data architecture

Data storage & business aplication layer



OLTP Vs. **OLAP**

- For daily business transaction in databases

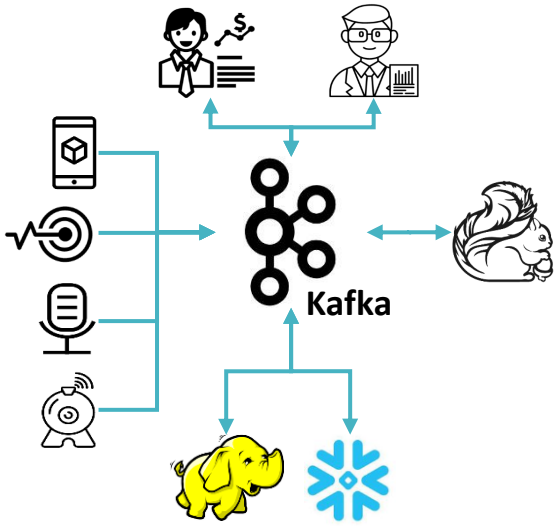
- Enables complicated analysis of multidimensional data in DWH
- New view of looking at data
- Supports filtering & sorting of data

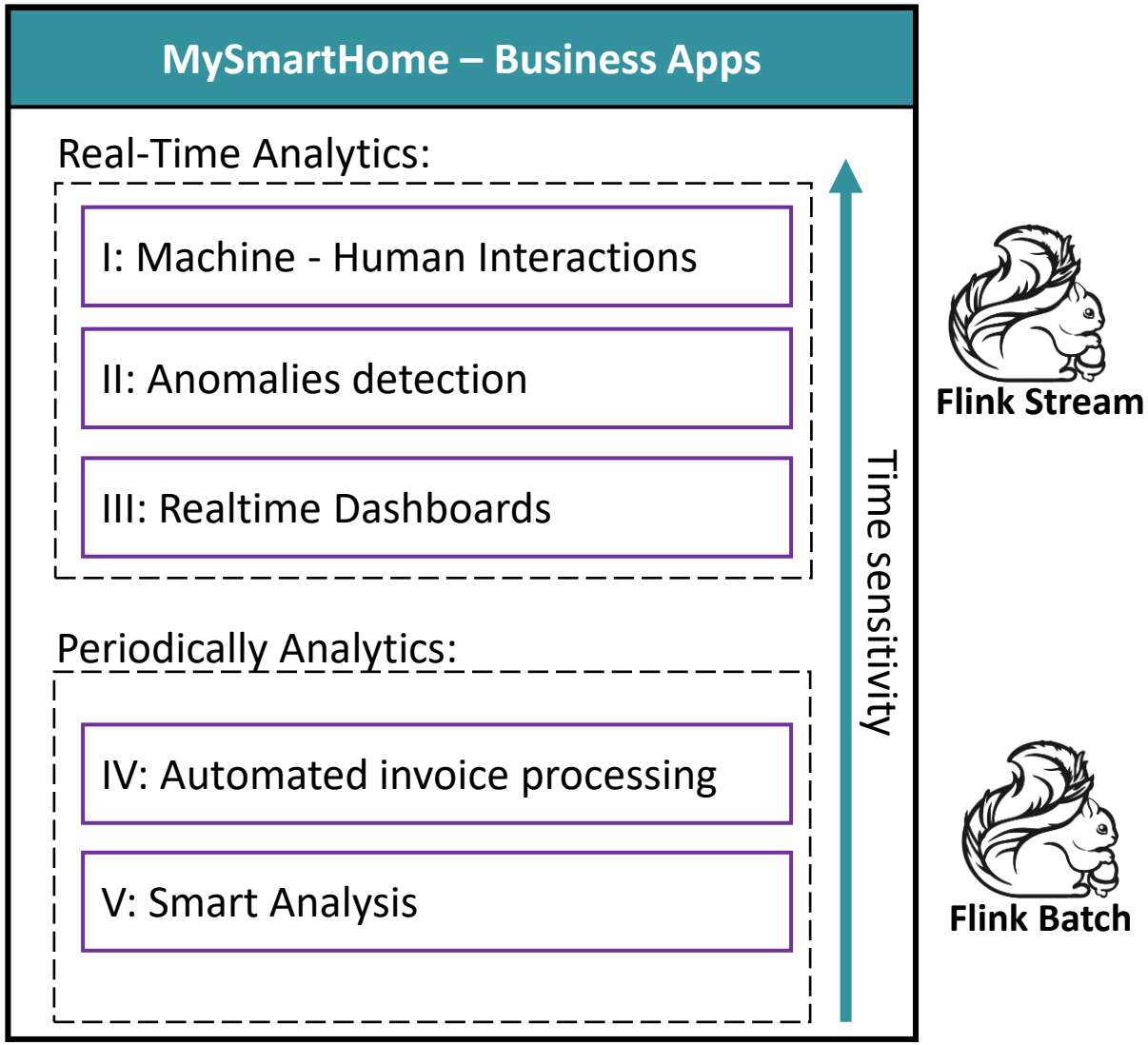
EDA: Explorative Data Analysis

See Kidd (2020); Patil (2018), Chaudhuri (n.a.)

Conclusion

- Reliable, maintainable and scalable real time streaming pipeline
  - Kafka as our data backbone enabling multi data ingestion & low latency connectivity
  - Real time analysis
- Next generation cloud data warehouse





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