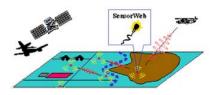


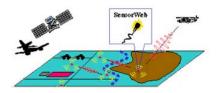
#### Stability and resource allocation

#### Tommi S. Jaakkola MIT AI Lab SensorWeb MURI Review Meeting June 14, 2002



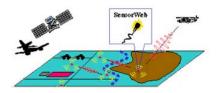
## **Research topics**

- Inference in large sensor networks (with M. Wainwright and A. Willsky); IT 1, RCA 5
- Robust combination of information sources (with A. Corduneanu); IT 1&2, RCA 5 (& 6)
- Competitive estimation (with A. Corduneanu); IT 1&2, RCA 5
- Scalable information acquisition (with H. Siegelman); IT 2, RCA 4&5



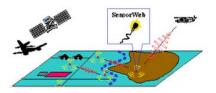
# Outline of the talk

- Stability and source allocation
  - Robust combination of information from heterogeneous sources
  - Extension to competitive estimation (adversarial context)
- Resource allocation
  - Efficient acquisition of information through a limited information channel



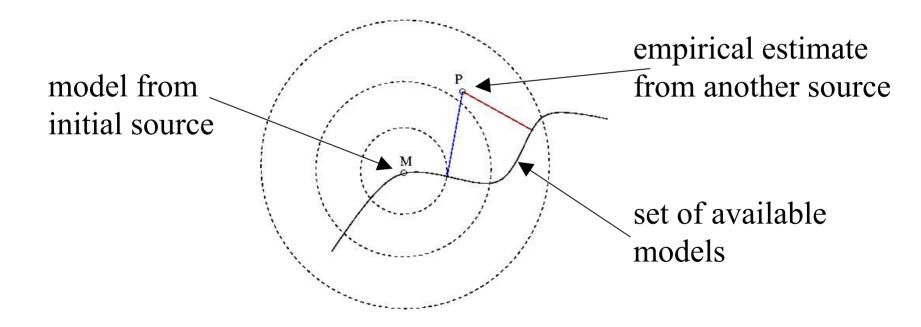
## Part I: source allocation

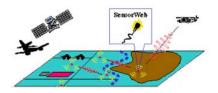
- Heterogeneous sensors (e.g., acoustic and infrared) yield complementary views
  - How much do we rely on each source?
  - How do we resolve conflicts among the data sources?
  - How do we ensure that the estimation process remains stable?

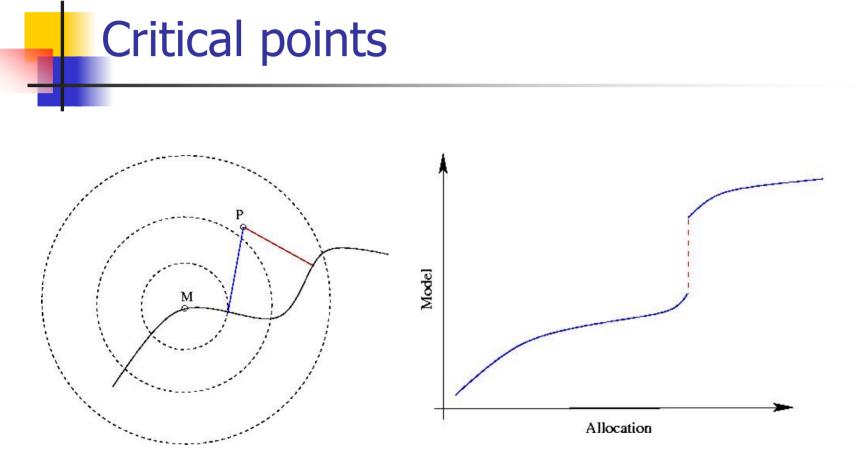


# The problem

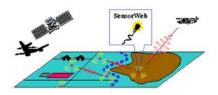
#### Estimation with heterogeneous sources is inherently unstable







The critical points appear almost surely as jumps, not as bifurcations



# **Example settings**

 The stability issue affects all estimation methods reducible to fixed point computations

#### Example: estimation with incomplete data

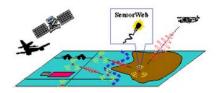
empirical estimates

- Model Q(x,y)
- Complete data log-likelihood:  $D(\hat{P}_c(x,y)||Q(x,y))$
- Incomplete data log-likelihood:  $D(\hat{P}_I(x) || Q(x))$
- Estimation criterion:

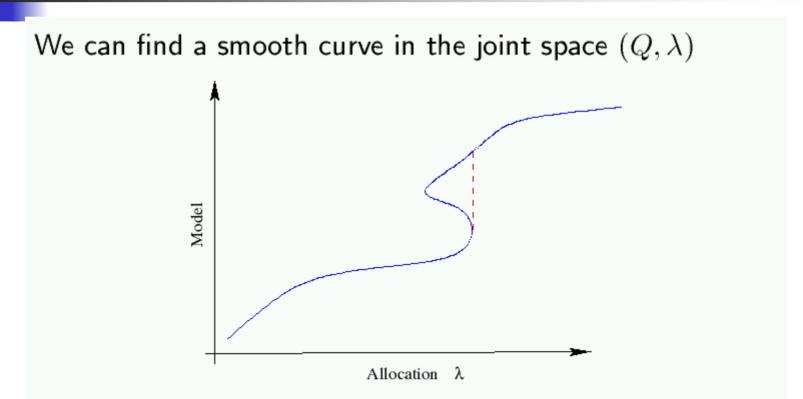
$$J(Q,\lambda) = (1-\lambda)D(\hat{P}_c(x,y)||Q(x,y)) + \lambda D(\hat{P}_I(x)||Q(x))$$
  
allocation

Fixed point equation:  $abla_Q J(Q,\lambda) = 0$ 

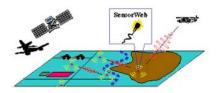
parameter



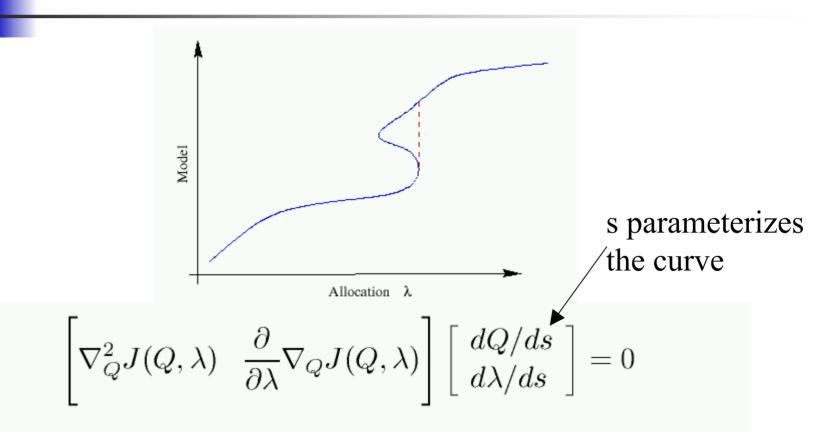
# Stable identification of critical points



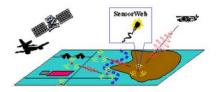
Provided that the Jacobian of  $T(Q, \lambda) = \nabla_Q J(Q, \lambda)$  has full rank,  $T(Q, \lambda) = 0$  defines a smooth 1-dim manifold in the joint space  $(Q, \lambda)$ .



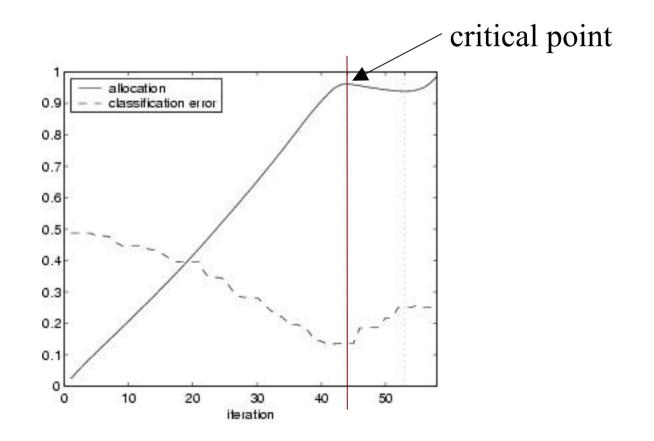
#### Homotopy continuation

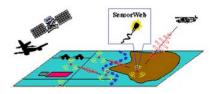


Each point along the curve necessarily satisfies the fixed point condition  $\nabla_Q J(Q, \lambda) = 0$ 



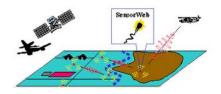
### **Typical results**





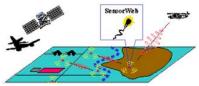
# Summary of part I

- Data fusion is often unstable
- We can restore stability by identifying and avoiding critical points
  - homotopy continuation provides an efficient way of identifying stable data allocations
  - the methodology is applicable for most estimation settings

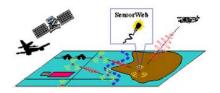


## Extension: competitive estimation

- Estimation/decisions often have to be made in an adversarial context
- Robust decisions can be found with competitive (game theoretic) estimation

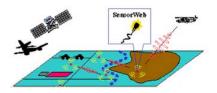


#### Competition, solution Two interpretations, two criteria $\max_{R} \min_{Q} \quad \text{Loss}(Q, R) - \text{Loss}(Q)$ loss resulting from adversary interaction decision $\min_{Q} \max_{R} \left| \operatorname{Loss}(Q, R) - \operatorname{Loss}(R) \right|$ maker homotopy continuation applies as before critical points arise as before (but can desirable in this context)



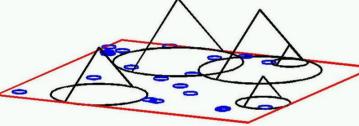
## Part II: resource allocation

- The problem here is information acquisition (e.g., locating assets) with minimal resources
- The key question is how the available resources should be used/allocated
- Technical components:
  - sensor models
  - information channel
  - beliefs and inference (scalability)

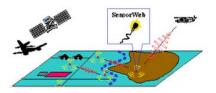


# The framework

Model:

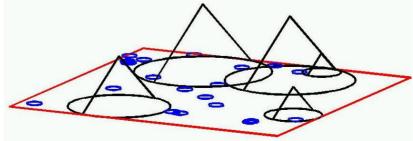


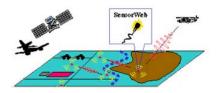
- Multi-resolution sensors
  - response model
- Limited information channel
  - number of sensors that can be queried in parallel
- Processing
  - maintaining beliefs
  - query optimization
- Key requirement: scalability



## Sensors

- The sensors are assumed to appropriately cover the domain (identifiability)
- Characteristics of sensors (detectors)
  - static or dynamic definition
  - resolution, sensitivity
  - cumulative detection
- Sensor responses are captured by the detection probabilities P(y = 1|r)





# Beliefs, expected response

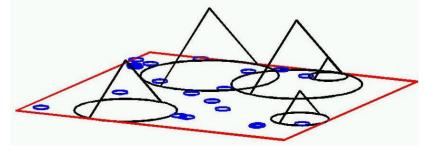
We maintain a factored belief over elements/locations

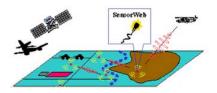
$$P(r|\theta) = \prod_{x \in \mathcal{X}} \theta_x^{r_x} (1 - \theta_x)^{1 - r_x}$$

The expected response from a sensor is given by

$$P(y_c = 1|\theta) = \sum_r P(y_c = 1|r)P(r|\theta)$$

where  $y_c = 1$  signifies "detection"



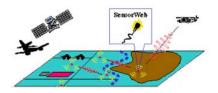


# Maintaining beliefs

 We have to revise our beliefs (e.g., about asset locations) after each sensor response

We project the posterior back into the factored beliefs

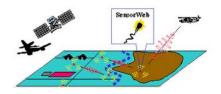
$$P(r; \theta') = \arg\min_{Q \in \mathcal{P}} D(P(r|\hat{y}_c, \theta) ||Q(r))$$



# Query optimization

- The expected information rate from a sensor often cannot be evaluated efficiently.
- We instead optimize a lower bound

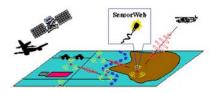
$$I(y_c; r | \theta) \ge E_{y_c} \left\{ \sum_{x \in c} D\left(\theta_{x; y_c} \| \theta_x\right) \right\} \stackrel{def}{=} I_p(y_c; r | \theta)$$



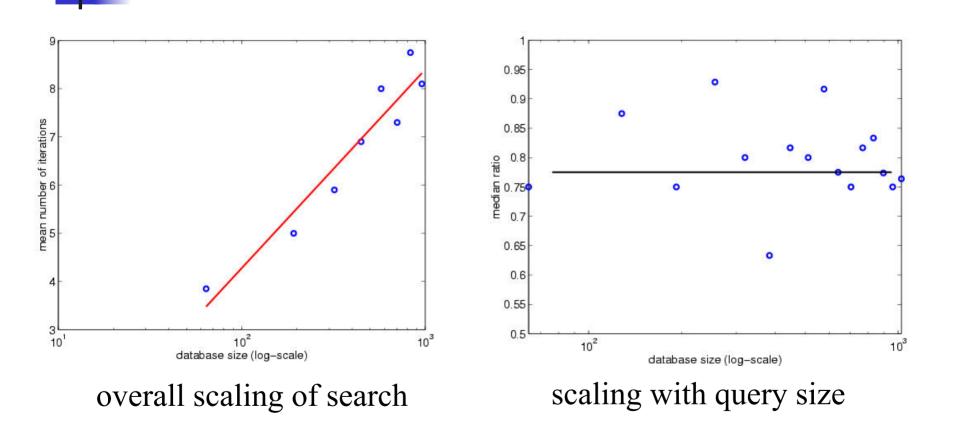
# Query optimization cont'd

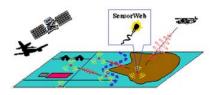
 To select k sensors for a query, we combine the lower bound with a series of conditional projections

 $\Rightarrow k$  selections in time  $\mathcal{O}(kn)$  (with cached reconstruction of non-additive components)



#### Example results





# Summary

- Information queries from a collection of sensors can be performed in a scalable manner
  - The algorithms scale linearly with domain/channel size
  - The sensors/detectors limited by "cumulative" detection
- Extensions:
  - Incorporation of specific sensors characteristics
  - Analysis and coordination of heterogeneous sensors