Distributed Intelligent Systems – W11

Division of Labor: Threshold-Based and Market-Based Algorithms
Outline

• Division of labor in natural systems
• Threshold-based algorithms
• Market-based algorithms
• Threshold-based and market-based algorithms applied to multi-robot coordination
• Comparison between threshold-based and market-based algorithms for multi-robot coordination
Division of Labor in Natural Systems: Motivation and Overview in Social Insects
The Division of Labor and its Control

Talking about division of labor means that there is a potential redundancy in the role/contribution of individuals and coordination in role/task allocation helps in decreasing redundancy and increasing efficiency as a group.

The control of task allocation

• The most obvious sign of the division of labor is the existence of castes.

• We distinguish between three kinds of castes: physical, temporal (temporal polyethism) and behavioral.

• The individuals belonging to different castes are usually specialized for the performance of a series of precise tasks.
In *Pheidole guilelmimuelleri* the minors show ten times as many different basic behaviors as the majors.

Average fraction of time spent in a given activity/behavior.
Temporal Polyethism

Behavioral changes in worker bees as a function of age

Young individuals work on internal tasks (brood care and nest maintenance). Older individuals forage for food and defend the nest.
Behavioral Castes

Allocation of the daily activities in a colony of desert harvester ants (Portal, AZ)

From D. Gordon, “Ants at Work”, 1999
The number of individuals performing different tasks and the nature of the tasks to be done are subject to constant change in the course of the life of a colony.

The proportions of workers performing the different tasks varies in response to internal or environmental perturbations.

This is true under certain conditions even when hard morphological differences exist or irreversible aging processes take place.

→ The division of labor in social insects must be flexible.
How is flexibility implemented at the level of the individual?
The Division of Labor and the Flexibility of Social Roles

The control of task allocation

Task 1  Task 2  Task 3

How is dynamic task allocation achieved?

A threshold-based behavioral response appears to be a biologically plausible mechanism for achieving the flexibility of social roles.
The control of task allocation explained with a fixed-threshold model

The lower the threshold, the lower can be the stimulus for achieving a given response; respectively, the lower the threshold, the higher will be the response of an individual for a given stimulus.
An Example of Control of the Division of Labor
Implying the Existence of Fixed Response Thresholds
Pheidole dentata
The Division of Labor and its Control

- The ratio of the majors in a colony artificially increased
- Majors replace missing minors confirming the idea of the response threshold

**Pheidole pubiventris**

- Social behavior
- Self-grooming

**Tasks typically performed by minors**

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**P. guilelmimiuelleri**

- Social behavior
- Self-grooming
A Macroscopic Model based on Fixed Thresholds for 1 Task and 2 Castes
Using a Model for Explaining Wilson’s Results and more …

- Macroscopic model, continuous time
- Response to stimuli based on fixed thresholds
- No detailed microscopic mechanism for stimulus perception and answer incorporated in the model
- Assumptions: nonspatial model, i.e. equiprobable exposure of individuals to the stimulus associated with the task and stimulus homogeneously distributed over space
- 1 task (e.g., behavioral acts), 2 castes (e.g., minor and major)
The Division of Labor and its Control

An example of a response threshold

Given Task

\[ T_{\theta_i}(s) = \frac{s^n}{s^n + \theta_i^n} \]

- \( s \): intensity of the stimulus associated with the task
- \( \theta_i \): response threshold of caste \( i \) to the task
- \( n \): nonlinearity parameter, e.g. \( n = 2 \)
Properties and Parameters of the Threshold-Based Response Function

Different $\theta$ for $n = 10$

Different $n$ for $\theta = 50$
Deterministic vs. Probabilistic Responses

Deterministic response for $\theta = 50$ and various levels of Gaussian noise (1000 runs)

Deterministic with noise ($\sigma = 9$) vs. probabilistic response ($n = 10$) for $\theta = 50$ (1000 runs)
## Note on the Aggregation of Variables in Macroscopic Models

<table>
<thead>
<tr>
<th>Concerned Variable</th>
<th>Mainly in the lecture slides</th>
<th>Mainly in the handouts</th>
</tr>
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<tbody>
<tr>
<td>$n_{ij}, N_i$</td>
<td>caste $i$ = set of individuals with the same threshold</td>
<td>1 individual = 1 caste</td>
</tr>
<tr>
<td>$x_{ij}$</td>
<td>Average number of active individuals in caste $i$ carrying out task $j$</td>
<td>Average time spent by an individual $i$ carrying out task $j$</td>
</tr>
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</table>

**Note 1:** depending on the significance of the variable some model parameter might slightly change their meaning (per unit step, per individual, etc.)

**Note 2:** at the macroscopic level we do not deal with details, just need statistical meaningful state variables; self-organization has among its ingredients multiple interactions; that can be achieved with a lot of individuals or a few individuals interacting a lot over time and repeated runs

**Note 3:** see also week 7 lecture slides and Lerman et al, SAB 2004 paper
Fixed Threshold Model with 1 Task and 2 Castes

Two castes of individuals in the colony (physical, behavioral, or age-based castes); each individual can perform the task or doing nothing. Note $n_i$ and $N_i$ swapped in comparison to your handout!

\[ N_1 = \text{number of individuals of type 1} \]
\[ N_2 = \text{number of individuals of type 2} \]
\[ n_1 = \text{mean number of individuals of type 1 engaged in carrying out the task} \]
\[ n_2 = \text{mean number of individuals of type 2 engaged in carrying out the task} \]

\[ x_1 = \frac{n_1}{N_1} : \text{fraction of individuals of type 1 engaged in carrying out the task} \]
\[ x_2 = \frac{n_2}{N_2} : \text{fraction of individuals of type 2 engaged in carrying out the task} \]

\[ 1-x_1: \text{fraction of individuals of type 1 not performing the task} \]
\[ 1-x_2: \text{fraction of individuals of type 2 not performing the task} \]

\[ N_1 + N_2 = N = \text{total number of individuals in the colony} \]
Dynamics of the fraction of active individuals in each caste:

\[ \frac{\partial_t x_1}{s^2 + \theta_1^2} = \frac{s^2}{s^2 + \theta_1^2} \left(1-x_1\right) - r_a \, x_1 \]

\[ \frac{\partial_t x_2}{s^2 + \theta_2^2} = \frac{s^2}{s^2 + \theta_2^2} \left(1-x_2\right) - r_a \, x_2 \]

Note: \( \partial_t x = \frac{dx}{dt} \)

- \( s \): intensity of the stimulus associated with the task
- \( \theta_i \): response threshold of caste \( i \) to the task
- \( r_a \): rate of task abandoning (i.e. probability per infinitesimal time interval that an active individual abandons the task on which it is engaged for moving to idle)
- \( 1/r_a \): average time spent by an individual performing a task before abandoning it (probabilistic delay model, see Week 7 lecture)
Dynamics of demand associated with the task

\[ \partial_t s = \delta - \frac{\alpha}{N} (n_1 + n_2) \]

\( \delta \): rate of stimulus increase (demand common to both castes)
\( \alpha \): normalized effectiveness rate for the individual contribution on the task

(in this case an active individual of type 1 contribute in the same way as an active individual of type 2 when performing the task)
Fixed Threshold Model with 1 Task and 2 Castes

Comparison between the macroscopic model and experimental results

Parameters of the simulation

\[ N = 10, 100 \]
\[ \theta_1 = 8, \theta_2 = 1 \]
\[ \alpha = 3 \]
\[ \delta = 1 \]
\[ r_a = 0.2 \]
Variable Threshold Model for Controlling the Division of Labor
Polist Wasps: an Interesting Example
Origins of the Division of Labor in the Polist Wasps

Polists : primitive eusocial species

• Colonies usually contain only a small number of individuals (ca 20).

• These species do not show morphological differences between castes in the adult stages, nor any control or physiological determination of the role an individual will play in the colony as an adult.

• Individual behavior is very flexible; all individuals are able to perform the whole range of tasks which determine the survival of the colony.

• The integration and coordination of individual activities is achieved through the interactions which occur between the members of the colony, and between the members of the colony and the local environment.

• Specialists can be created from generalists
The control of task allocation explained with a variable-threshold model

The lower the threshold, the lower can be the stimulus for achieving a given response; respectively, the lower the threshold, the higher will be the response of an individual for a given stimulus.
Variable Threshold Model with 1 Task and m Castes

Individual behavioral algorithm

\[ \Theta_i \rightarrow \Theta_i - \xi \quad \text{when } i \text{ performs the task} \]
\[ \Theta_i \rightarrow \Theta_i + \varphi \quad \text{when } i \text{ does not perform the task} \]

\[ T_{\Theta_i}(s) = \frac{s^2}{s^2 + \Theta_i^2} \]

Parameters of individuals

i : caste index [1 …m]
s : intensity of stimulus associated with the task
\( \Theta_i \) : response threshold of individual i to the task: \( \Theta_i \in [\Theta_{\text{min}}, \Theta_{\text{max}}] \)
\( \xi \) : incremental learning parameter (the threshold of an individual carrying out a task is reduced by \( \xi \))
\( \varphi \) : incremental forgetting parameter (the threshold of an individual not carrying out a task increases by \( \varphi \))
Variable Threshold Model with 1 Task and m Castes

Description of the algorithm

System of DE:
\[
\partial_t x_i = T_{\theta_i}(s)(1-x_i) - r_a x_i
\]

\( r_a \): abandoning rate (as before for fixed thresholds)
Example of dynamics of the overall stimulus (demand) associated with a task

\[ \partial_t s = \delta - \frac{\alpha}{N} \left( \sum_{i=1}^{m} n_i \right) \]

\( \delta \): rate of stimulus increase  
\( \alpha \): normalized effectiveness rate for the individual contribution to the task (in this case all the active individual belonging to different castes contribute in the same way)  
\( n_i \): number of active individual belonging to caste \( i \)
Example with 6 Castes ($\theta_1 \ldots \theta_6$)

Model Parameters

$\theta_i = [1 \ldots 1000]$, initial random distribution

$\alpha = 3$

$\delta = 1$

$r_a = 0.2$

$\xi = 10$

$\phi = 1$

Red and blue caste lower the threshold -> specialists (note started from low thresholds)
Example with 6 castes ($\theta_1 \ldots \theta_6$)

Evolution of the fraction of active individuals in each caste with overlapped demand.
Example with 6 Castes and one Caste Removed at $t = 150$

Light gray specialist removed (similar to the red specialist in the previous example)
The Control of the Division of Labor in a Variable Threshold Model with 2 Tasks
Variable Threshold Model with 2 Tasks and m Castes

**Individual behavioral algorithm**

\[ \theta_{ij} \rightarrow \theta_{ij} - \xi \text{ when caste } i \text{ performs task } j \]
\[ \theta_{ij} \rightarrow \theta_{ij} + \varphi \text{ when caste } i \text{ does not perform task } j \]

\[ T_{\theta_{ij}}(s_j) = \frac{s_j^2}{s_j^2 + \theta_{ij}^2} \]

**Variable and parameters**

- \( s_j \): intensity of the stimulus associated with the task \( j \)
- \( \theta_{ij} \): response threshold of the caste \( i \) to task \( j \), \( \theta_{ij} \in [\theta_{\min}, \theta_{\max}] \)
- \( \xi \): incremental learning parameter (the threshold of an individual carrying out task is reduced by \( \xi \))
- \( \varphi \): incremental forgetting parameter (the threshold of an individual not carrying out a task increases by \( \varphi \))
Dynamics of the demand associated with a task

\[ \partial_t s_j = \delta_j - \frac{\alpha_j}{N} \left( \sum_{i=1}^{m} n_{ij} \right) \]

Parameters of the demand associated with a task

- \( \delta_j \): rate of stimulus increase associated with a task \( j \)
- \( \alpha_j \): normalized effectiveness rate for the individual contribution to the task \( j \) (in this case all the active individual belonging to different castes contribute in the same way)
- \( m \): total number of castes in the colony
- \( n_{ij} \): number of active individuals belonging to caste \( i \) and carrying out the task \( j \)
Variable Threshold Model with 2 Tasks and m Castes

Dynamics of response thresholds

![Graphs showing dynamics of response thresholds for Task 1 and Task 2 with different castes. Each graph plots response threshold against time. The graphs show how response thresholds change over time for each caste.](image-url)
Dynamics of the proportion of active individuals per caste involved in each task

Task 1

Task 2
Examples of Threshold-Based Multi-Robot Coordination
Seed-Assembling Experiments

- See Week 7 (multi-level modeling)
- Crude discrimination between small objects (seeds) and the rest
- All robots always active in assembling seeds
Macroscopic Model


Robots always active
(no worker allocation)

See Week 7
Some Results (1, 5, 10 robots always active)

**Metric:** average cluster size (20 seeds)

Saturation phase: all seeds in a single cluster or in the robots’ grippers

Threshold-Based Control of Assembly Activities

- Added a “parking lot” for robots, all around the assembly zone
- Stimulus estimated as the time to find a seed to manipulate

[Agassounon and Martinoli, AAMAS 2002]
Motivations for Regulating the Assembly Activity

• Evolution of manipulation sites: number of manipulation sites decreases with progress of assembly → more competition (interference) among robots for the same manipulation sites

• End criterion: a power-efficient building system should stop working when the task is accomplished

• Increasing the final cluster (assembly) size: at the end all the seeds should belong to the single cluster/assembly (only those on the ground count for the assembly metrics)

[Agassounon and Martinoli, AAMAS 2002]
• **1 task:** aggregation → 1 threshold per robot
• **Fully distributed algorithm** (demand evaluation and worker allocation)
• **Key choices for minimizing complexity and maximizing interchangeability:**
  – Robots have **the same capabilities**, no reason to have different threshold
  – **Probabilistic response** even with a single threshold will suffice to regulate the activity; not all the robots stop at the same time, when one drop the work, direct influence on aggregation demand
  – How do we implement: deterministic response + noise = probabilistic response → exploit local perception based on on-board sensors as noise generator!
• **Chosen stimulus:** time needed to find a seed to manipulate; the larger the time, the lower the stimulus associated with the assembly demand
• **Special case of demand evolution:** it does not increase automatically but stay constant if nothing is done. Initial condition: \( s(0) = S_0 \) and \( \delta = 0 \) (instead of \( s(0) = 0 \) \( \delta > 0 \) as in the previous examples) → **switching mechanism asymmetric:** active → idle possible; idle → active not implemented
Macroscopic Model

Robots can go resting (worker allocation)

See Week 7
Results with 10 Robots and Activity Regulation

20 seeds, threshold for abandoning the arena = 25 min, 10 robots

No more saturation: growing phase beyond 10-seeds single cluster

Average cluster size

Number of active robots

Performance Comparison of Different Algorithms in Different Arenas

Integrated Cost (IC)

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Arena1</th>
<th>Arena2</th>
<th>Arena3</th>
</tr>
</thead>
<tbody>
<tr>
<td>W/o W.A.</td>
<td>227.4 ± 4.8</td>
<td>310.8 ± 8.8</td>
<td>197.2 ± 5.9</td>
</tr>
<tr>
<td>PrFT</td>
<td>138.9 ± 7.0</td>
<td>324.9 ± 10.8</td>
<td>154.5 ± 7.9</td>
</tr>
<tr>
<td>PrVT</td>
<td>155.1 ± 8.0</td>
<td>231.9 ± 10.7</td>
<td>152.2 ± 8.7</td>
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<tr>
<td>PuFT</td>
<td>138.2 ± 6.9</td>
<td>337.6 ± 10.7</td>
<td>122.4 ± 6.4</td>
</tr>
<tr>
<td>PuVT</td>
<td>141.3 ± 5.2</td>
<td>227.2 ± 9.4</td>
<td>134.2 ± 9.1</td>
</tr>
</tbody>
</table>

\[
F_{\text{cost}}(t) = \gamma_x (X_{\text{opt}} - x_t)^2 + \gamma_y (Y_{\text{opt}} - y_t)^2 + \gamma_z (Z_{\text{opt}} - z_t)^2
\]

- \(x_t\): avg. cluster size at time \(t\) (\(X_{\text{opt}}\) is the optimal value = 20)
- \(y_t\): number of clusters at time \(t\) (\(Y_{\text{opt}}\) = 1)
- \(z_t\): number of active workers at time \(t\) (\(Z_{\text{opt}}\) = 0)
- \(\gamma_x\), \(\gamma_y\), and \(\gamma_z\): weight coefficients

\[
IC = \int_{0}^{T} F_{\text{cost}}(t) dt
\]

Where \(T\) is the total duration of the experiment.

- Arena 1: 80 x 80 cm, 20 seeds
- Arena 2: 178 x 178 cm, 20 seeds
- Arena 3: 80 x 80 cm, 20 seeds + 5 seeds after 2 hours

- PrFT: Private, Fixed-Threshold
- PrVT: Private, Variable-Threshold
- PuFT: Public, Fixed-Threshold
- PuVT: Public, Variable-Threshold

Idea: exploiting communication to share demand estimation

[Agassounon and Martinoli, AAMAS 2002]
Market-Based Algorithms
Market-Based Coordination

Robots model market economy:
- Resources, tasks have precise worth
- They are traded over the market
- Accomplish task $\rightarrow$ paid revenue
- Consume resources $\rightarrow$ incurs cost
- Goal: maximize profit (i.e. revenue - cost)

Pursuit of individual profit $\rightarrow$ good global solution
Allocation uses Auctions

- Task(s) offered in a task announcement
- Robots bid (often marginal cost/utility)
- Auctioneer (can be a robot) clears auction and awards
Distributed Sensing Mission
A Simple Example

Reward: 120

Reward: 150

Robot 1
Profit: 70

Robot 2
Profit: 80

Bids Placed for Tasks

<table>
<thead>
<tr>
<th></th>
<th>tA</th>
<th>tB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robot 1</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Robot 2</td>
<td>X</td>
<td>70</td>
</tr>
</tbody>
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System cost: 50 + 70 = 120

No bid since min bid > reward (called also reserve price)
A Simple Example

Reward: 120
Reward: 150

Bids Placed for Tasks

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System cost: 50+70=120
System cost: 50+30=80

Robot 1
Profit: 70
Profit: 190

Robot 2
Profit: 80
Profit: 0
Formally

• Team has:
  – decomposable objective (e.g. visit a set of locations)
  – limited set of resources (e.g. time, energy, sensors)

• A global objective function $C$ (\(C: \text{Allocation}_i \rightarrow \mathbb{R}^+\))

• A local utility (or cost) function $U_j$ (\(U_j: \text{Actions}_j \rightarrow \mathbb{R}^+\))

• A mapping $M$ for credit-assignment (\(M: U \leftrightarrow C\))

• Market mechanism for redistribution (e.g. auction)
Auctions and Bidding
Types of Auctions

- Single task
- Combinatorial \( \{1, 12, 13, \ldots ,1234\} : 2^T \)
- Multitask \( \{12, 34\} : 2 \)
Costs v. Utilities

• Cost-based auction:
  – Minimize global cost function
  – Lowest bidder wins

• Utility-based auction:
  – Quality, value - cost:
    • more/less important tasks
    • more/less capable robots
  – Maximize global utility
  – Highest bidder wins

• Capture multiple factors: quality, time, energy, etc.
  ▫ How to combine units of quality and cost?
  ▫ Weighted sum: $\alpha$ quality + $\beta$ time + $\gamma$ energy ...
  ▫ How to find weights? 1 unit of quality = ? units of time
Computation Complexity and Uncertainty
Task Valuation

• Valuation functions may
  – rely on accurate information
  – require solving complex problems (e.g. tsp)

• Solution: heuristics and approximations

• Problem: inaccurate bids ⇒ poor allocation
Uncertainty

• Uncertainty in
  – local state
  – teammate state
  – task state
  – environment

• Solution:
  – heuristics: bid assuming optimal conditions
  – learning: use prior information about environment
  – solution repair: re-auction tasks to teammates
Examples of Market-Based Multi-Robot Coordination
Market-Based Frameworks

- Murdoch [Gerkey, Mataric]
  - loosely coordinated tasks
  - demonstrated on box pushing
  - demonstrated robustness, fast auctioning

- TraderBots [Dias, Stentz, Zlot]
  - loosely coordinated tasks
  - demonstrated on exploration tasks
  - demonstrated robustness, scalability, auction types, task trees

- Hoplites [Kalra, Stentz]
  - tightly coordinated, spatial tasks
  - robots auction *plans* not tasks
  - demonstrated on perimeter sweeping, constrained exploration
  - relatively new
Murdoch
TraderBots

Dias, 2005
Zlot et. al., 2002
Hoplites

Kalra et. al., 2004
Comparing Threshold-Based and Market-Based Approaches for Multi-Robot Coordination
Division of Labor in Multi-Robot Systems

• Who does what? How many do what?
  – how many robots scan a room?
  – which robots track this object?
  – who plays goalie?
  – how many inspect each structure?
  – who is pulling first the stick?

• Who is actively engaged in a task and who is not?
Description of Tasks

Object $o_j$ is of type $T_o$ at $(x_j, y_j)$

There are $n_o$ objects of type $t_o$

There are $T$ types of objects

Retrieve different objects

Task: Each object $o_j$
Which robot to which object?

Task: Each type $t_o$
How many types of robots? How many robots per type?

No division of labor (if all active all the time)

Task allocation problem and solution depend heavily on task description
## Differences

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<tr>
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<td>Lots of task knowledge</td>
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<tr>
<td>Use few resources</td>
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<td>Tasks = Behaviors/Activities</td>
<td>Tasks = specific jobs</td>
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What are costs and benefits of these fundamental features?
Comparison: Event Handling Domain

- Random events handled by robots
  - Machine malfunctions, toxic spills, requests for delivery, fires
  - Tasks:

  \[ E = \{(x_1, y_1)(x_2, y_2)\ldots(x_n, y_n)\}\]

  - One robot must handle each event
  - Instantaneous assignment (no lookahead)
Metrics

• Cost of producing allocation:
  – Communication frequency
  – Computation

• Quality of allocation:
  – Number of events handled
  – Total distance traveled
The Market-Based Approach

• Goal: assign event to nearest robot

• Allocation:
  – Sequential ordered auctions
  – Bid: distance to nearest event
  – Reserve price: $d_{\text{expected}}$
Threshold-Based Approach

- Goal: robot handles closest event w/o duplicating work

- $\theta_e = \frac{1}{d_{expected}}$

- $\sigma_e = \frac{1}{d_e}$

- Deterministic response

- Random walk
Aaxes

- Communication range (0 to full)
- Accuracy in state estimation (perfect to very noisy)
- Accuracy in task estimation (perfect to very noisy)
- Range in task estimation (0 to full)
Experiments

- 10, 20, and 40 robots
- 100 x 100 environment
- 20 random events at all times
- 100 trials per experiment
- 100 steps per trial
- Microscopic agent-based model (perfectly holonomic vehicles)
Quality: Baseline

Events Handled v Team Size

Distance v Team Size

Perfect global com, no noise, parameters optimized for both
Noisy Task Estimation

Events Handled vs Noise

Crossover!

Identical to adding noise to local state

\[ \sigma_x = \sigma_y = 8 \]

\~10\% error
Poor Communication Range

Market
Threshold
Team Size

Crossover!

robots/auction

Communication Range

# Events Handled
Summary of Results

• Quality of information:
  – Markets “worth it” only with good information
  – Else, thresholds: same quality, less expensive
  – Markets worse in some respects!

• Robust to range of information
  – Markets successful with short comms
  – Both successful with short perception range
Conclusion
Take Home Messages

- Existence of several castes in natural societies (age-based, behavioral, morphological) are evident signs of division of labor
- From macroscopic models for natural systems to microscopic algorithms for artificial systems: non-trivial design choices must be carried out
- Two different classes of threshold-based algorithms: fixed and variable thresholds
- Market-based algorithms exploit points of centralization and networking for allocating more efficiently tasks
- Market-based algorithms can be more efficient than threshold-based ones at the price of more resources used; market-based allocation works efficiently only with accurate information but do not suffer too much about short communication ranges
Additional Literature – Week 11

Papers


Additional Literature – Week 11

Papers


