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Identifying the Challenges in Reducing Latency in GSN using Predictors

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WowKiVS - March 6th 2009

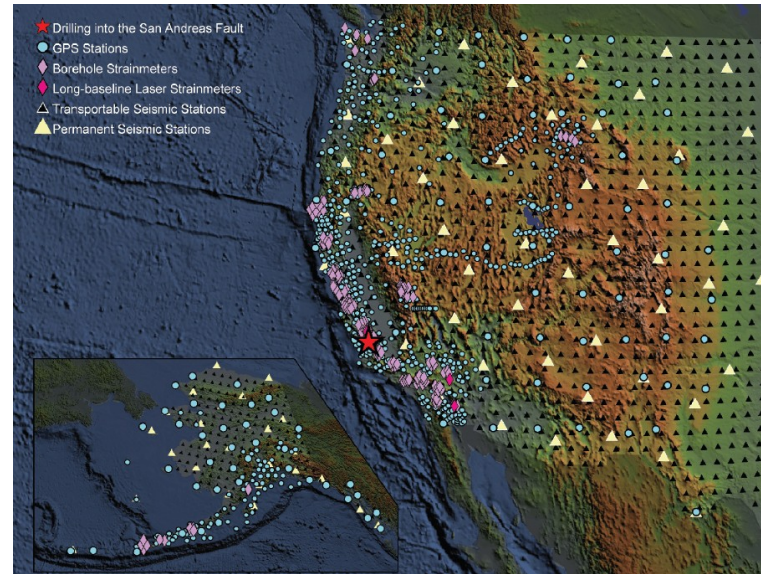
Outline

- Motivation
- System Description
- Predictors
- Challenges
- Summary



Motivation

- Simulations depend on **accurate and timely** sensor information
 - Weather Monitoring
 - Early detection of hurricanes
 - **Seismic Monitoring**
 - Volcanic Eruptions
 - Earthquakes
 - Traffic Monitoring
 - Supply Chain Management
- Global Sensor Networks produce a **huge amount of data**
 - **In-network processing** and **filtering** reduce data, but also incur additional **latency overhead**

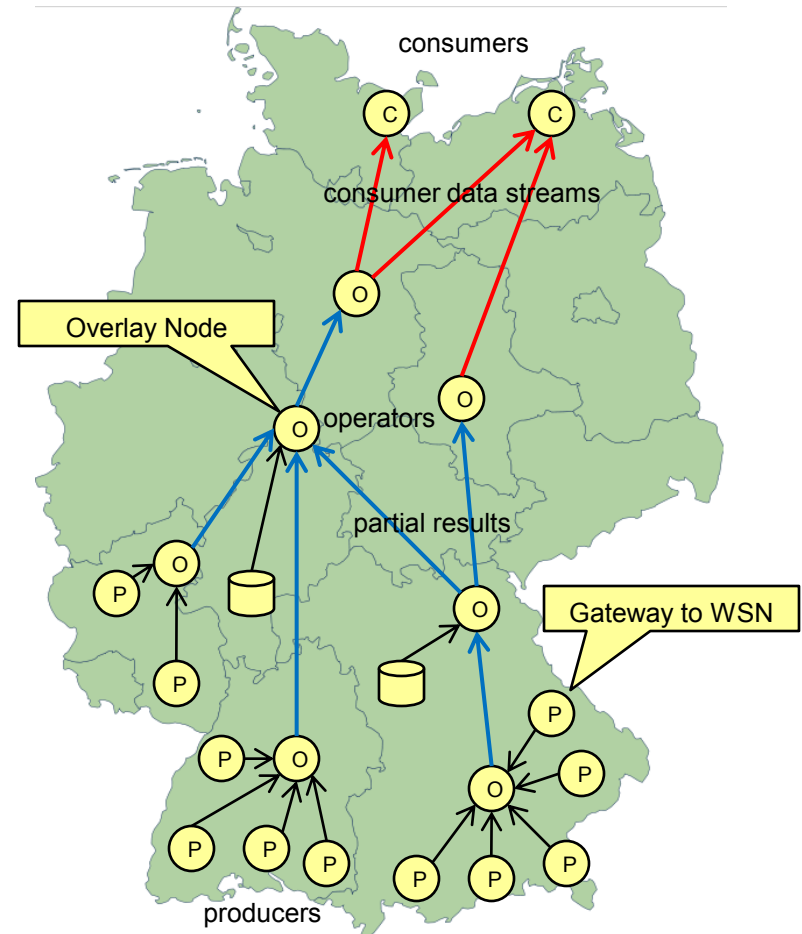


www.earthscope.org Source: Matt Welsh



Distributed Stream Processing

- Sensors produce **data streams**
- Applications pose queries as **extended SQL** statements
- Approach
 - **Decompose** each query to allow partial results
 - **Distribute** query in network
 - Results in **overlay network** formed by logical point-to-point connections
- Challenges
 - Highly **bursty traffic**
 - Placement of operators to achieve **low latency**



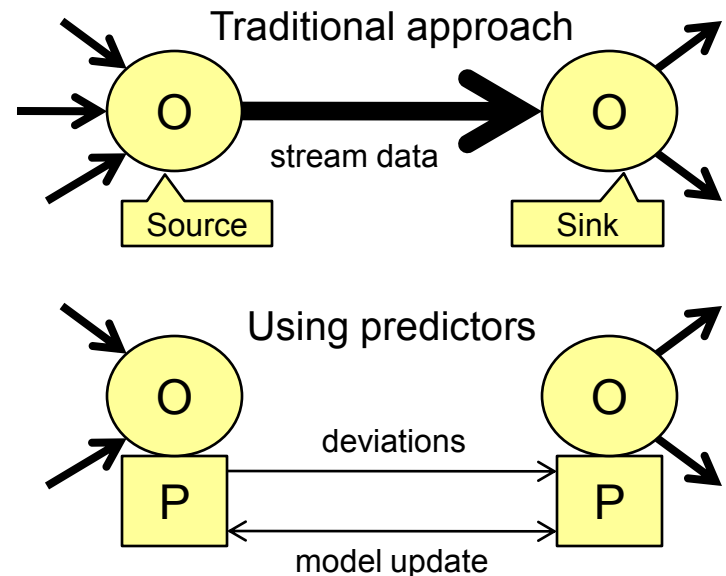
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 - Working Principle
 - Classification of Predictors
- Challenges
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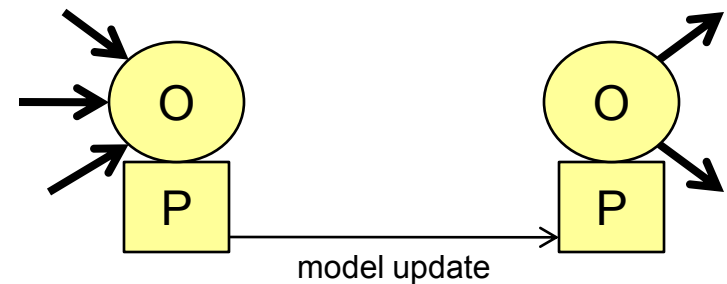
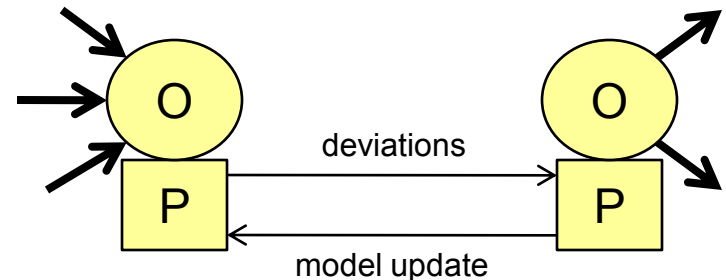
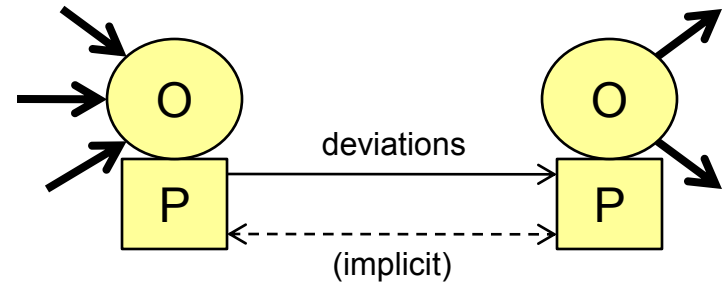
Working Principle

- Future measurements can be estimated from preceding ones
- Nodes in GSN negotiate on **value predictors**
 - Nodes exploit **local knowledge** to create predictors or
 - **Application pushes** predictors into GSN
- If a predictor is running, updates are only sent on deviation
 - Reduction of **bandwidth** usage
- Current value can be **instantly estimated on sink**
 - Reduction of **latency**



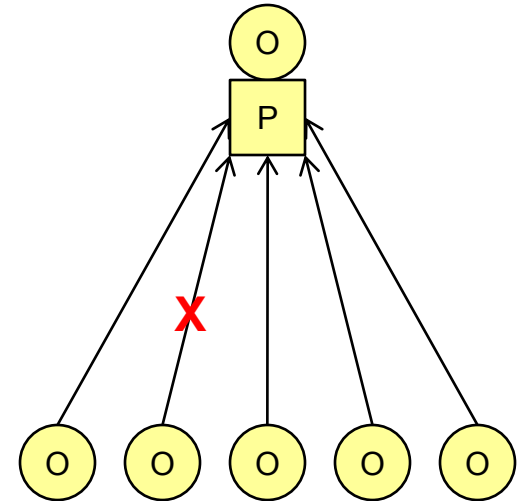
Temporal Predictors

- Synchronous
 - Next sensor reading is predicted using the **same model** on source and sink
- Asynchronous
 - Prediction model is **generated on the sink** and **sent to source** where it is validated
 - Prediction model is derived on source and **only model update** is sent to sink



Spatial Predictors

- Basic approach in WSN: Query only sensors that **most increase confidence** in currently modeled world
 - Application specifies **confidence threshold**
- Exploit **correlation** between sensors
 - **Different sensors** (on the same node)
 - E.g. temperature readings and battery voltage
 - Proximate sensors of the **same type**
- **Reduced number** of actual sensor readings required
 - No need to wait for all nodes' results
 - **Improved latency**



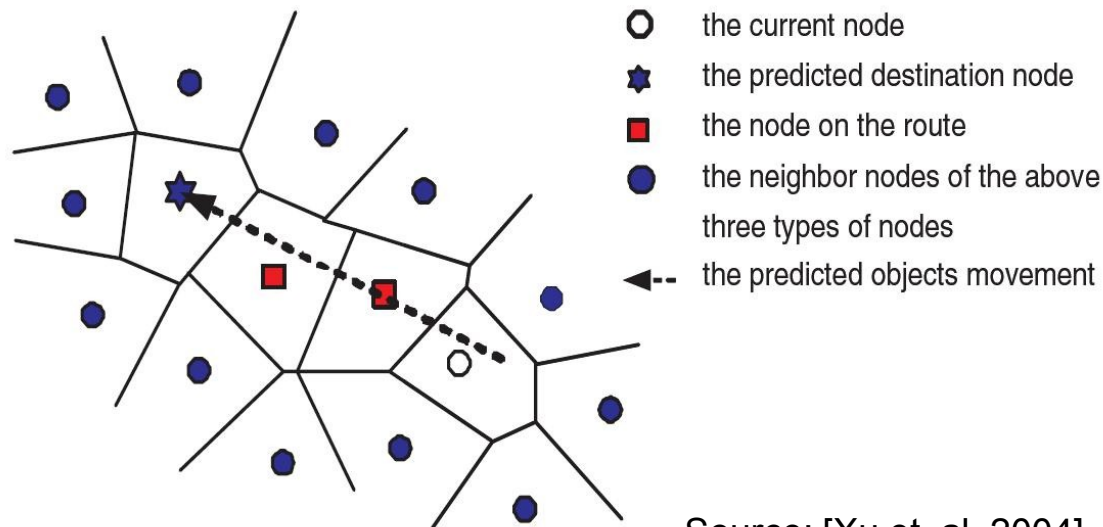
Spatio-Temporal Predictors

- Exploit knowledge about **stream phenomena** of air or water
 - E.g. stream of warm air leads to rising temperatures
- Employ MPEG motion **pattern predictors**
 - Treat sensors as **pixels of an image**
 - Value patterns represent **video**
 - Derive **value predictor** for single pixel and **push** it to the corresponding sensor node



Location Predictors

- Main use in **Object Tracking** Sensor Networks
- Dual predictor moves with the object
- Usage of behavior profiles / movement patterns to improve predictions



Source: [Xu et. al. 2004]



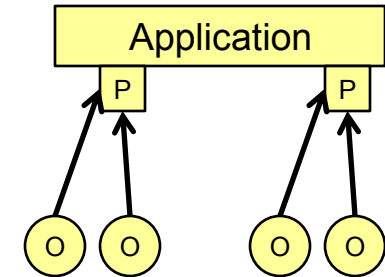
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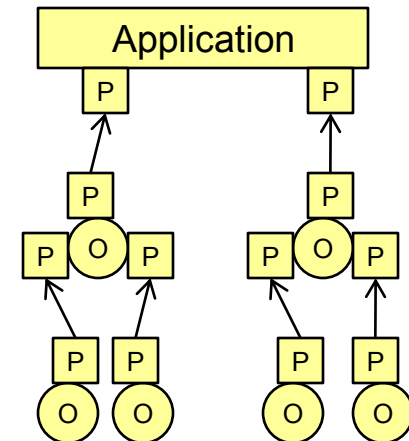


Placement

- Predictors close to the **application**
 - Improved **latency** due to direct connection
 - Data of **all relevant sensors** is available



- Predictors close to the **sensors**
 - **Bandwidth** reduction with temporal predictors
 - Data required by aggregating operators **multi-hop predictor**



- Transition from / to WSN via **gateways**
 - **Heterogeneous architecture** and optimizations inside WSN



Distributed Stream Processing

- Window operators
 - **Materialize stream** for join and aggregate operations
 - Join temperature and humidity measurements to single stream
 - Average temperature over last 10 measurements or last 5 minutes
 - **Semantics** of tuple-based window operators **changes** with predictors since number of tuples is not preserved
 - Conversion to **time-based windows required**
- Discrete events
 - **Continuous occurrence rate** can be predicted but no common models for the **time of the next event**



Application Interaction

- Applications have different **quality of data / service** requirements
 - **Transparent re-usage** of data streams requires adjustment
 - **Tradeoff** precision vs. latency
- Predictors can be used for intelligent **load shedding**
 - **Link overload**: Coarser update threshold can reduce data
 - **Node overload**: Switch to simpler predictor model
- Supplying **application knowledge** also requires **unified interface**
 - Movement patterns for objects
 - **Correlations** between sensors
 - Expected and historical **measurement patterns**



Conclusion & Future Work

- Conclusions
 - Predictors can also be used in DSPS
 - In-time approximate query results
 - Reduction of data rates for load shedding
 - Predictors need a transparent unified interface
 - Application on arbitrary data links
 - Combination with arbitrary operators
- Future work
 - Additional application knowledge required to improve predictors
 - QoD/QoS restrictions, movement patterns, correlations, ...
 - Find and adapt existing data streams for re-usage



Questions?

Thank you for your attention!

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