# Emergent Coordination in Distributed Sensor Networks

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# Networks are different

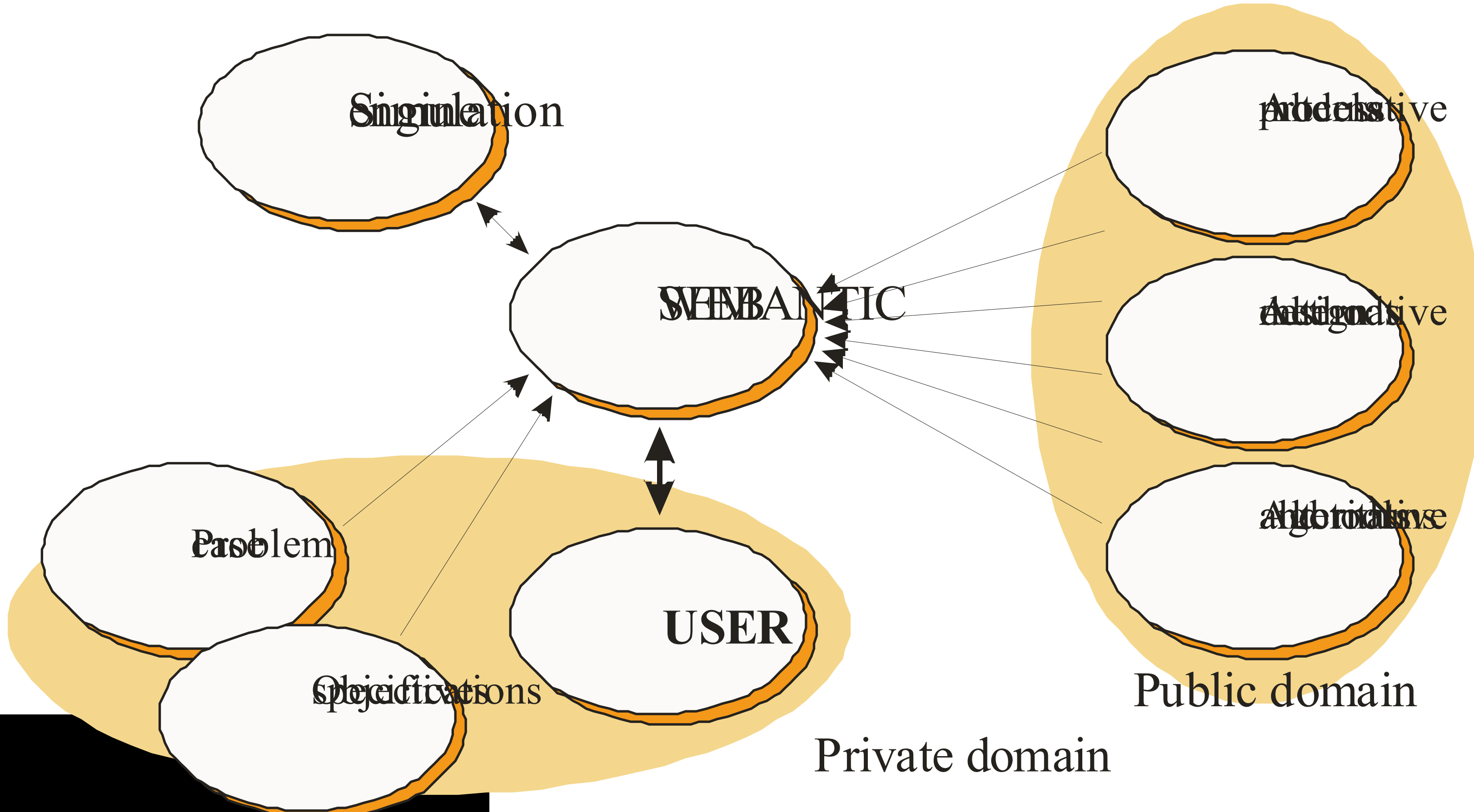
- Claim: Bottom-up approaches give more substance to discussions than generic top-down approaches
- This presentation studies a very special application field of network technologies in a very special manner
- However, it can be claimed that *all fields are special*
- Real semantics is domain-area specific, and also the ways of coding that semantics should differ
- This presentation gives an example of what can be reached when a *distributed network of measurement sensors* is modeled in a bottom-up way rather than applying centralized strategies

# About semantics

- Traditionally in Semantic Web (”Wisdom Web”) field knowledge is explicitly coded as rules
- Remember the experiences with Expert Systems!
- To reach savings with coding efforts, rather than implementing *ontologies* one can implement *epistemologies*
- To reach autonomous behaviors that are beyond what has explicitly been coded, some level of ”understanding” is necessary: The *meaning* or *semantics* has to be captured
- If behaviors can be evaluated in numerical form, semantics can sometimes be formalized
- [illegible] constructed: There is no more need for a [illegible]ter”

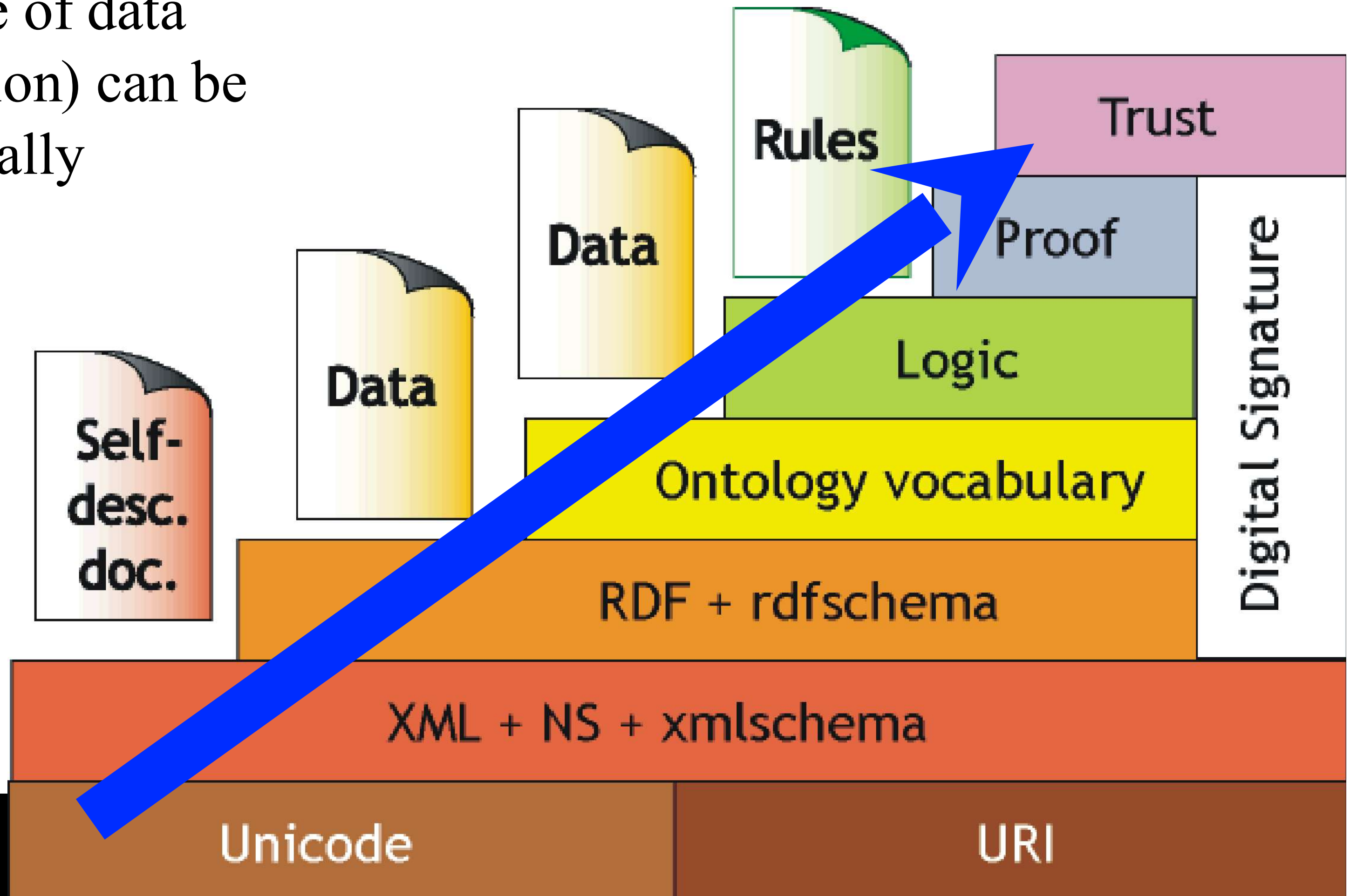
# Formalized semantics: Larger visions

- Remember ”Semantic Web Kick-Off”



# From data directly to knowledge

- Relevance of data (information) can be automatically evaluated



# Capturing semantics

- The challenge of semantics is huge; only a subset can be attacked here
- Only study *naturalistic* and *contextual* semantics
- Meaning of a variable is determined to which observations it is connected to, and to which other variables it is connected to: How the variable is affected by its environment, and how it affects its environment
- In concrete terms, this kind of semantics is revealed by *correlations* among entities
- Does this sound too simple? – Not when boosted with modern [illegible] tools!

# Modeling of correlations

- Assume that $u$ is the vector containing the measurements
- The correlations are captured by the correlation matrix

$$E\left\{ uu^T \right\} \approx \frac{1}{k} \sum_{i=1}^{k} uu^T$$

- The correlation matrix can be decomposed as

$$E\left\{ uu^T \right\} = \Phi^{-1} \Lambda \Phi$$

- Here, $\Phi$ contains the eigenvectors and $\Lambda$ the eigenvalues on its diagonal
- The eigenvalues reveal how much variation is distributed in the [illegible]sponding eigenvector

# PCA and subspace identification

- Measurements can be compressed by projecting the data onto the $n$ most significant (orthonormal) eigenvectors
- Assume these eigenvectors are collected in $\phi$
- The *latent variables* are found as

$$x(u) = \phi^T u$$

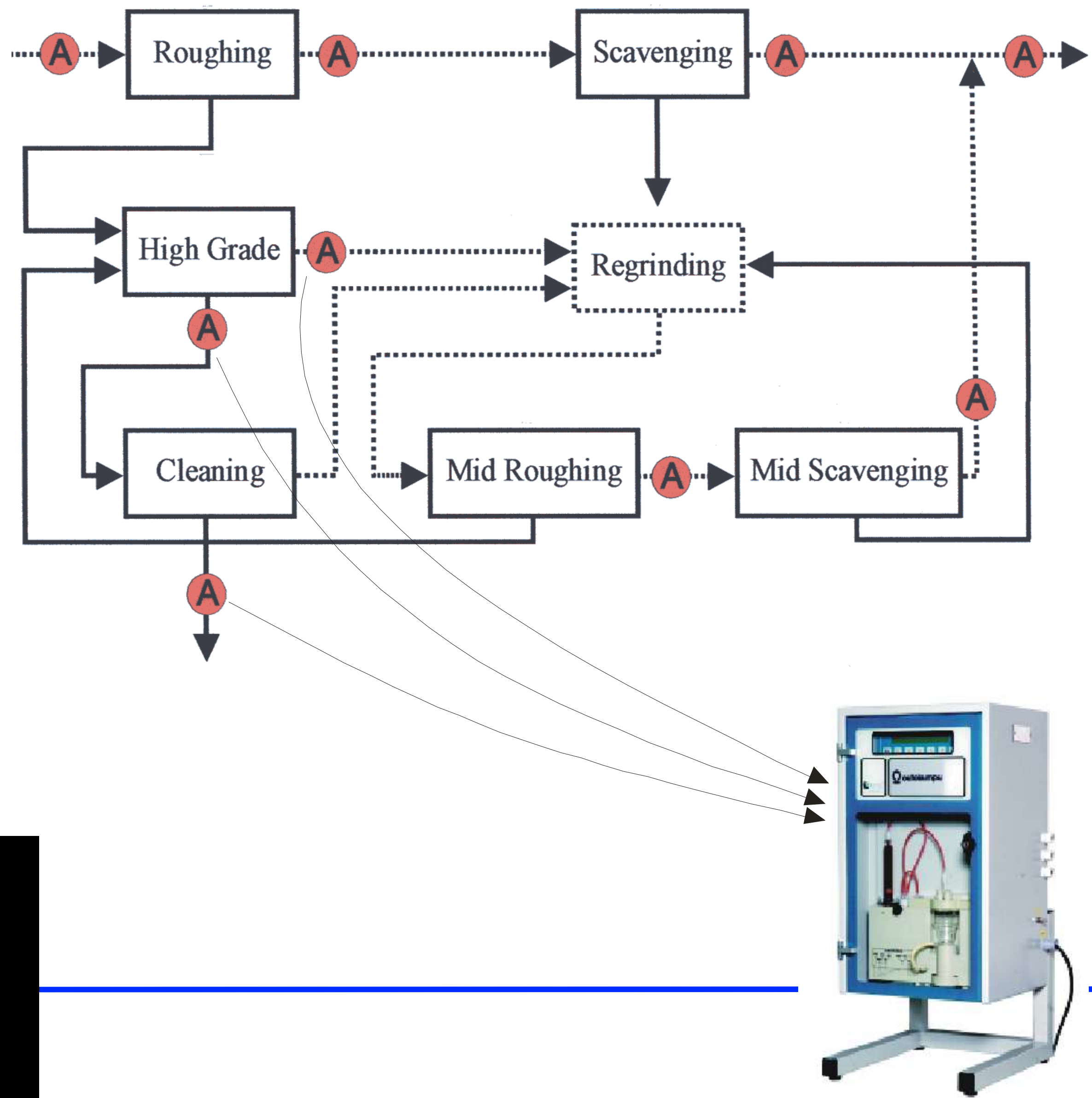
- This is known as *principal component analysis* PCA
- Principal component regression where noise hopefully is filtered is then given as

$$\hat{u} = \phi x(u)$$

- , one has *subspace identification*

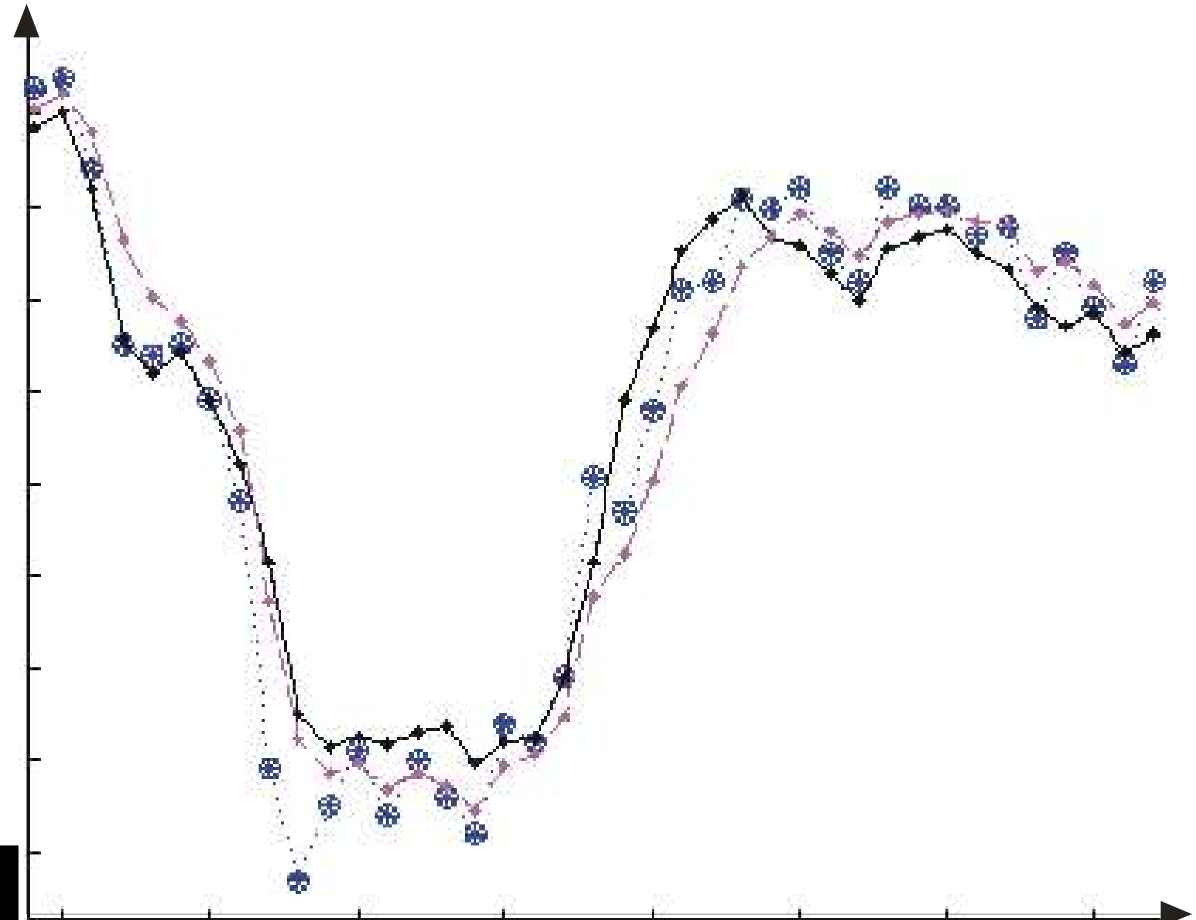
# Experiment

- Pyhäsalmi Mine zinc flotation circuit
- Measurements using X-ray analyzer
- Noisy data can be enhanced if dependecies (correlations) are modeled



# ”Good results”

- Measurements utilize causal dependencies among data
- However, the process is very time variant



# Distributed PCA

- It has been recognized that the system with

$$\frac{dx}{dt} = -Ax + Bu \qquad \text{where} \qquad \frac{dA}{dt} = -\lambda A + \lambda x x^T$$

$$\frac{dv}{dt} = -Av + x \qquad \qquad \frac{dB}{dt} = -\lambda B + \lambda x u^T$$

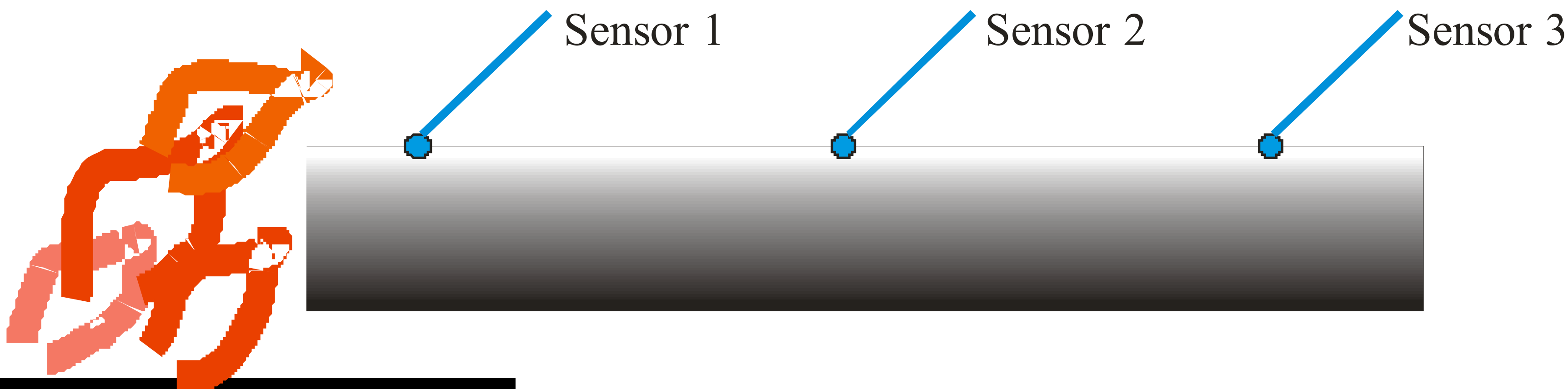
and, finally,

$$\hat{u} = B^T v$$

can be distributed among sensors; sensor states and state changes are [redacted]ors

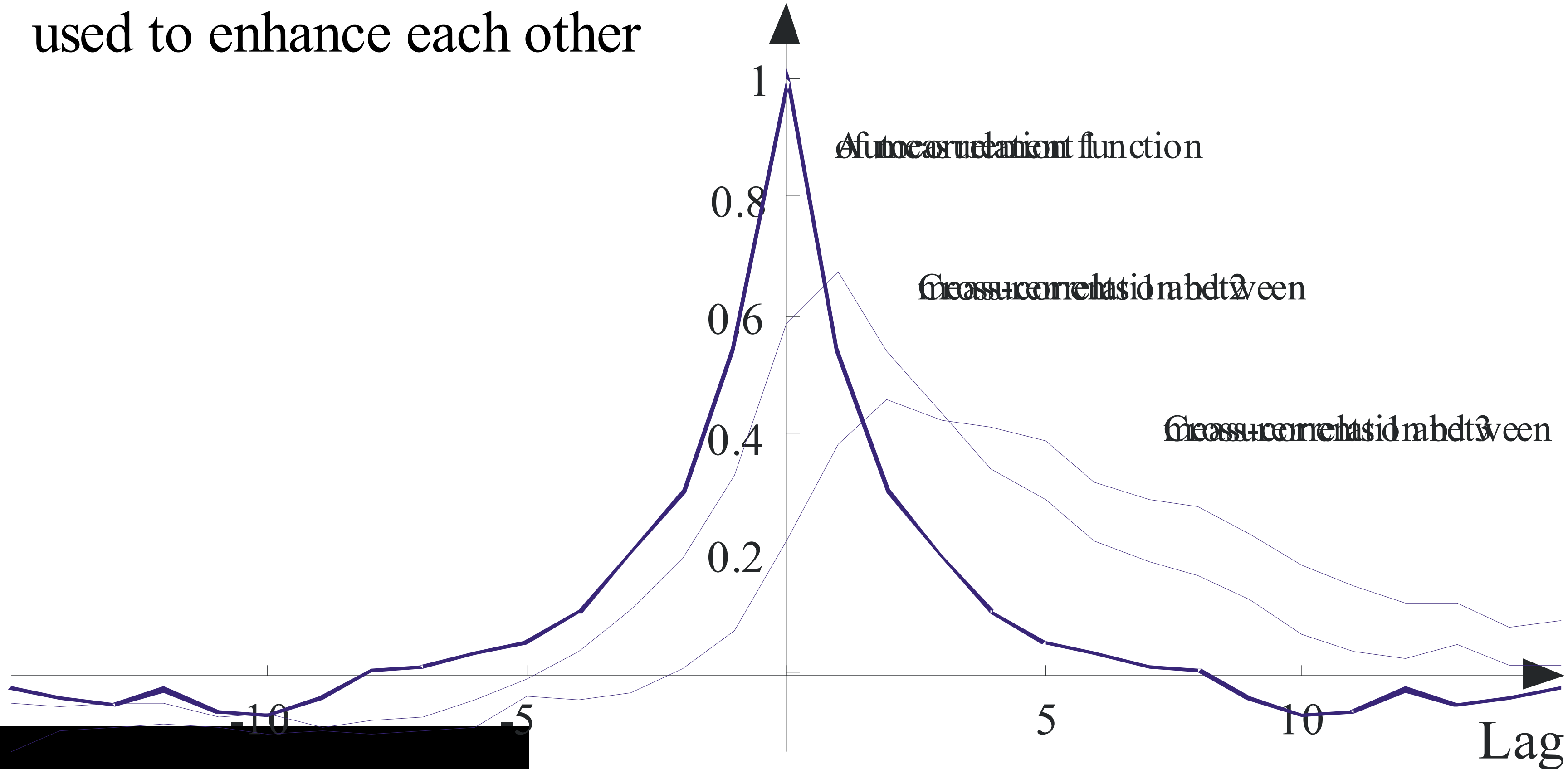
# Simulation: Heat transfer

- Typical processes are infinite-dimensional
- How to determine the process state appropriately?
- How to enhance the measurements?

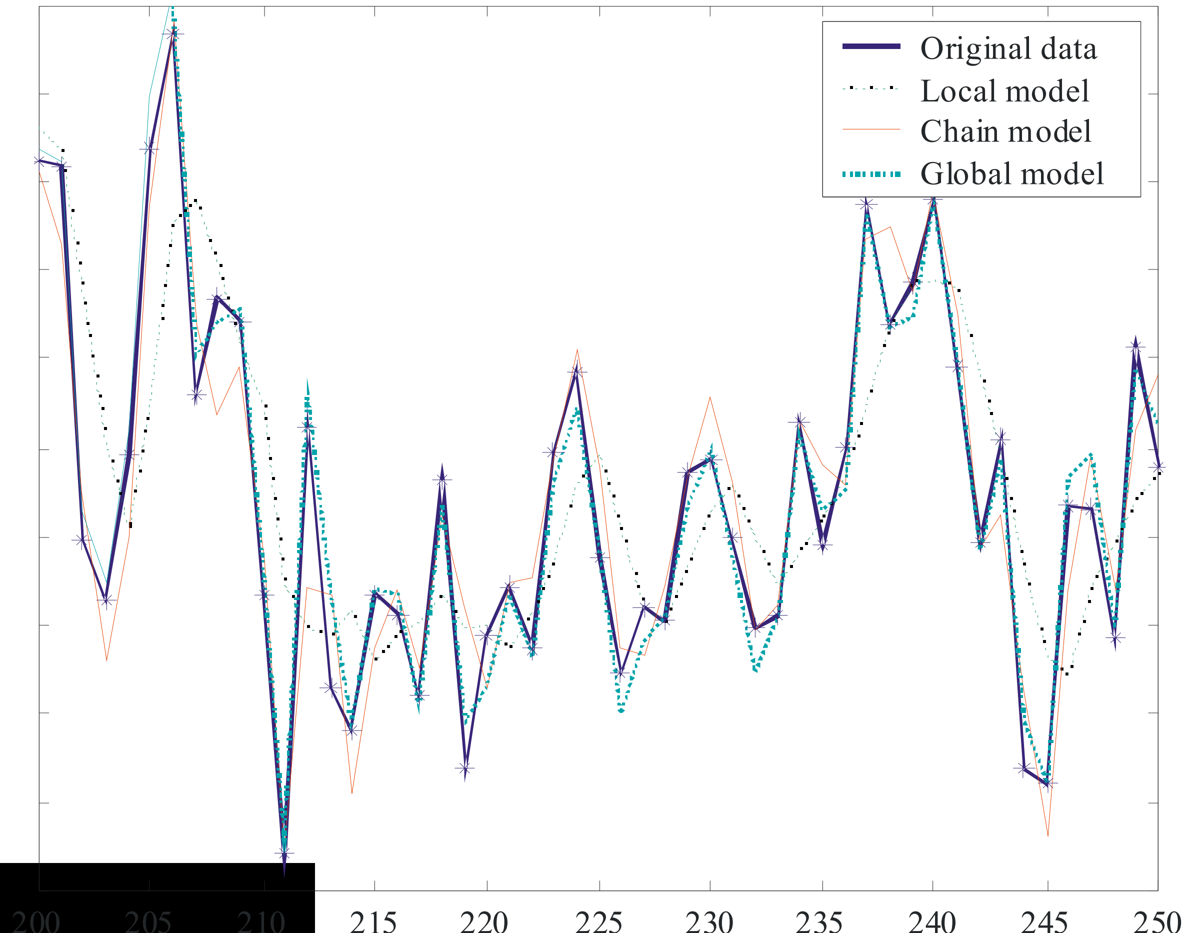


# Correlations between measurements

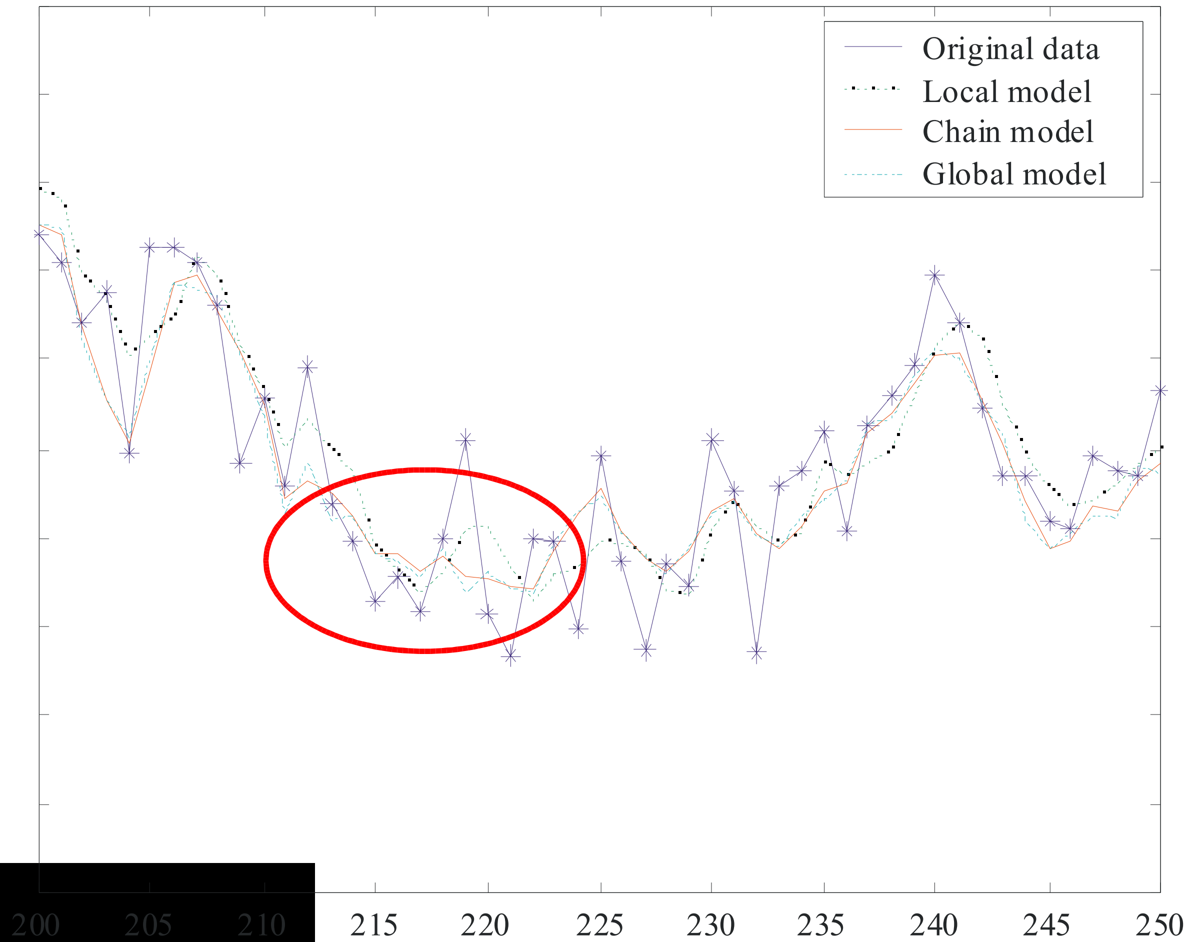
- The measurements can be used to enhance each other



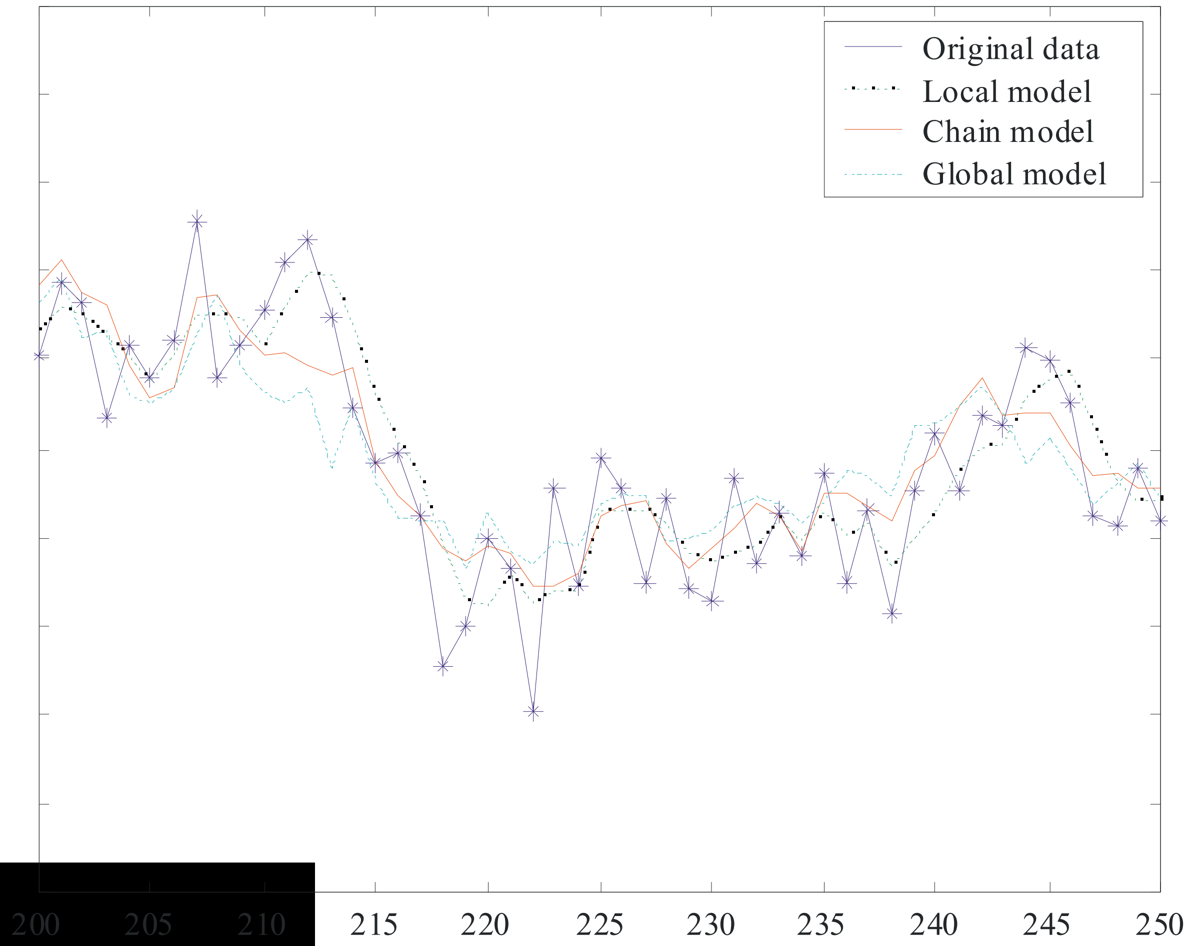
# Measurements: First sensor



# Measurements: Middle sensor



# Measurements: Last sensor



# Experiences

- If sensors are fully connected, ”trivial” (distributed) principal component regression functionality is obtained
- More interesting results are reached if the network is not fully connected (”chain” structure above)
- Incomplete, localized information results in *better* estimates
- The local models are low-dimensional: Only appropriate information is present, resulting in fast adaptation, and enhanced robustness
- As compared to mainstream approaches to distributed sensors, now one has overlapping ”fuzzy” clusters of sensors
- There does not exist global-level optimality criterion – distributed [redacted], not only practical interest