Data-Driven Processing In Sensor Networks

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What is a sensor network?

- Tiny, untethered nodes with severe resource constraints
  - Sensors, e.g., light, moisture, ...
  - Tiny CPU and memory
  - Battery power
  - Limited-range radio communication
    - Usually dominates energy consumption
- Nodes form a multi-hop network rooted at a base station
  - Base station has plentiful resources and is typically tethered or at least solar-powered

Sensor network applications

- Medical
- Environmental
  [Mainwaring et al., WSNA 2002]
- Urban
  [Hu et al., SenSys 2006]

What do ecologists want?

- Collect all data (to within some precision)
  - Continuous “SELECT *”: the most boring SQL query
- Fit stochastic models using data collected
  - Cannot be expressed as SQL queries

- Sorry—this talk doesn’t cover any of our favorite SQL queries (selection, join, aggregation…)

Duke Forest deployment

- Use wireless sensor networks to study how environment affects tree growth in Duke forest
  - Collaboration with Jim Clark (ecology) et al. since 2006

Model-driven data collection: pull

- Exploit correlation in sensor data
  - Representative: BBQ
    [Deshpande et al., VLDB 2004]

  Model $p(X_1, X_2, …)$
  - Base station
  - Confidence interval not tight enough?
  - Confidence interval tightened
  - Additional observations: $X_3 = x_3$

Answer correctness depends on model correctness
Risk missing the unexpected
Data-driven philosophy

- Models don’t substitute for actual readings
  - Correctness of “SELECT *” should not depend on correctness of models
  - Particularly when we are still learning about the physical process being monitored
- Models can still be used to optimize “SELECT *”

Data-driven: push

- Exploit correlation in data + put smarts in network
  - Representatives: Ken Chu et al., ICDE 2006, Conch [Silberstein et al., ICDE 2006, SIGMOD 2006]

Temporal suppression example

- Suppress transmission if |current reading – last transmitted reading| ≤ \( \varepsilon \)
  - Model: \( X^t = x^{t-1} \)
- Effective when readings change slowly
- What about large-scale changes?

Spatial suppression example

- “Leader” nodes report for cluster
  - Others suppress if |my reading – leader’s reading| ≤ \( \varepsilon \)
  - Model: \( X^t_{\text{rep}} = x^t_{\text{leader}} \)
- Effective when nearby readings are similar

Combining spatial and temporal

Spatiotemporal suppression condition = ?

- Temporal AND spatial?
  - I.e., suppress if both suppression conditions are met
  - Results in less suppression than either!
- Temporal OR spatial?
  - I.e., suppress if either suppression condition is met
  - Base station cannot decide whether to set suppressed value to the previous value (temporal) or to the nearby value (spatial)!

Outline

- How to combine temporal and spatial suppressions effectively
  - Conch [Silberstein et al., SIGMOD 2006]
- What to do about ______ — the dirty little secret of suppression
  - BaySail [Silberstein et al., VLDB 2007]
Conch = constraint chaining

Temporally monitor spatial constraints (edges)
- $x_i$ and $x_j$ change in similar ways $\Rightarrow$ temporally monitor edge difference $(x_i - x_j)$
- “Difference” can be generalized
- One node is reporter and the other updater
  - Reporter tracks $(x_i - x_j)$ and transmits it to base station if its value changes
  - Updater transmits its value updates to reporter
    - i.e., temporally monitor remote input to the spatial constraint

Recovering readings in Conch

- Base station “chains” monitored edges to recover readings
- Discretize values to avoid error stacking
  - $[k\epsilon, k\epsilon + \epsilon) \rightarrow k$
  - Monitor discretized values exactly
    - Discretization is the only source of error
    - No error introduced by suppression

Conch example

- A spanning forest is necessary and sufficient to recover all readings
  - Each edge is a temporally monitored spatial constraint
  - Each tree root is temporally monitored
  - Start of chain
    - (For better reliability, more edges can be monitored at extra cost)
- Some intuition
  - Choose edges between correlated nodes
  - Do not connect erratic nodes
    - Monitor them as singleton trees in the forest

Cost-based forest construction

- Observe
  - In pilot phase, use any spanning forest to collect data
    - Even a poor spanning forest correctly collects all data
- Optimize
  - Use collected data to assign monitoring costs
    - # of rounds in which monitored value changes
  - Build a min-cost spanning forest (e.g., Prim’s)
- Re-optimize as needed
  - When actual costs differ significantly from those used by optimization

Wavefront experiment

- Simulate periodic vertical wavefronts moving across field, where sensors are randomly placed at grid points
  - Conch beats both pure temporal and pure spatial
  - Communication tree is a poor choice for monitoring; optimization makes a huge difference
Conch discussion

- Key ideas in **Conch**
  - Temporally monitor spatial constraints
  - Monitor locally—with cheap two-node spatial models
  - Infer globally—through chaining
  - Push/suppress not only between nodes and base station, but also among nodes themselves
  - Observe and optimize
- Vision for ideal suppression
  - Number of reports $\propto$ description complexity of phenomenon

**What's the catch?**

Outline

- How to combine temporal and spatial suppressions effectively
  - **Conch** [Silberstein et al., SIGMOD 2006]
- What to do about **failures**—the dirty little secret of suppression
  - **BaySail** [Silberstein et al., VLDB 2007]

Failure and suppression

- Message failure common in sensor networks
  - Interference, obstacles, congestion, etc.

- Is a non-report due to suppression or failure?
  - Without additional information/assumption, base station has to treat every non-report as plain “missing”—no accuracy bounds!

A few previous approaches

- Avoid missing data: ACK/Retransmit
  - Often supported by the communication layer
  - Still no guaranteed delivery $\rightarrow$ does not help with resolving ambiguity
- Deal with missing data
  - Interpolation
    - Point estimates are often wrong or misleading
    - Uncertainty is lost—important in subsequent analysis/action
  - Use a model to predict missing data
    - Can provide distributions instead of point estimates
    - But we have to trust the model!

BayBase: basic Bayesian approach

- Model $p(X | \Theta)$ with parameters $\Theta$
  - Do not assume $\Theta$ is known
  - Any prior knowledge can be captured by $p(\Theta)$
- $x_{obs}$: data received by base station
- Calculate posterior $p(X_{miss}, \Theta | x_{obs})$
  - Joint distribution instead of point estimates
  - Quantifies uncertainty in model; model can be improved

- Problem: non-reports are treated as generically missing
  - But most of them are “engineered”
  - Non-report $\neq$ no information!

BaySail

Bayesian Analysis of **Suppression and Failure**

- Bayesian, data-driven
- Add back some redundancy
- Infer with redundancy and knowledge of suppression scheme
Suppression-aware inference

- Temporal suppression with $\epsilon = 0.3$, prediction = last reported
- Actual: $(x_1, x_2, x_3, x_4) = (2.5, 3.5, 3.7, 2.7)$
- Base station receives: $(2.5, 3.5, 3.7, 2.7)$
- With Temporals ($r = 1$)
  - $x_1, x_2, x_3, x_4 > 0.3$
  - $|x_2 - x_3| > 0.3$
- With Timestamps + Direction Bits ($r = 1$)
  - $x_1, x_2, x_3, x_4 > 0.3$
  - $|x_2 - x_3| > 0.3$
- With Counter
  - One suppression and one failure in $x_4$ and $x_5$, not sure which
  - A very hairy constraint!

- Posterior: $p(x_{\text{mis}}, \Theta | x_{\text{obs}})$, with $x_{\text{mis}}$ subject to constraints

Inference

- Arbitrary distributions & constraints: difficult in general
  - Monte Carlo methods generally needed
  - Various optimizations apply under different conditions
    - A simplified soil moisture model: $y_{\text{mis}} = \zeta + \phi y_{x_{\text{mis}}} + \epsilon_{x_{\text{mis}}}$
    - $\zeta$ is a series of known precipitation amounts
    - $\zeta$ is a set of known precipitation amounts
    - $\phi \in (0, 1)$ controls how fast moisture escapes soil
    - $r$ controls the strength of the spatial correlation over distance
  - Given $y_{\text{mis}}$, find $p(y_{\text{mis}}, \Theta, r | y_{\text{obs}})$ subject to constraints
  - Gibbs sampling
    - Markovian = okay to sample each cluster of missing values in turn
    - Gaussian + linear constraints = efficient sampling methods

Benefit of modeling/redundancy

- No knowledge of suppression
  - Just data
  - BayBase
  - $x_1$, $x_2$, $x_5$
  - $x_3$, $x_4$

- Knowledge of suppression & Timestamps
  - $x_1$, $x_2$, $x_3$, $x_4$
  - $x_5$

- Knowledge of suppression & Timestamps + Direction Bits
  - $x_1$, $x_2$, $x_3$, $x_4$
  - $x_5$

Redundancy strikes back

- At app level, piggyback redundancy on each report
  - **Counter**: number of reports to base station thus far
    - Good systems idea!
  - **Timestamps**: last $r$ timesteps when node reported
    - Not that cute…
  - **Timestamps + Direction Bits**: in addition to the last $r$ reporting timesteps, bits indicating whether each report is caused by (actual – predicted > $\epsilon$) or (predicted – actual > $\epsilon$)
    - Why on earth?!

Redundancy design considerations

- Benefit: how much uncertainty it helps to remove
  - Counter can cover long periods, but helps very little in bounding particular values
- Energy cost
  - Counter < Timestamps < Timestamps + Direction Bits
- Complexity of in-network implementation
  - Coding app-level redundancy in TinyOS was much easier than finding the right parameters to tune for ACK/Retransmit!
- Cost of out-of-network inference
  - May be significant even with powerful base stations!

Inference cost

- Timestamps translate to “|…| > $r$” constraints (disjunction); difficult to work with; naive technique generates lots of rejected samples
- Timestamps + Direction Bits translate to a set of linear constraints; use [Rodriguez-Yam, Davis, Scharf 2004] and there are no rejections

>100x speed-up!

Major reason for adding the direction bits!
Energy cost vs. inference quality

- 30% message failure rate
- Roughly 60% suppression
- Cost: bytes transmitted (including any message overhead)
- Quality: size of 80% high-density region

Sampling is okay in terms of cost, but has trouble with accuracy

Suppression-aware inference with app-level redundancy is our best hope to get higher accuracy

BaySail discussion

- Suppression vs. redundancy
  - Goal of suppression was to remove redundancy
  - Now we are adding redundancy back—why?
  - Without suppression, we have to rely on naturally occurring redundancy ⇔ want to control where redundancy is needed, and how much

- Many interesting future directions
  - Dynamic, local adjustments to ε and degree of redundancy
  - In-network resolution of suppression/failure
  - Failure modeling
  - Provenance: is publishing received/interpolated values enough?

Concluding remarks

All models are wrong, but some models are useful
— George Box

- Data-driven approach
  - Use model to optimize, not to substitute for real data → suppression
  - Quantify uncertainty in models; use data to learn/refine → Bayesian
  - Conch: suppression by chaining simple spatiotemporal models
  - BaySail: suppression-aware inference with app-level redundancy to cope with failure (suppression’s dirty little secret)

- This model-based stuff is not just for statisticians!
  - Cost-based optimization
  - Interplay between system design and statistical inference
  - Representing and querying data with uncertainty

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BaySail: suppression-aware inference with app-level redundancy to cope with failure (suppression’s dirty little secret)

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Thanks!

Duke Database Research Group
http://www.cs.duke.edu/dbgroup/

Conch: suppression by chaining simple spatiotemporal models

Related work

- Sensor data acquisition/collection
  - BBQ [Deshpande et al. VLDB 2004], Snapshot [Kotidis ICDE 2005], Ken [Chu et al. ICDE 2006], PRESTO [Li et al. NSDI 2006], contour map [Xue et al. SIGMOD 2006], …

- Sensor data cleaning

- Uncertainty in databases
  - MYSTIQ [Dalvi & Suciu VLDB 2004], TrinoULDB [Benjelloun et al. VLDB 2006], MauveDB [Deshpande & Madden SIGMOD 2006], factors [Sen & Deshpande ICDE 2007], …
**Conch redundancy**

- Monitor more edges/nodes!

- $d = a + 5 + 10$ and $d = a + 9 + 8$ cannot both be true!

  *A failure occurred—but where?*

**Conch recovery**

- Constraints
  - True node and edge values $x_t$ must be consistent
  - Received values $x_{\text{obs}}$ are true
  - Non-reported values stay same (as time $t - 1$) or reports failed

- Maximum likelihood approach: roughly speaking, find $x_t$ that maximizes $p(x_{\text{obs}} | x_t, x_{t-1})$

  - Assume independent failures with known probabilities
    $$\sum_{i \in I_t} x_i \log \frac{p_i}{1 - c_i} + \sum_{i \notin I_t} p_i \log \frac{1 - p_i}{c_i}$$

  - Assume known change probabilities
  - Can formulate as MIP

**BaySail: infer with spatial correlation**

- Spatial correlation definitely helps!
  - Can you tell which nodes got less help?

**Error stacking**

- Chaining starting point; temporally monitored

  Suppressed because $|1.9 - 1.0| \leq \epsilon = 1$

  Errors stack: $0.9 + 0.9 + 0.9 = 2.7!$

**Discretization**

- Chaining starting point; temporally monitored