Revisiting Concept Learning in MAS

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What do we know so far?

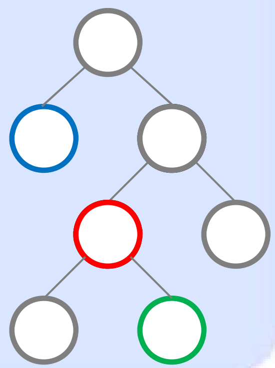
- The formal definition of an agent
- Properties of agents:
  - Autonomy
  - Rationality
  - Reflectivity/Reactivity
  - Sociality
  - Ability to learn
- Multi Agent Systems

What do we know so far? (cont'd)

- Ability to learn in agents
  - mostly important in a MAS
  - concept vs. object
  - conceptualization
  - ontology & its formal definition
  - problems & proposed solutions
  - learning methods

What do we know so far? (cont'd)

- Multi Agent Systems:
  - positive vs. negative interaction
    - Cooperation
    - Collaboration
    - Competition
  - agent formal definition in a MAS
  - MAS formal definition
  - concept learning
    - partial access to environment
  - ontology learning
    - learning from objects: pex vs. nex



Collaborative Concept Learning in Multi Agent Systems

- Traditionally:
  - communication based on group commitment to a common ontology
    - often too strong or unrealistic
- In reality:
  - we prefer to enable agents to exchange information while they keep their own individual ontology
    - knowledge representation more independent
    - more flexibility
    - much more complexity of the communication

Collaborative Concept Learning in Multi Agent Systems (cont'd)

- Solution?!
- Agents can overcome this by using their learning capabilities
  - a concept you don't know but want to communicate about?!
  - learn that concept from other agents in MAS
- A general method for agents using ontologies, teaching other concepts
  - to improve communication
  - to improve cooperation abilities

The general method

- A particular agent understands a concept only ambiguously
- Intends to learn it by receiving positive and negative examples for that concept from the other agents
- Utilizes a known concept learning method to learn the concept in question
- Asks for votes from other agents to get involved in case of conflicts

The general method (cont'd)

- Allows agents not to share common ontologies
- Enables agents to establish common grounds on concepts known only to some of them
- Improves the autonomy of agents using them significantly
- Learner agent learns a concept from **a group of agents** rather than **one peer agent**

Collaborative Concept Learning in Multi Agent Systems (cont'd)

- Agents may differ in their ontologies in two dimensions:
  - the set of features representing the concepts
  - the set of relations that connect concepts to each other
- Agents should be able to learn each other's conceptualization despite:
  - using different but overlapping sets of features
  - different sets of relations that connect concepts to each other

Feature Diversity

- Feature Vector to represent objects
  - each feature has its domain (a set of values that defines possible values the feature)
  - an object is characterized by a unique combination of the features
  - a concept is denoted by a set of possible values for the features
- Feature Diversity:
  - there need not be any correspondence between the set of features representing an object or generally a concept in one conceptualization and the set of features in another

Feature Diversity (cont’d)

- Feature Diversity may cause:
  - each agent to have its own set of features to conceptualize the world
  - one agent’s conceptualization of the world difficult or even impossible to be understood by another agent
    - RGB vs. Gray-Scale
    - Shape vs. RGB

Collaborative Concept Learning in Multi Agent Systems (cont'd)

- Basic assumptions:
  - agents come with different sets of features which are used by each to observe the world and conceptualize it
  - only some base features that are known, and respectively can be recognized by all agents with the same meaning

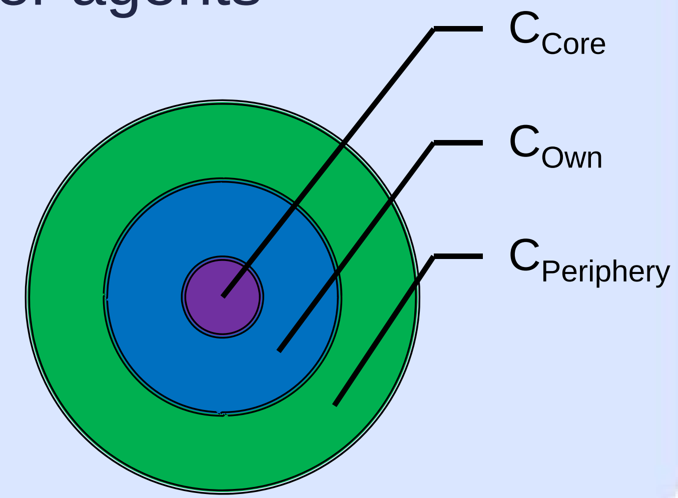
Collaborative Concept Learning in Multi Agent Systems (cont'd)

- Basic assumptions:
  - common knowledge:
    - base concepts that are known to all agents
      - names
      - feature values for base features
      - objects covered by them
  - teachers may not be unanimous on concepts:
    - different features (values)
    - different names for one concept
    - same name for different concepts
    - different relations in ontologies
  - a conflict resolution mechanism needed

Non-Unanimous Concepts

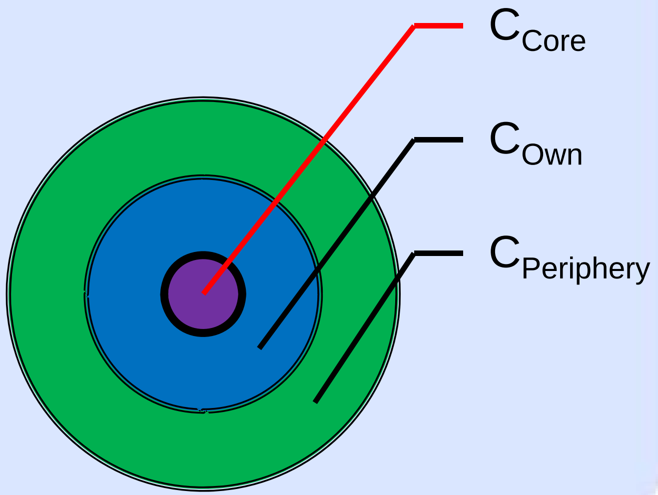
- Product of F.D. in a MA concept learning
- Allows us to express
  - different *"shades"* of agreements
  - on a particular concept
  - based on what an agent learns
  - from a group of teacher agents

$$C = (C_{Core}, C_{Own}, C_{Periphery})$$



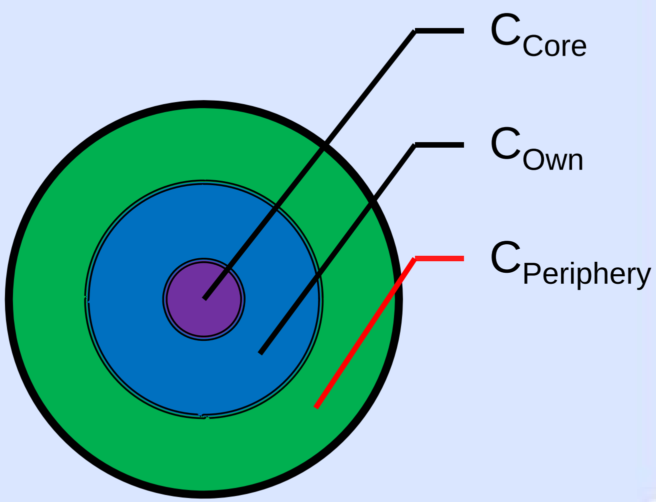
Non-Unanimous Concepts (cont'd)

- Core:
  - boundary around the area that there is no conflict among agents regarding the objects in it



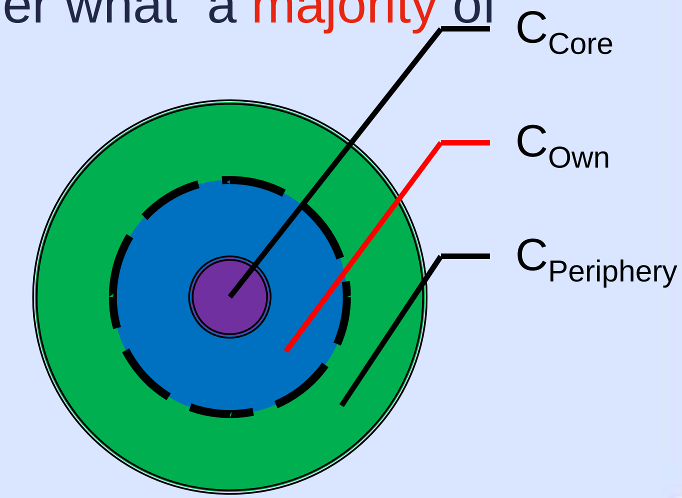
Non-Unanimous Concepts (cont'd)

- Periphery:
  - boundary around the area that covers all teacher agents' viewpoints
  - every objects that even only one agent thinks belongs to the concept is in this boundary

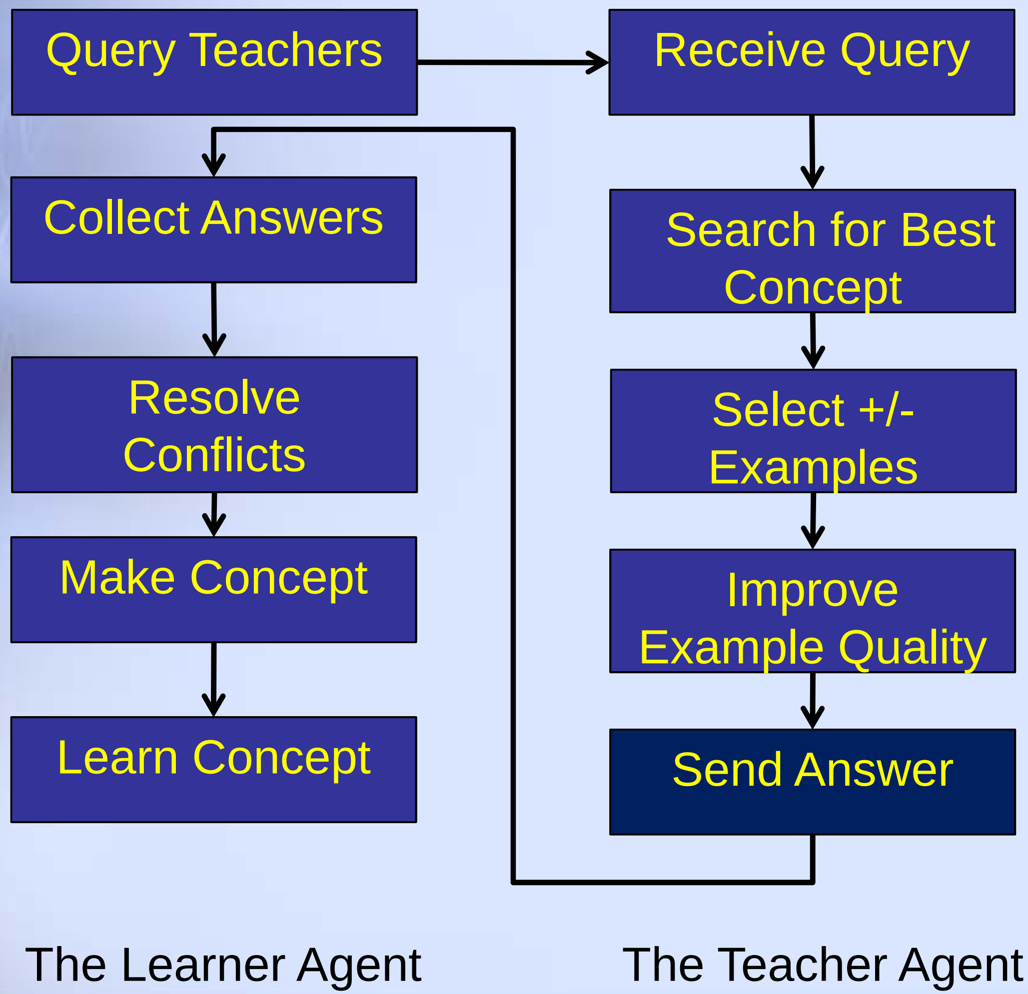


Non-Unanimous Concepts (cont'd)

- Own:
  - the learner agent itself then chooses a concept definition that:
    - encompasses the core
    - is itself encompassed by the periphery
  - a good candidate:
    - result of concept learner what a majority of teachers agree on



System overview



Using N-U Concepts in group communication

Is zero a natural number?!?!?

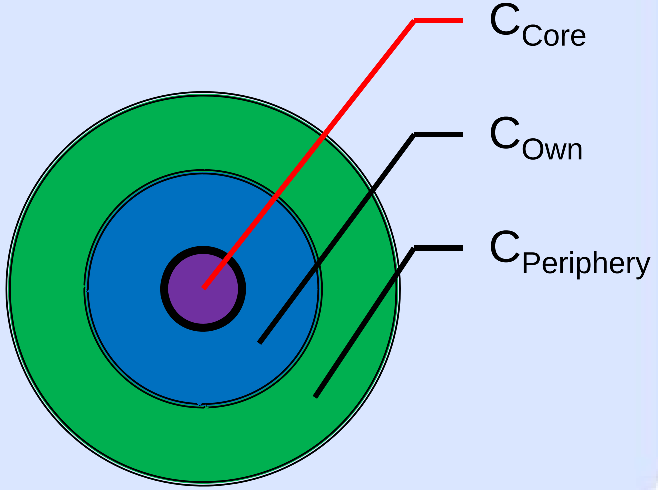
- Set theory:

YES

- Number theory:

NO

$C_{Core} = \{1, 2, 3, \ldots\}$



Using N-U Concepts in group communication (cont'd)

Is zero a natural number?!?!?

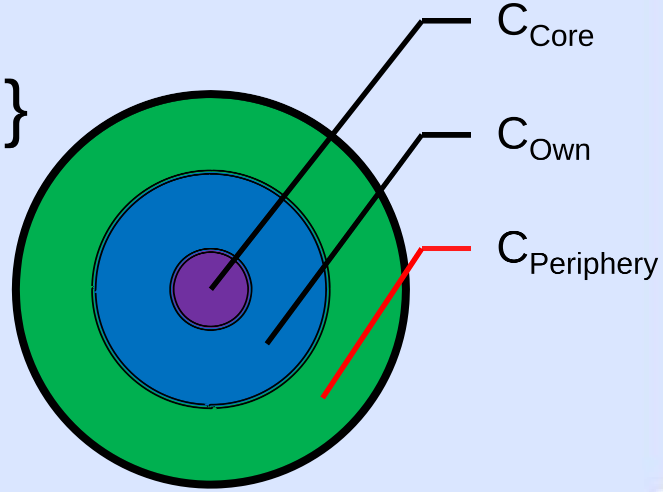
- Set theory:

YES

- Number theory:

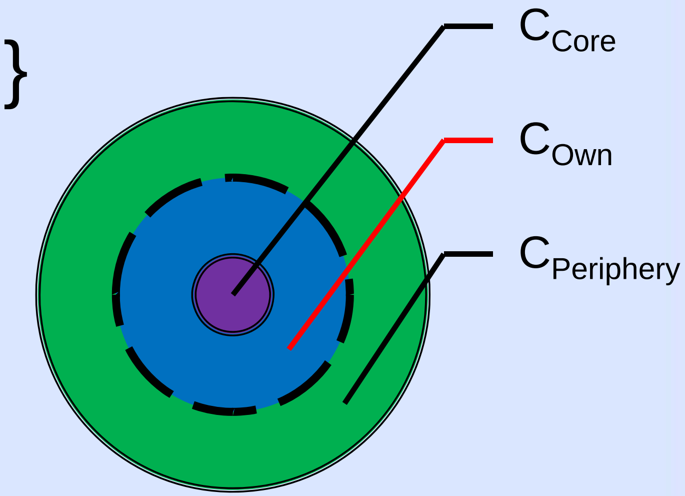
NO

$C_{Periphery} = \{0, 1, 2, 3, \ldots\}$

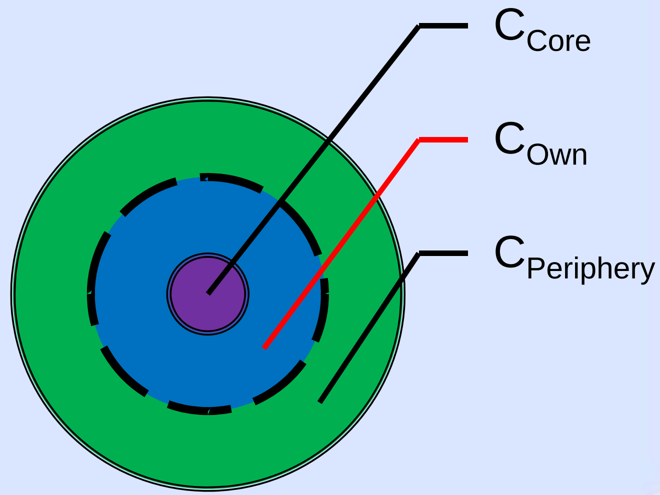


Using N-U Concepts in group communication (cont'd)

$C_{Own}^{Ag1} = \{0, 1, 2, 3, \ldots\}$



$C_{Own}^{Ag2} = \{1, 2, 3, \ldots\}$



Using N-U Concepts in group communication (cont'd)

Now what if these two agents want to communicate with a group of mathematicians, including both number and set theoreticians?!?!

- Ag1 decides:
  - $C_{Own} = C_{periphery}$
  - Zero is the sole element of $pex^{Own} - pex^{Core}$
  - Ag1 want to say something that holds for all natural numbers (inclusive manner)
  - Ag1's communication could be understood by everyone
  - Some redundancy may occur

Using N-U Concepts in group communication (cont'd)

Now what if these two agents want to communicate with a group of mathematicians, including both number and set theoreticians?!?!

- Ag2 decides:
  - $C_{Own} = C_{Core}$
  - Zero is the sole element of $pex^{Periphery} - pex^{Own}$
  - Ag1 want to say something that holds for no natural number (exclusive manner)
  - Ag1's communication could be understood by everyone
    - if she says that it also doesn't hold for zero

Problems to face in communication

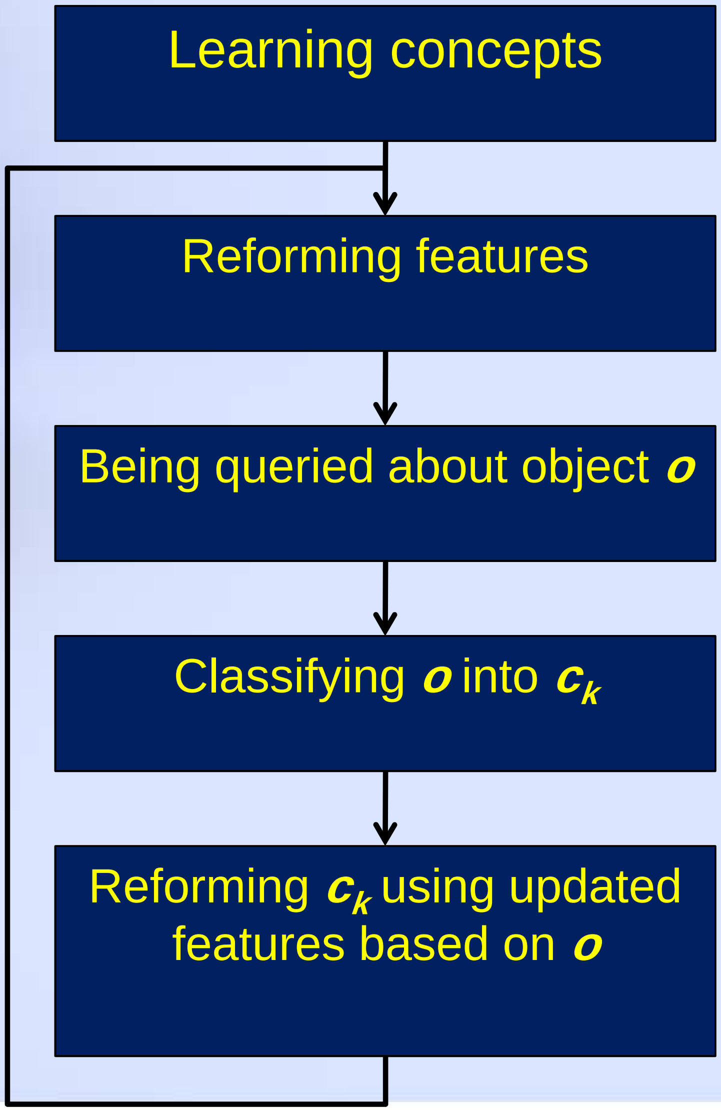
- Dynamically establishing common grounds is needed
- Different members of a group will differ in their ontologies
- Impossible to learn ontologies of all agents in a large group
- When talking to all agents at once: what ontology to use?

What have we done?

"Incremental Concept Reformation Through Queried Object Classification"

- New information that can help the agent to make the definition of a concept more concrete (*i.e. new objects*)
  - should be compatible with knowledge structure
  - keeping all objects not feasible
- Update concept definition by keeping the object in memory
- Feature-based representation of concepts (a modification to previous one)

ICRTQOC



General Concept Reform Process

ICRTQOC (cont'd)

- Generally, learning of new concepts is happening from *scratch*
  - no place for concept in agent's ontology before the learning process
- Incrementally updating the understanding of an agent about a specific concept
- Defining for any feature f_i and value v_{ij} in any boundary a conditional probability
  - use objects that has been collected by agent during the learning process of c_k

ICRTQOC (cont'd)

- We have for each boundary of C_{Own}, C_{Core} and $C_{Periphery}$ probabilities assigned to every combinations of features and values, as:

$$P(f_i = v_{ij} | c_{bu_k}) = \frac{|\{(f_i, v_{ij}) | f_i = v_{ij} \wedge v_{ij} \in V_i\}|}{|objects \in c_{bu_k}|}$$

- The probability of object o being an instance of concept c_k is as:

$$P(c_k | o) = P(c_k) \prod_{f_i} P(f_i = v_{ij} / c_k)$$

ICRTQOC (cont'd)

Algorithm 1 Probabilistic incrementally update of agent understanding regarding a specific concept

Observe an object o through a query

for all concept c_i in agent's ontology **do**

  $k = argmax_i \; P(c_i) \prod_{f_i} P(f_i = v_{ij}/c_i)$

end for

for all Boundary bu in $core$,own and $periphery$ of c_k **do**

  $P(c_{bu_k}/o) = P(o/c_{bu_k}) \times P(c_{bu_k})$

  for all f_i and possible value v_{ij} **do**

    $P_{new}(f_i = v_{ij}/c_{bu_k}) = P_{old}(f_i = v_{ij}/c_{bu_k}) + sgn(P(c_{bu_k}/o) - thr_{bu_k}) \times \alpha \times P(c_{bu_k}/o) \times (1 - P_{old}(f_i = v_{ij}/c_{bu_k})) \times P_{old}(f_i = v_{ij}/c_{bu_k})$

  end for

end for

harsh change inhibitor

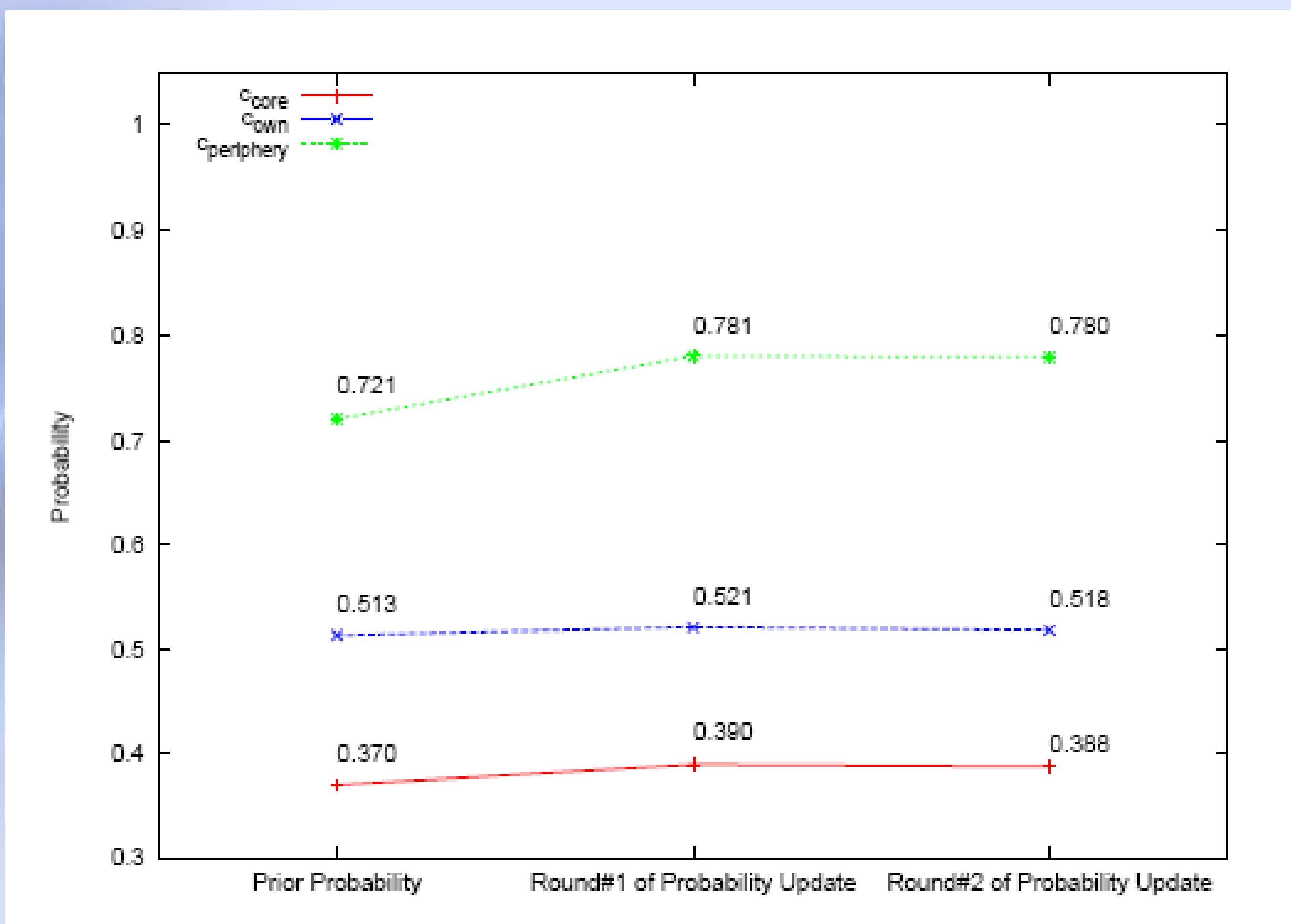
increase/decrease decision

ICRTQOC (cont'd)

Border	features	prior	round #1	round #2
c_{core}	$f_{web,algorithm,program}$	0.721	0.781	0.780
	$f_{design,processor,reliability}$	0.650	0.661	0.669
	$f_{performance,central,protocols}$	0.433	0.452	0.451
	$f_{proof,cryptography,undecidability}$	0.513	0.507	0.505
	$f_{power,image,electronic}$	0.303	0.297	0.301
	$f_{plasma,signal,circuit}$	0.257	0.246	0.251
c_{own}	$f_{web,algorithm,program}$	0.513	0.521	0.518
	$f_{design,processor,reliability}$	0.461	0.470	0.475
	$f_{performance,central,protocols}$	0.392	0.393	0.388
	$f_{proof,cryptography,undecidability}$	0.480	0.472	0.469
	$f_{power,image,electronic}$	0.419	0.416	0.425
	$f_{plasma,signal,circuit}$	0.473	0.461	0.467
$c_{periphery}$	$f_{web,algorithm,program}$	0.370	0.390	0.388
	$f_{design,processor,reliability}$	0.400	0.407	0.413
	$f_{performance,central,protocols}$	0.376	0.379	0.374
	$f_{proof,cryptography,undecidability}$	0.498	0.492	0.491
	$f_{power,image,electronic}$	0.721	0.700	0.711
	$f_{plasma,signal,circuit}$	0.619	0.601	0.610

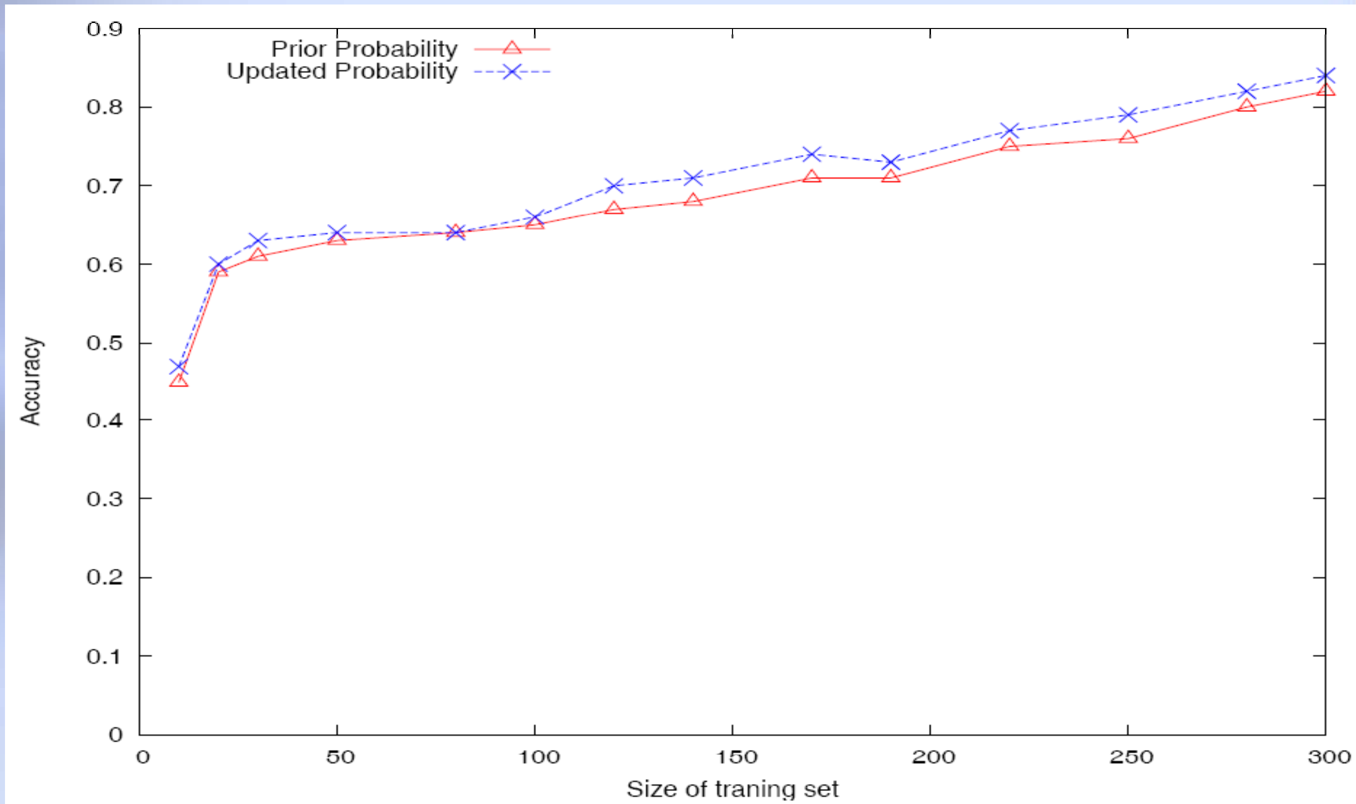
Sample features describing concept *computer science*

ICRTQOC (cont'd)



Updating the probability of feature $f_{web;algorithm;program}$

ICRTQOC (cont'd)



Two different set of features and their classification accuracy

Conclusion

- Non-Unanimous concepts allow us to make agents aware of possible misunderstandings when communicating to a group of agents
- New representation of Non-Unanimous Concepts enable us to incrementally update the agents understanding of a concept

References

1. **Mohsen Afsharchi**, *“Ontology-Guided Collaborative Concept Learning in Multi agent Systems”*, PHD Dissertation;
2. **Nima Mirbakhsh, Arman Didandeh, Mohsen Afsharchi**, *“Incremental Non-Unanimous Concept Reformation through Queried Object Classification”*, WI/IAT’09, Bicocca university, Milan, Italy;

Questions
are welcome