



Argumentation-based Distributed Induction



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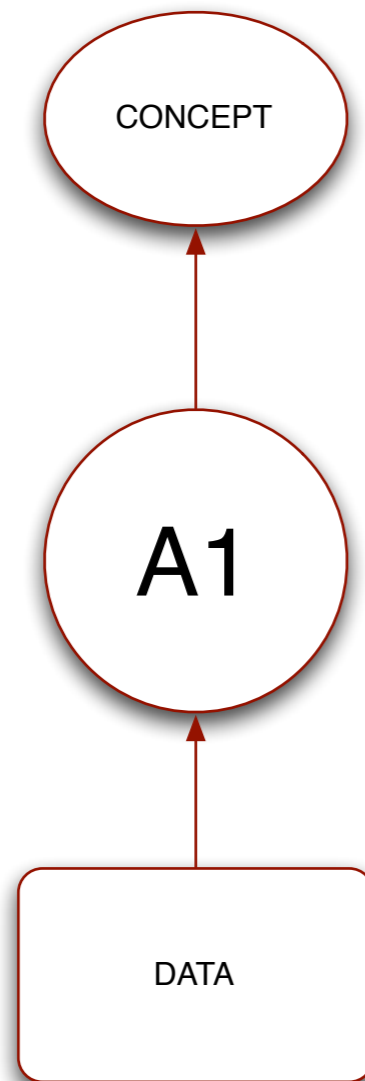
WAT-09, 9-11-2009, Seville



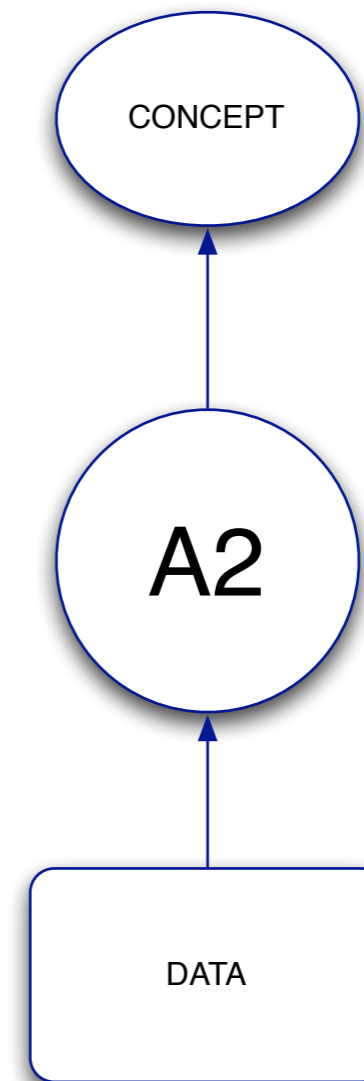
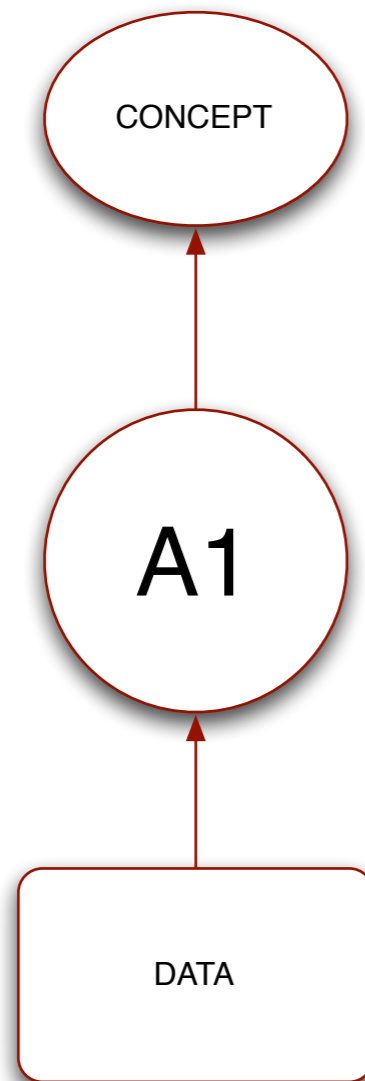
Outline

- Motivation
- Approach
- Evaluation
- Future

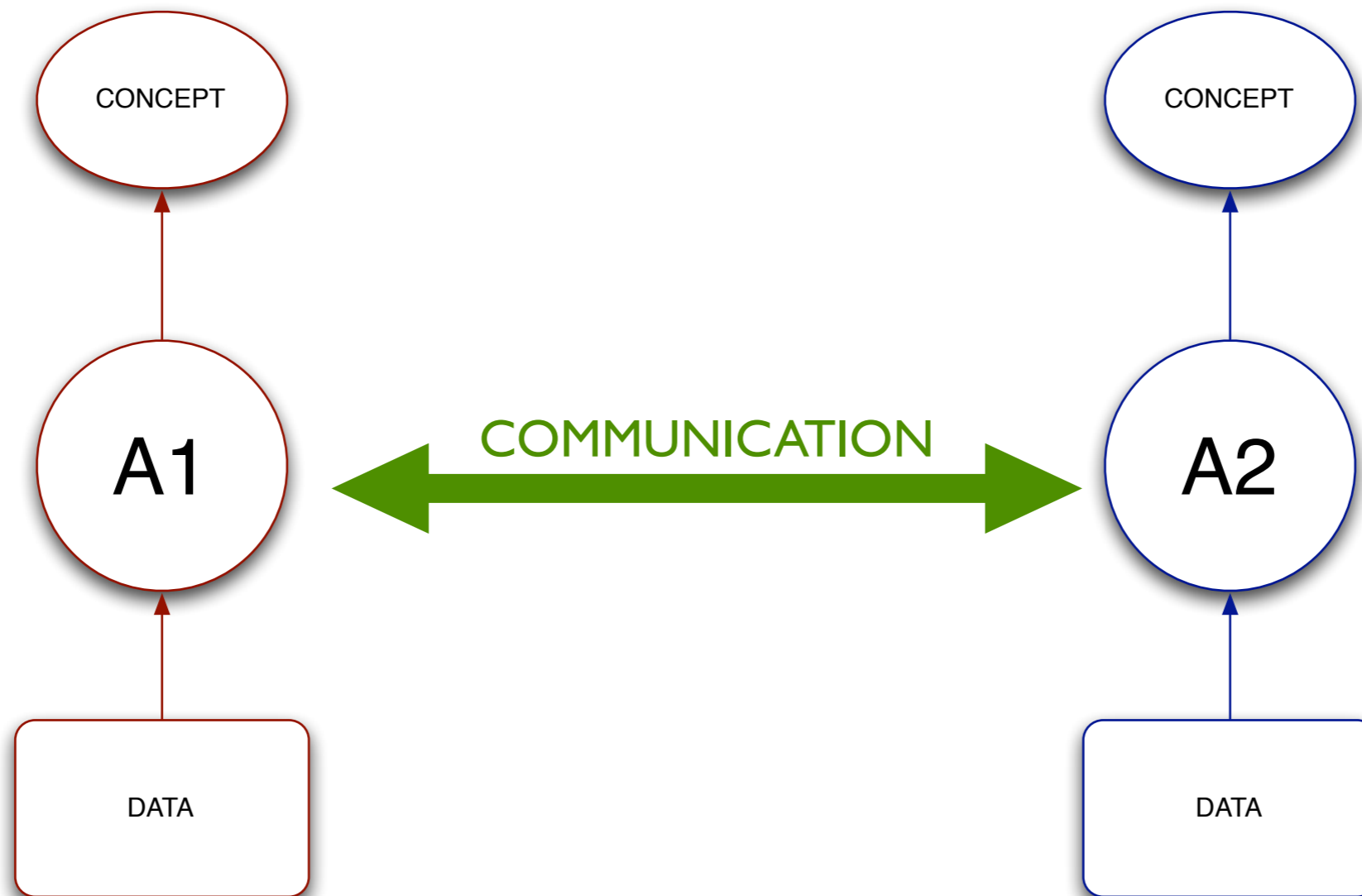
Motivation



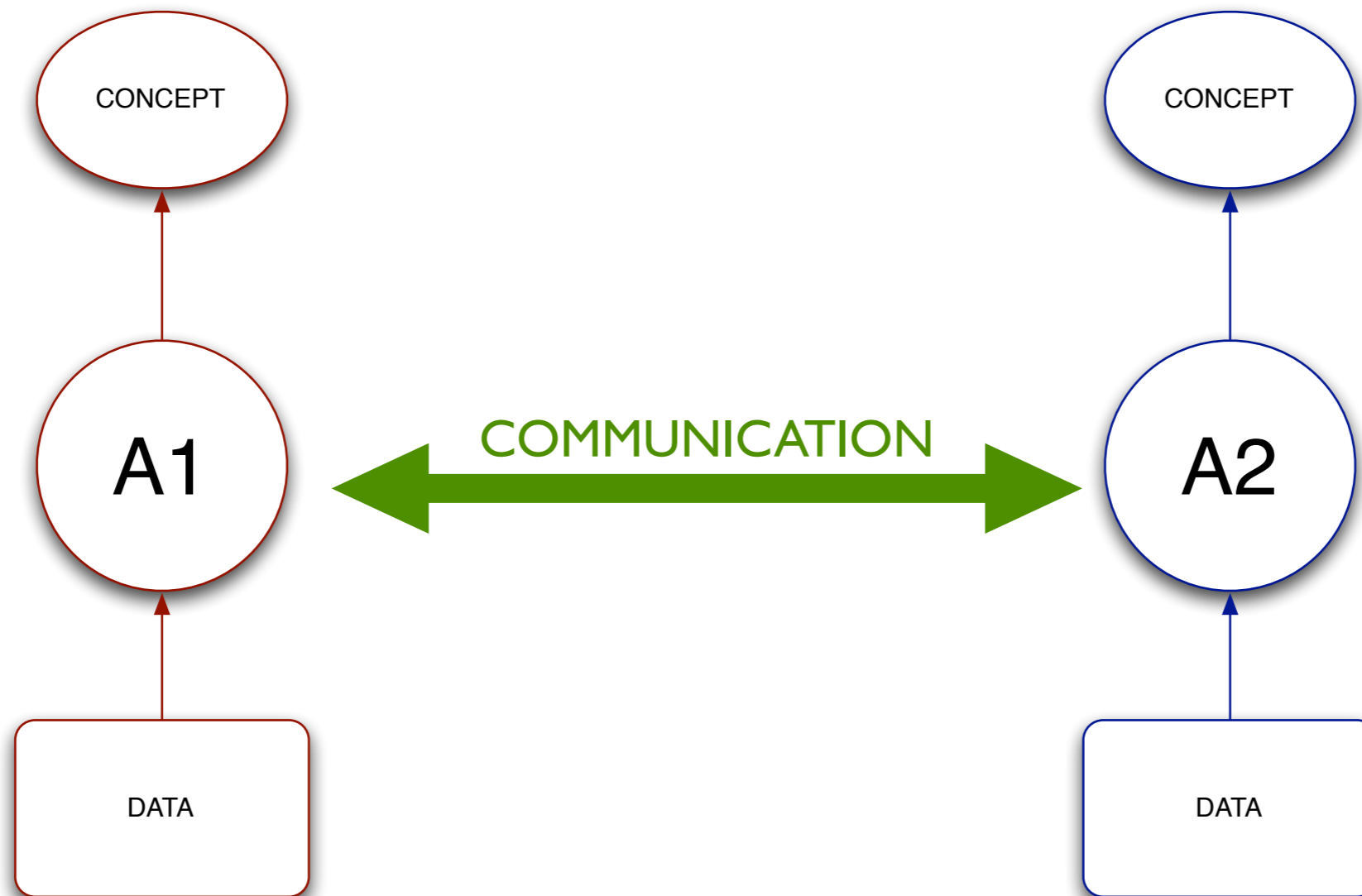
Motivation



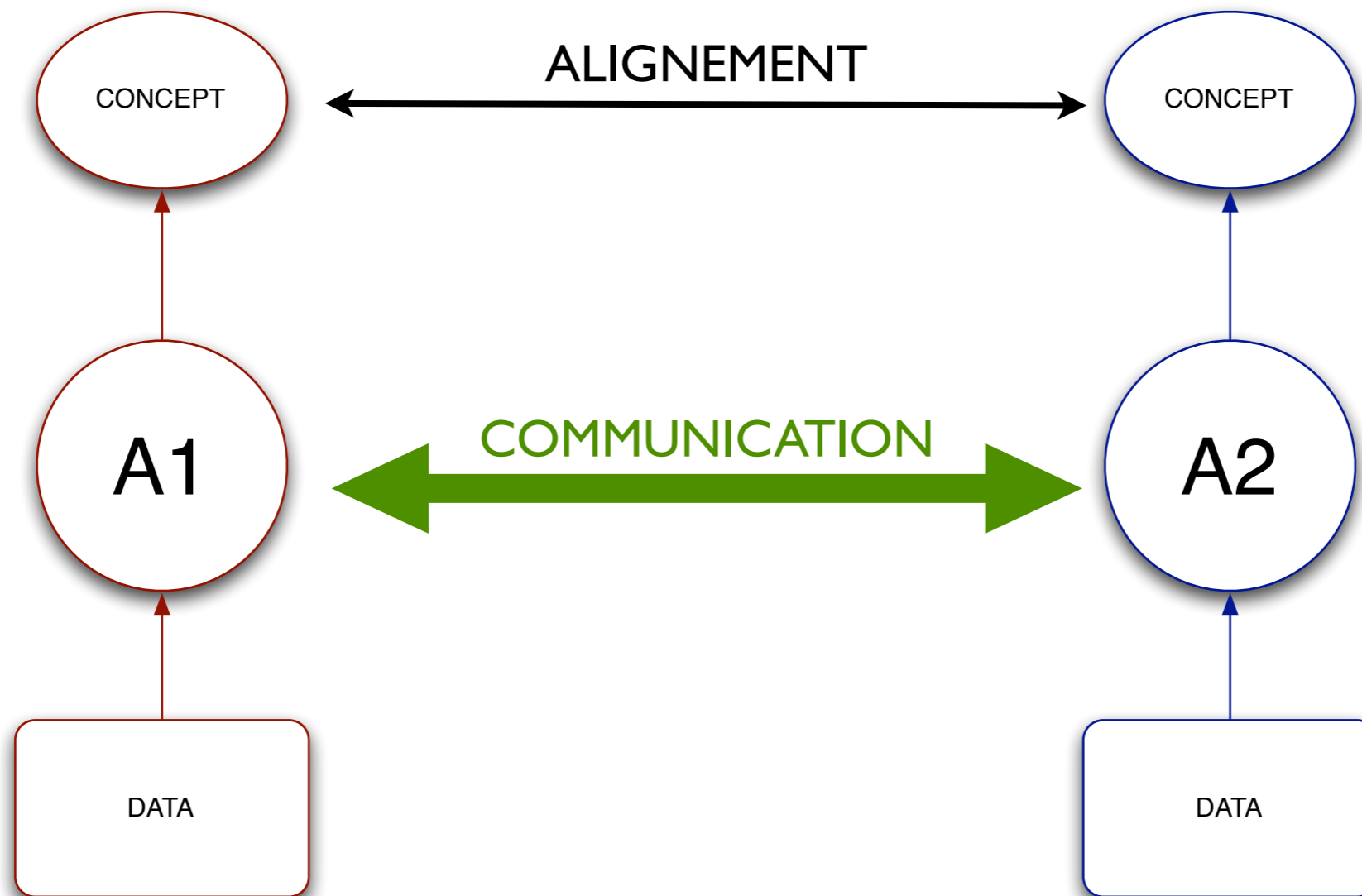
Motivation



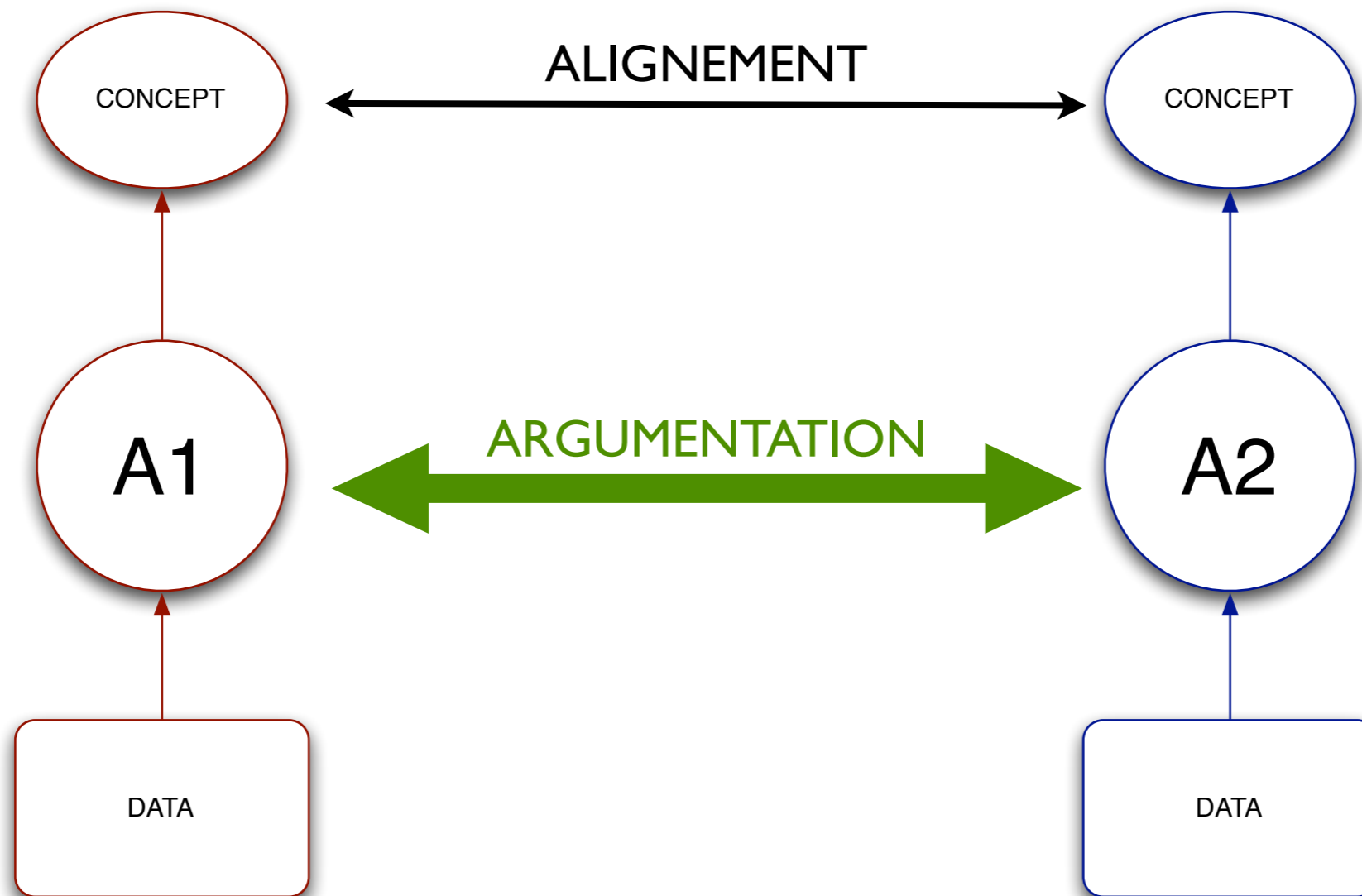
Motivation



Motivation



Motivation



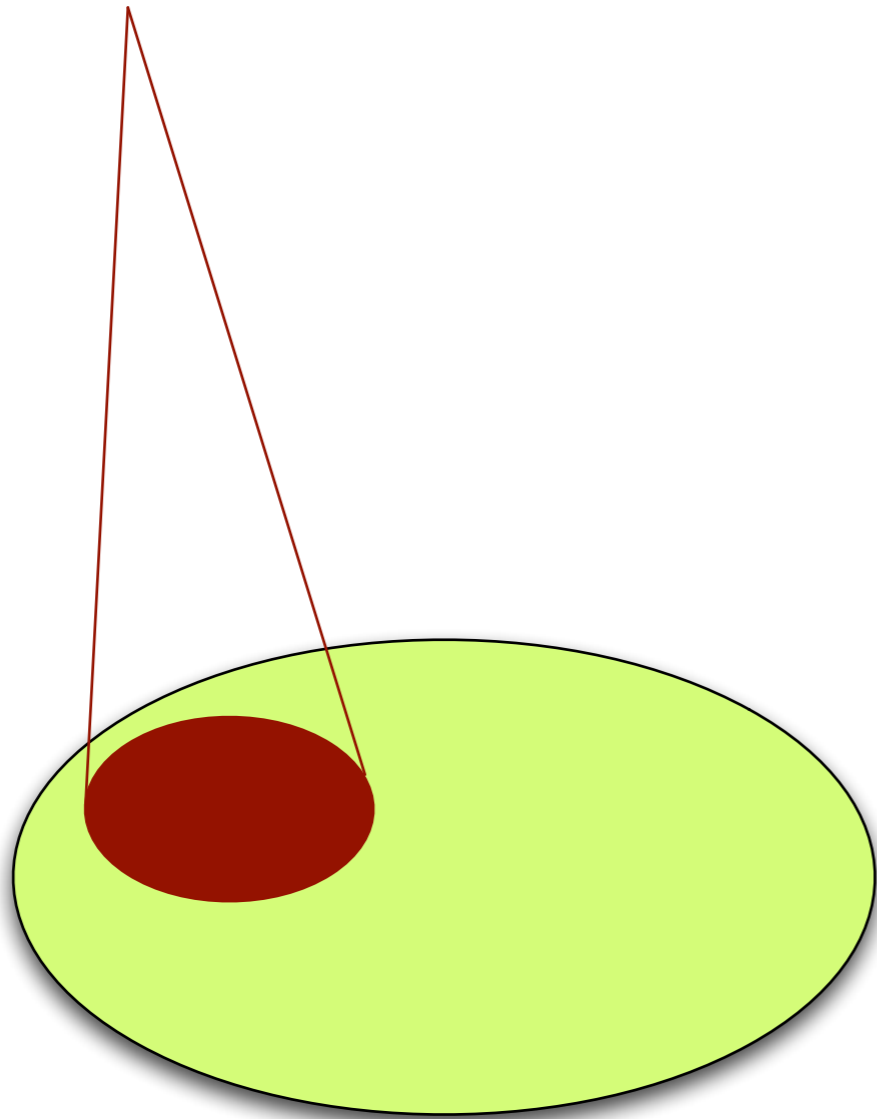


Goals

1. Distributed induction
2. argumentation-based communication process
3. on top of existing ML methods
 - ID3 (decision trees)
 - CN2 (rule induction)
 - INDIE (relational inductive learning)

Induction

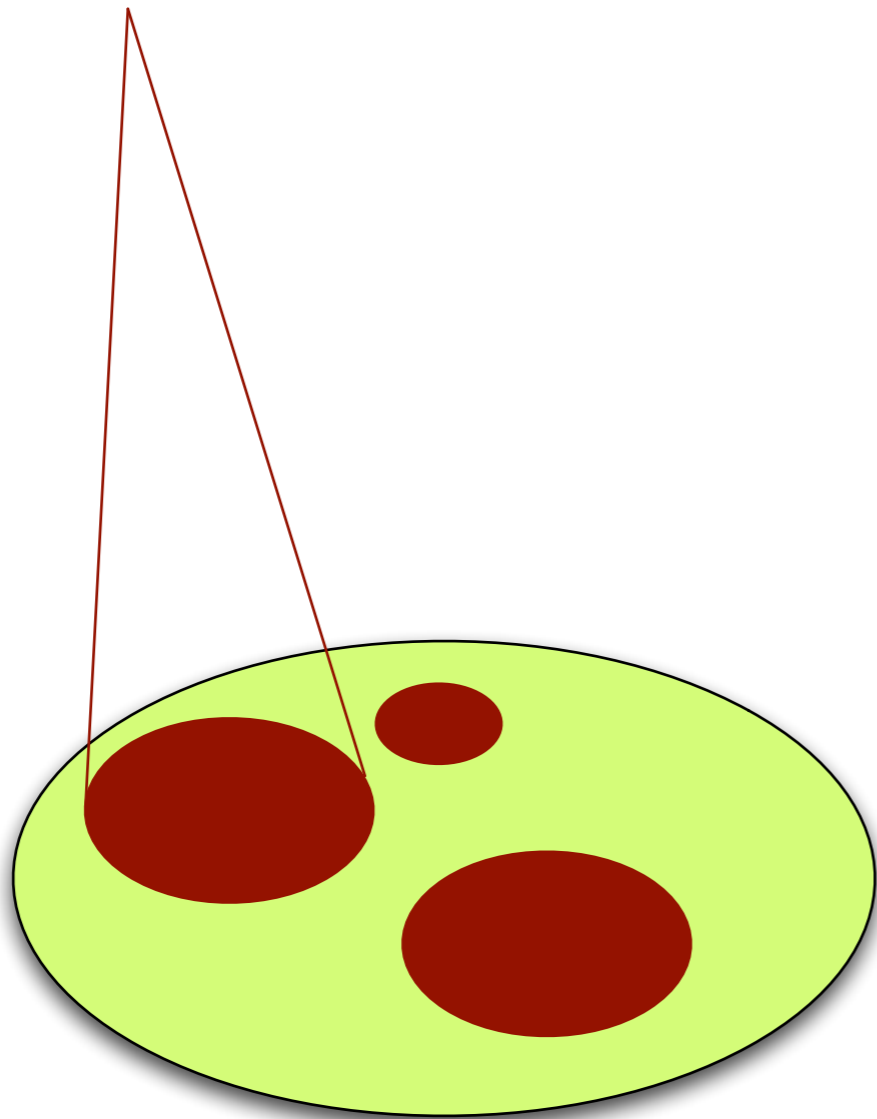
$$p_1 \wedge p_2 \wedge p_3 \longrightarrow C$$



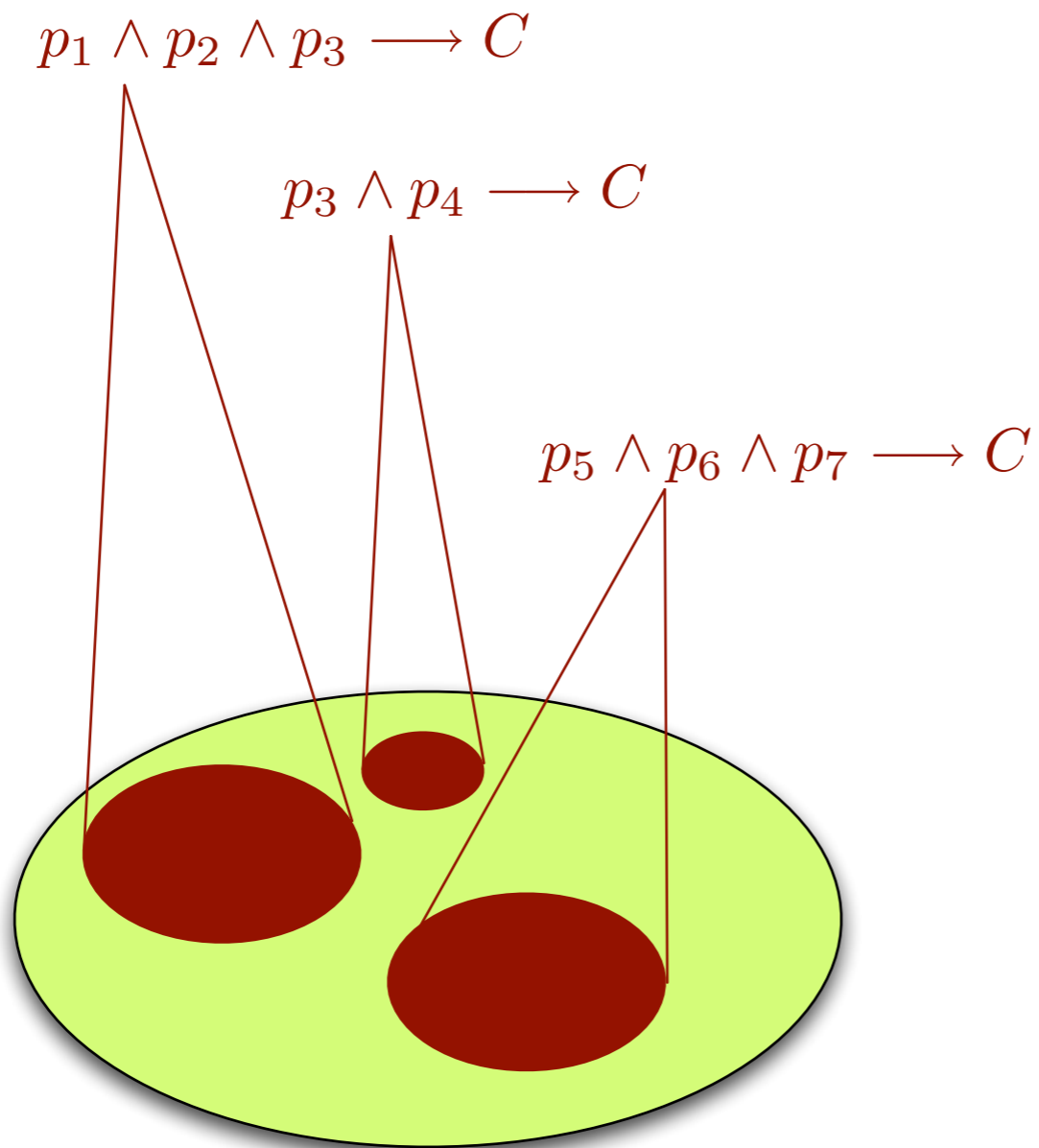
Hypothesis
(an example is a
concept C when
rule is satisfied)

Induction

$$p_1 \wedge p_2 \wedge p_3 \longrightarrow C$$

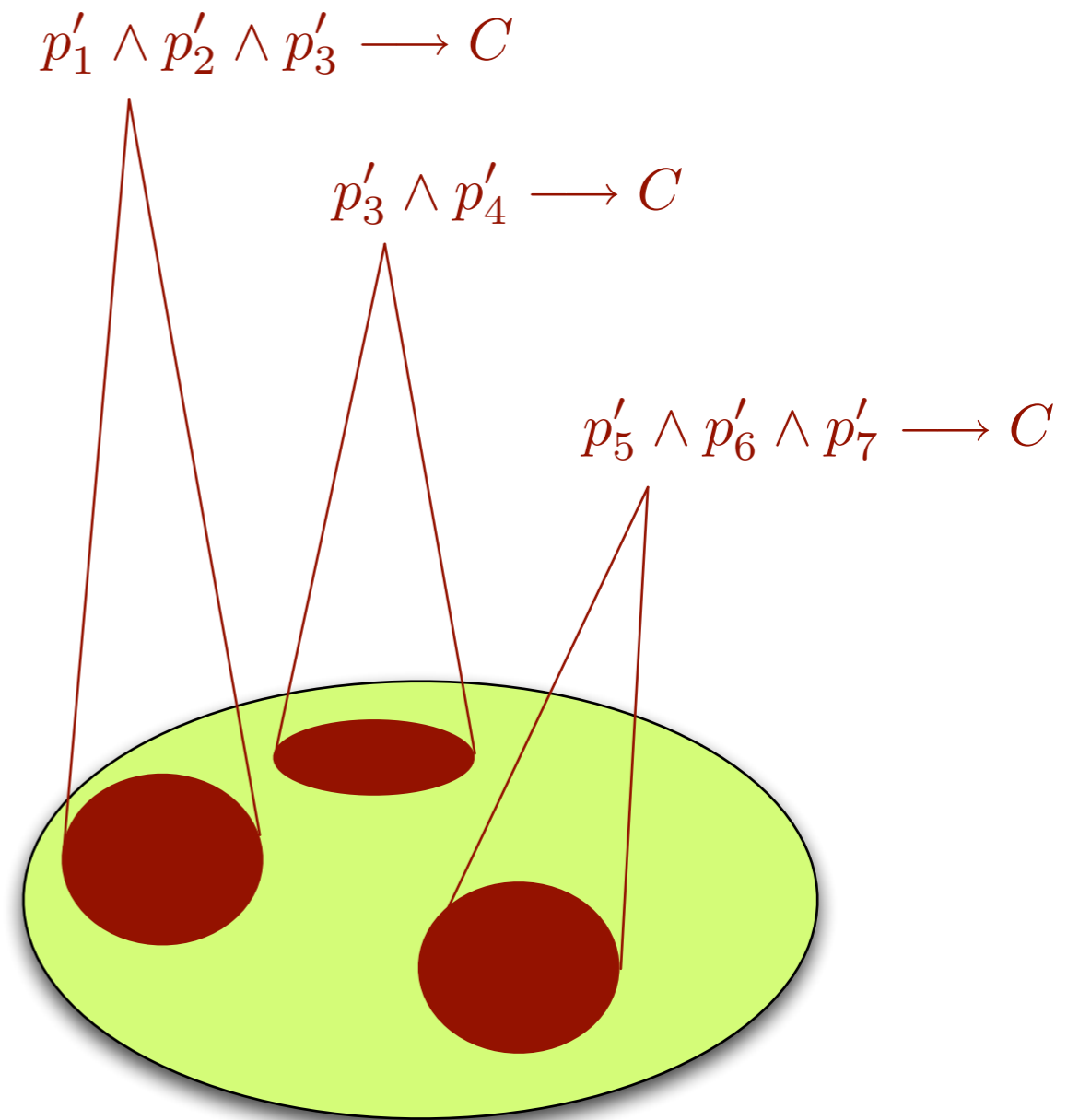
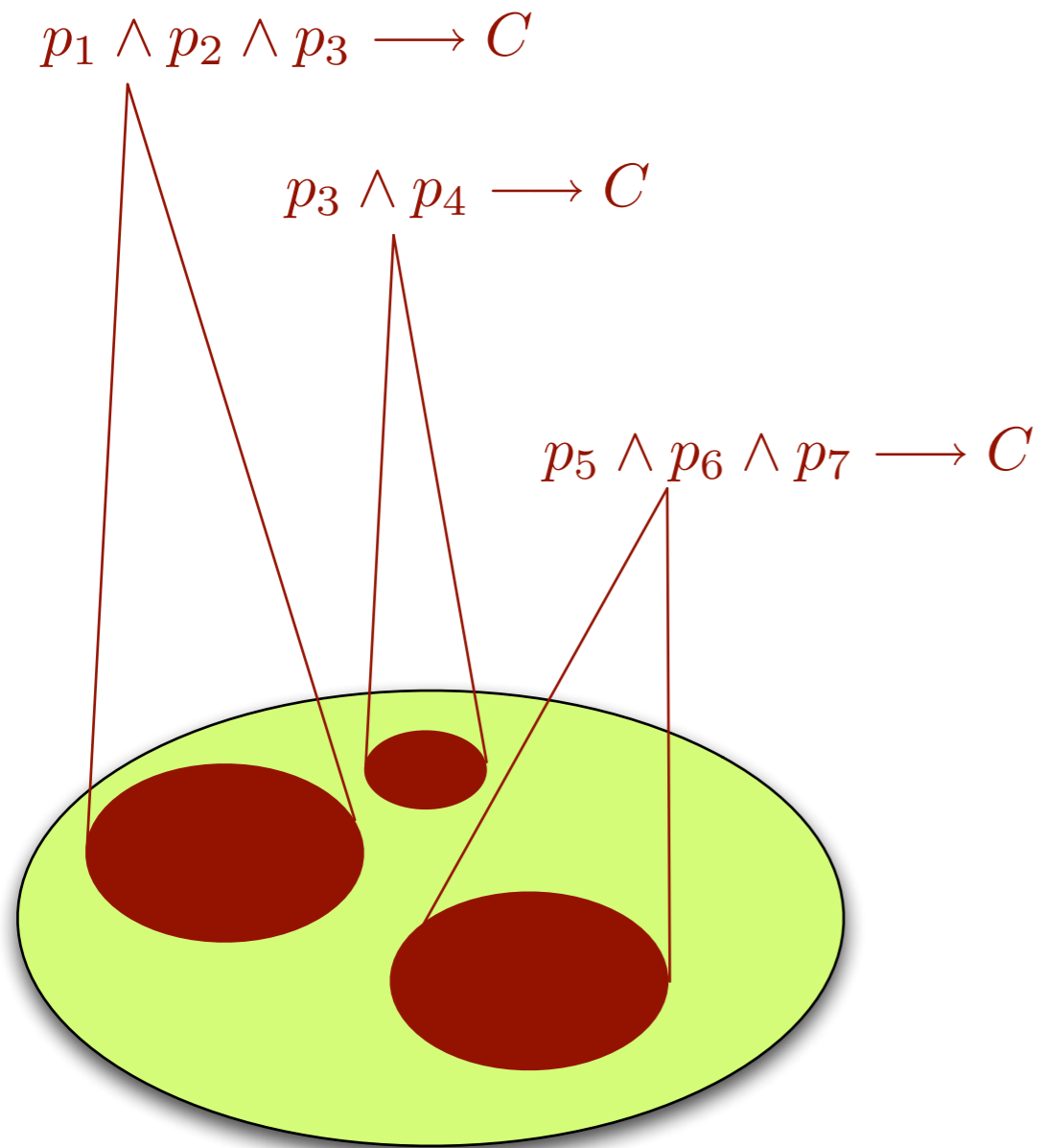


Induction



Hypothesis for C
=
disjunction of rules

Induction with 2 agents



Agreement?

$$p_1 \wedge p_2 \wedge p_3 \longrightarrow C$$

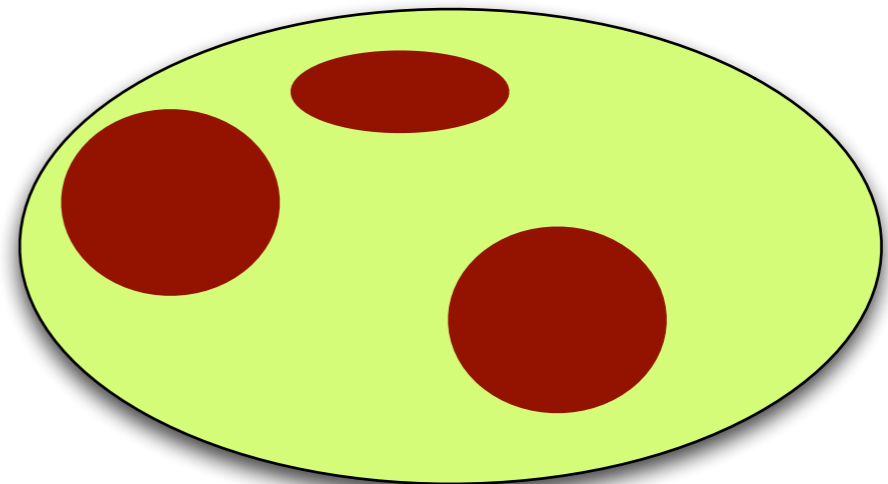
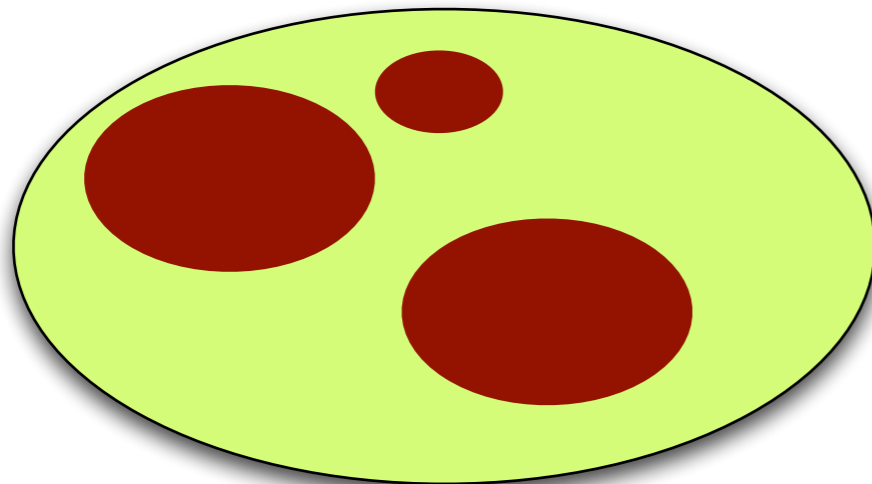
$$p_3 \wedge p_4 \longrightarrow C$$

$$p_5 \wedge p_6 \wedge p_7 \longrightarrow C$$

$$p'_1 \wedge p'_2 \wedge p'_3 \longrightarrow C$$

$$p'_3 \wedge p'_4 \longrightarrow C$$

$$p'_5 \wedge p'_6 \wedge p'_7 \longrightarrow C$$



Agreement?

$$p_1 \wedge p_2 \wedge p_3 \longrightarrow C$$

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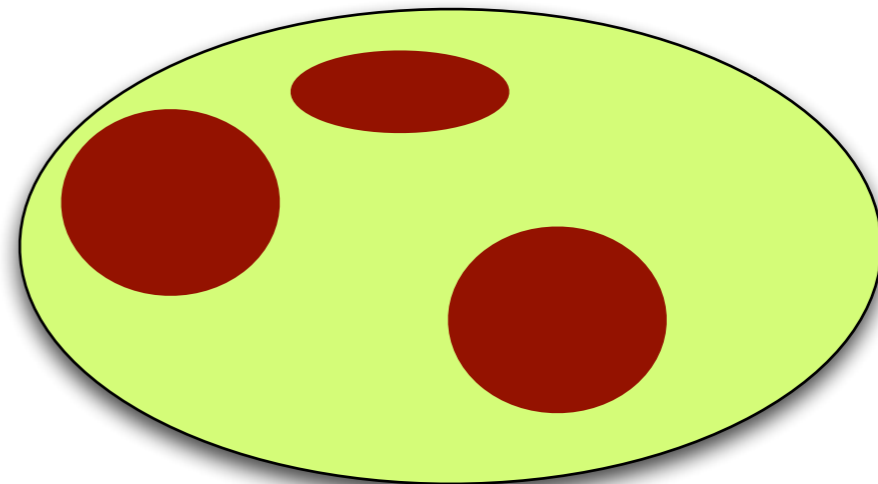
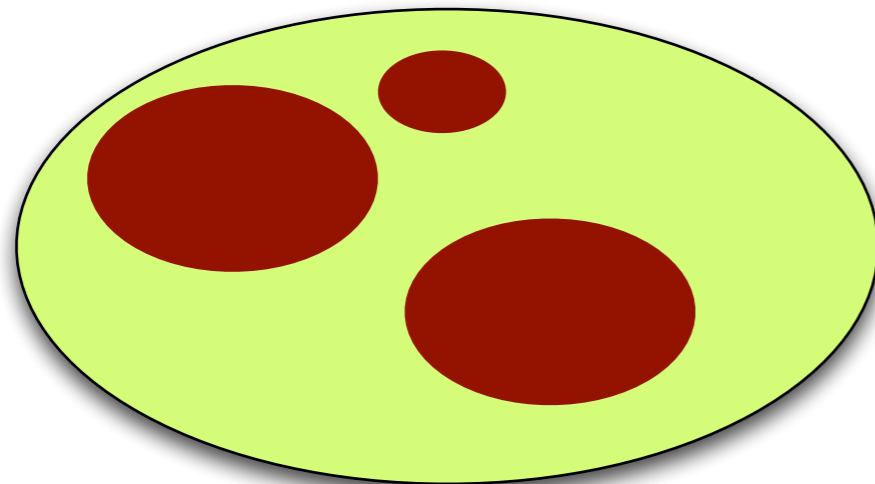
$$p_5 \wedge p_6 \wedge p_7 \longrightarrow C$$



$$p'_1 \wedge p'_2 \wedge p'_3 \longrightarrow C$$

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Agreement?

$$p_1 \wedge p_2 \wedge p_3 \longrightarrow C$$

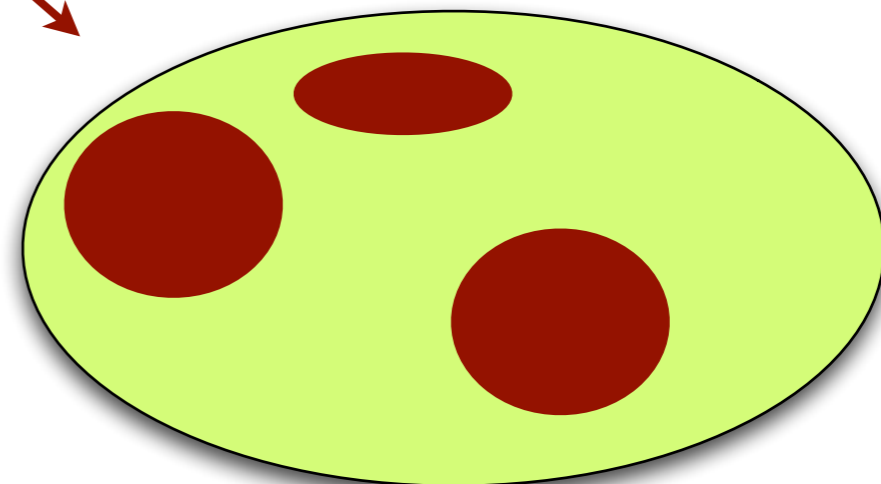
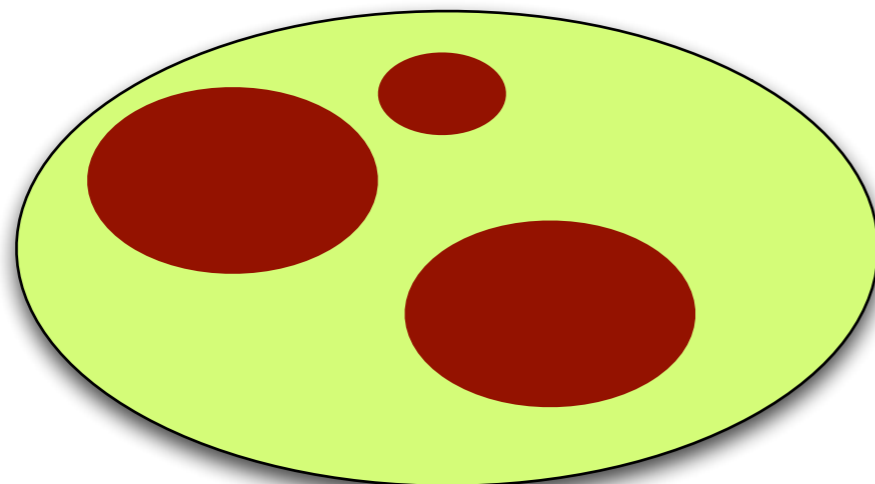
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Agreement?

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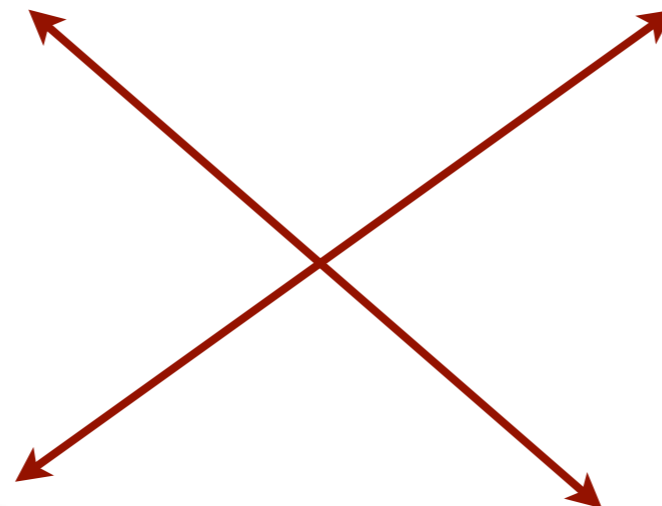
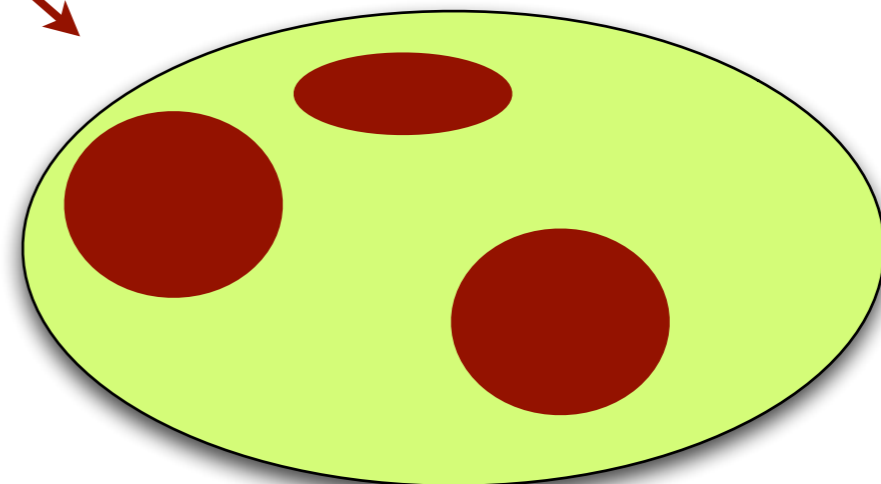
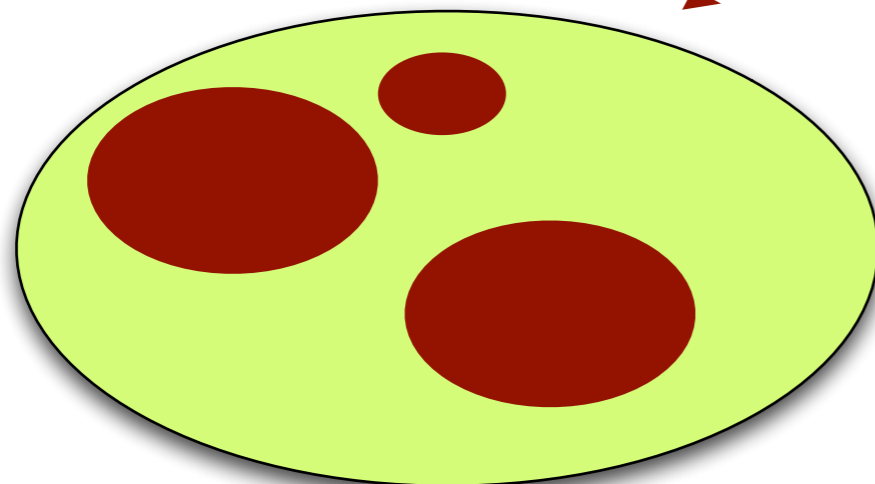
$$p_3 \wedge p_4 \longrightarrow C$$

$$p_5 \wedge p_6 \wedge p_7 \longrightarrow C$$

$$p'_1 \wedge p'_2 \wedge p'_3 \longrightarrow C$$

$$p'_3 \wedge p'_4 \longrightarrow C$$

$$p'_5 \wedge p'_6 \wedge p'_7 \longrightarrow C$$





Approach



Argumentation

- Argumentation as a process :
 - to reach an agreed concept between 2 agents
 - regulated interchange for contrasting, attacking, and revising beliefs
- Working upon existing ML induction methods
 - ID3
 - CN2
 - INDIE



Argumentation

Examples

$$e = \langle P, S \rangle \text{ where } (S \in \mathcal{S})$$

Hypotheses

$$\mathbb{H} = \{r_1, \dots, r_m\}$$

Rules

$$r = \langle H, S \rangle$$



Argumentation

Examples

$$e = \langle P, S \rangle \text{ where } (S \in \mathcal{S})$$

Hypotheses

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Rules

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Argumentation

Examples

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Rules

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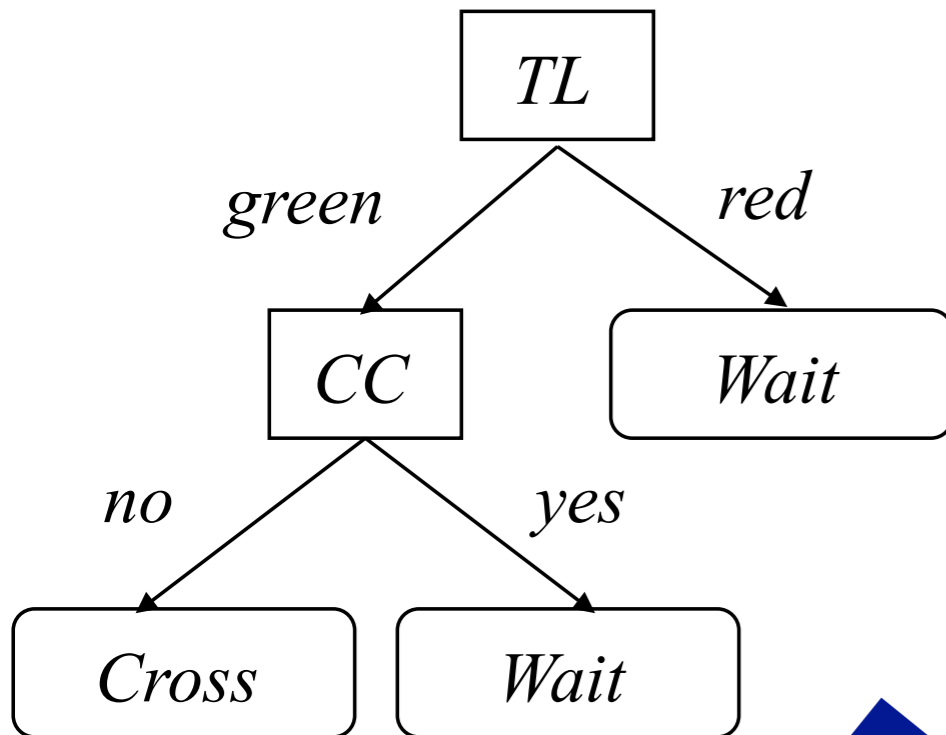
Argument

$$\alpha = \langle A, r \rangle$$

Counter-example

$$\beta = \langle A, e, \alpha \rangle$$

ID3 rule conversion



A large blue arrow points from the decision tree to the rule set below.

$$\left\{ \begin{array}{l} r_1 := \langle TL = green \wedge CC = no, Cross \rangle \\ r_2 := \langle TL = green \wedge CC = yes, Wait \rangle \\ r_3 := \langle TL = red, Wait \rangle \end{array} \right.$$

CN2 post-process

Post-processing removes order dependencies among rules used in CN2

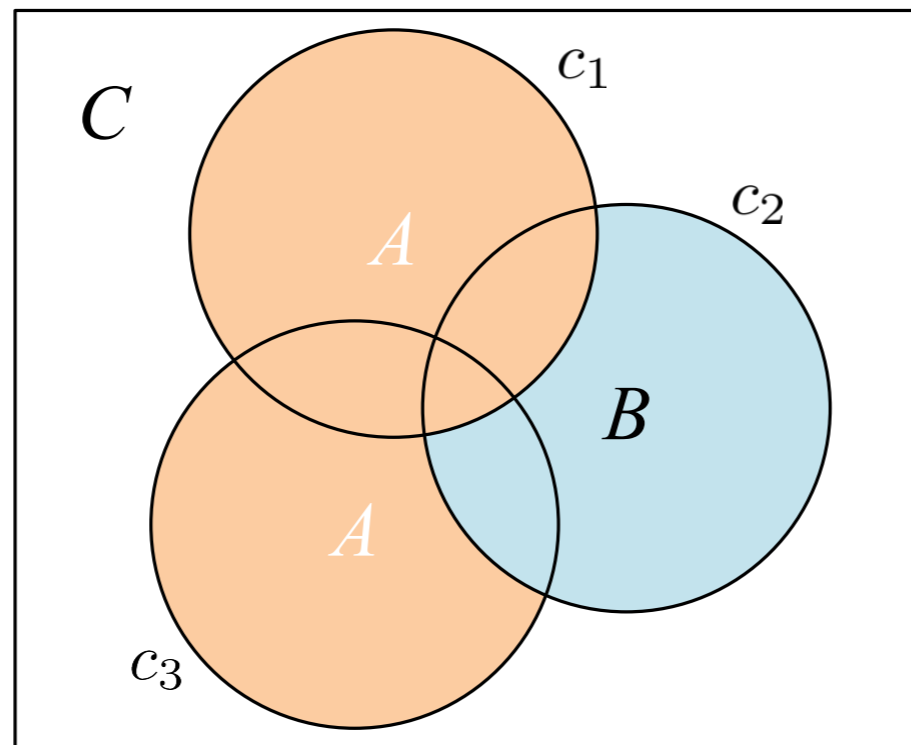
CN2 output:

$$r_1 = \langle c_1, A \rangle$$

$$r_2 = \langle c_2, B \rangle$$

$$r_3 = \langle c_3, A \rangle$$

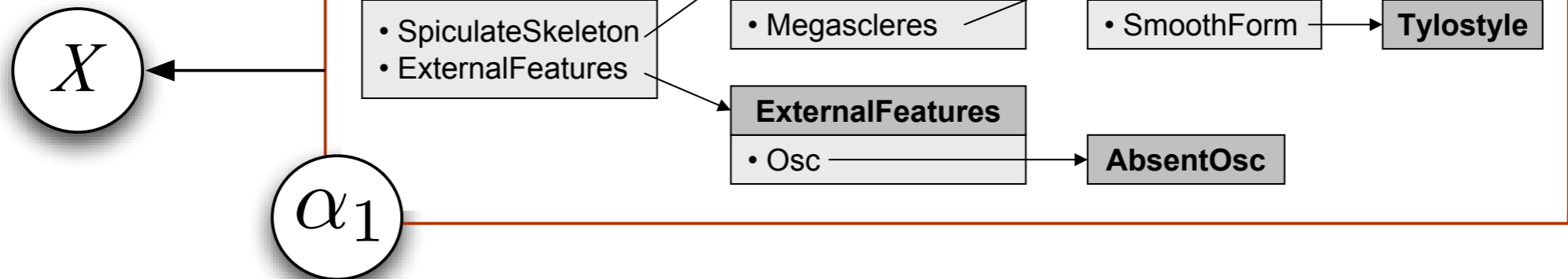
default: C



$$\left\{ \begin{array}{l} r'_1 = \langle c_1, A \rangle \\ r'_2 = \langle c_2 \wedge \neg c_1, B \rangle \\ r'_3 = \langle c_3 \wedge \neg c_1 \wedge \neg c_2, A \rangle \\ r'_4 = \langle \neg c_1 \wedge \neg c_2 \wedge \neg c_3, C \rangle \end{array} \right.$$

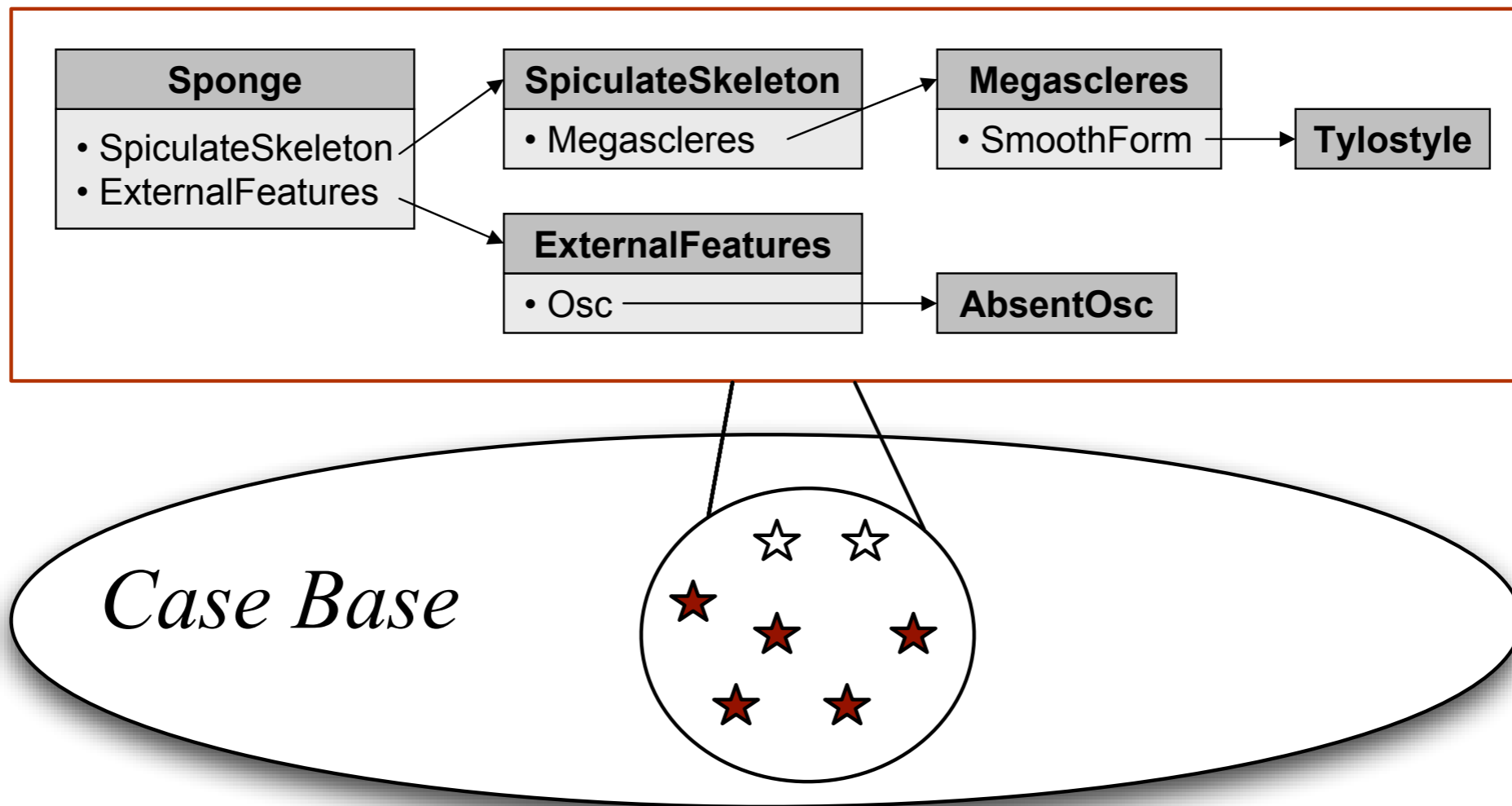
Argument

Solution



Argument evaluation

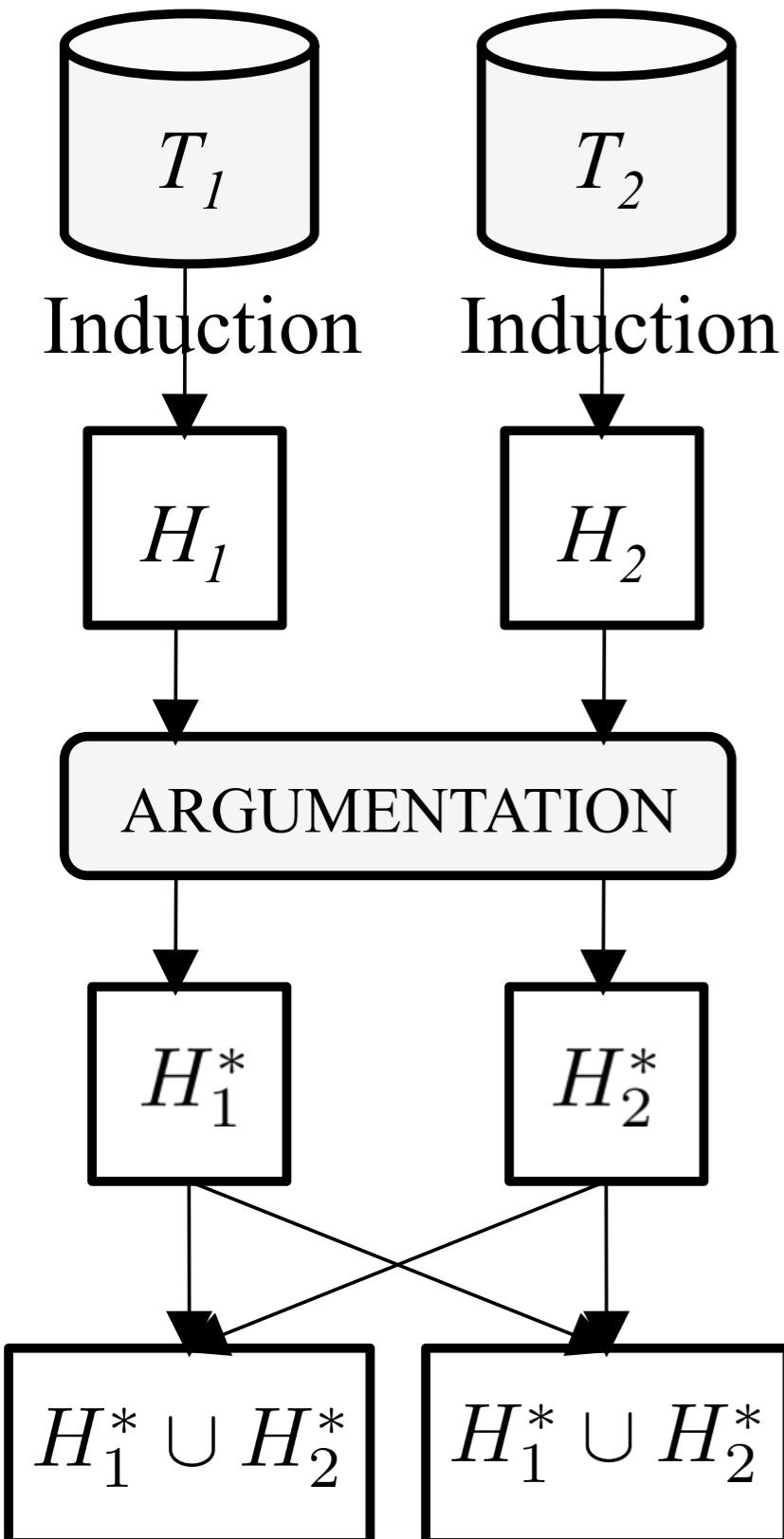
*The other's arguments
are contrasted with one's examples*



Finding Counter-examples of an argument

ADI

Argumentation-based
Distributed Induction

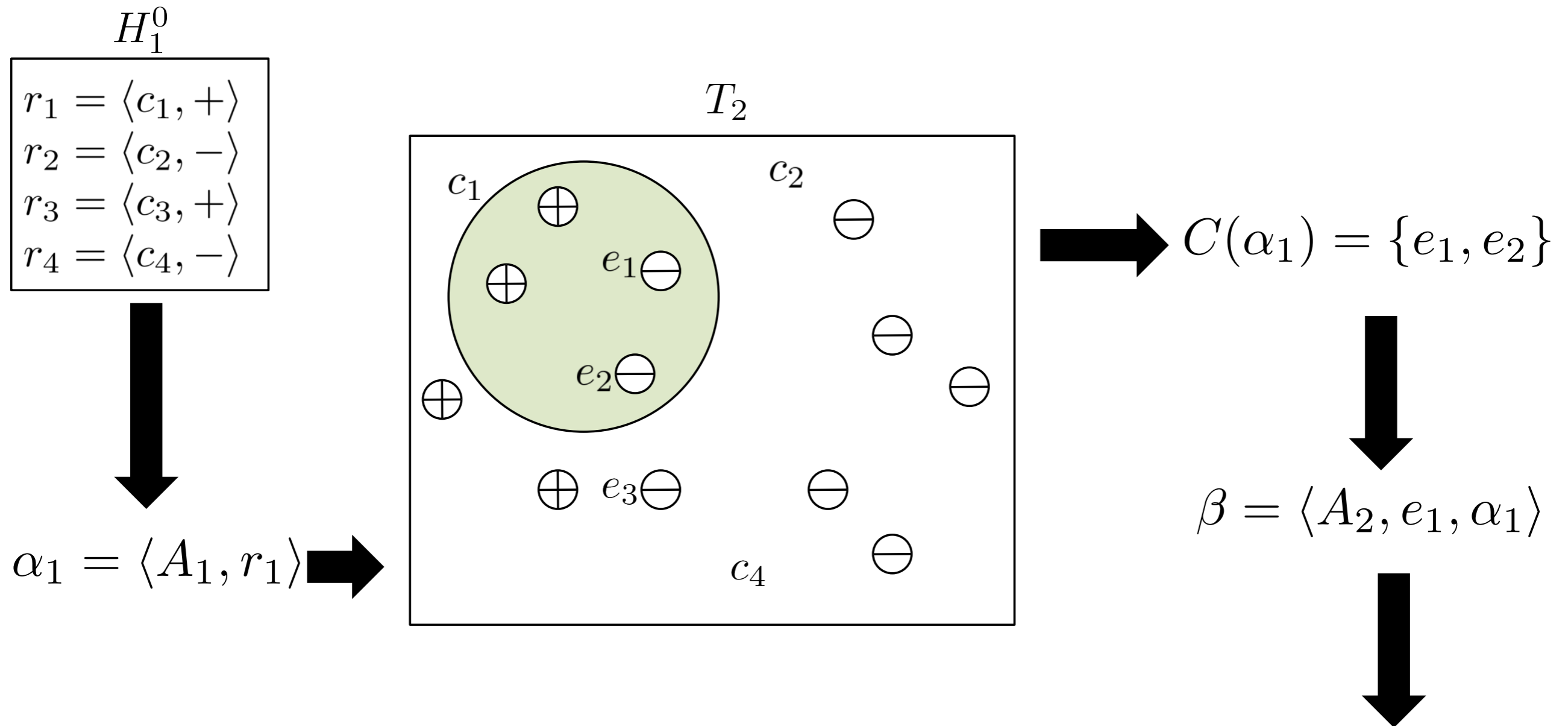


Induction by individual agent
using a specific ML method
(ID3, CN2, INDIE)

Argumentation about each
rule held by an agent (first
one agent then the other)

Hypotheses union
eliminating redundancies

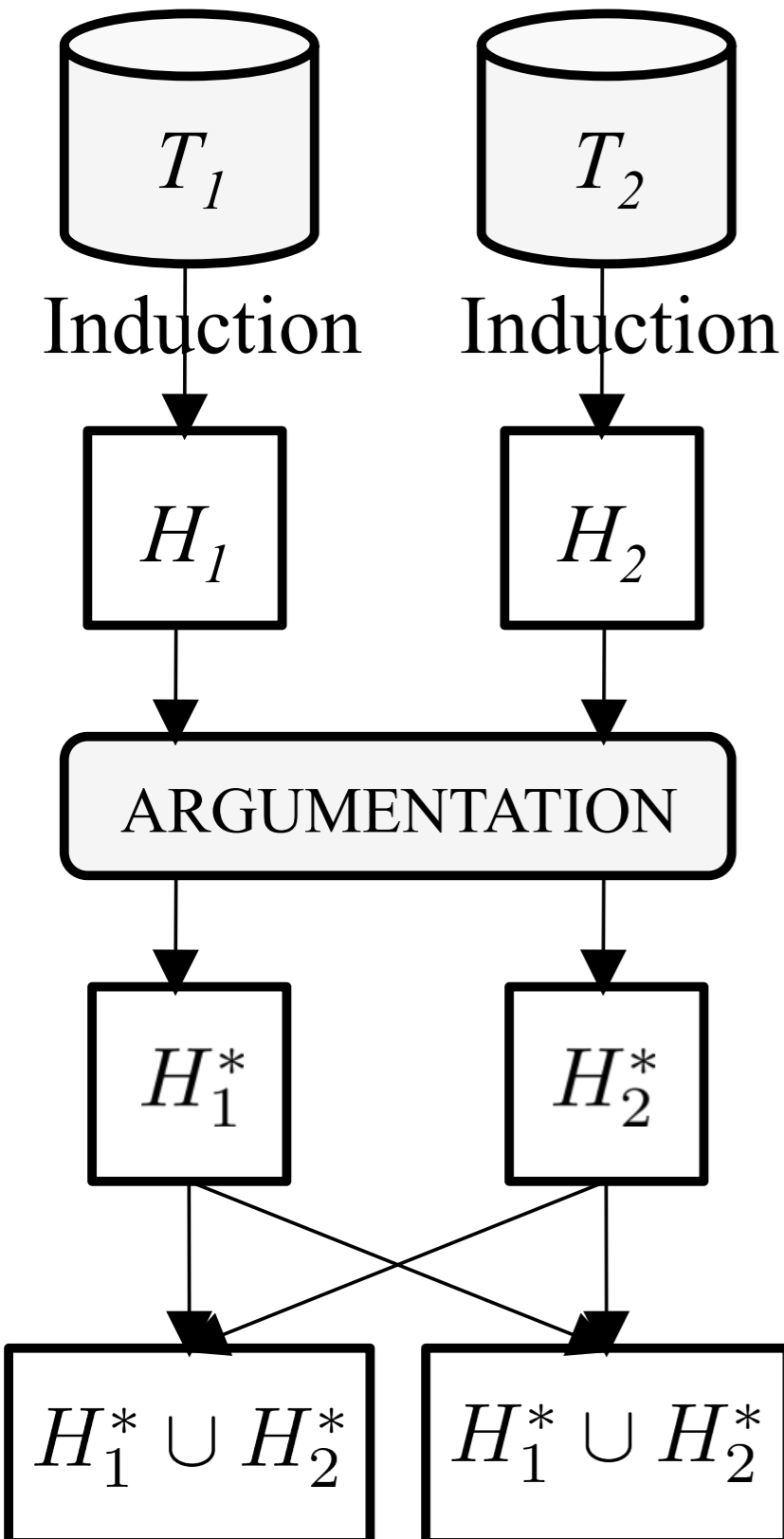
ADI argumentation



Belief revision: Agent A_1 incorporates counter-exmple e_1 and updates induction hypotheses

RADI

Reduced Argumentation- based Distributed Induction



Induction by individual agent
using a specific ML method
(ID3, CN2, INDIE)

Argumentation about
hypothesis of one agent
(then the other agent)

Hypotheses union
eliminating redundancies

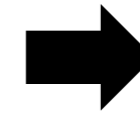
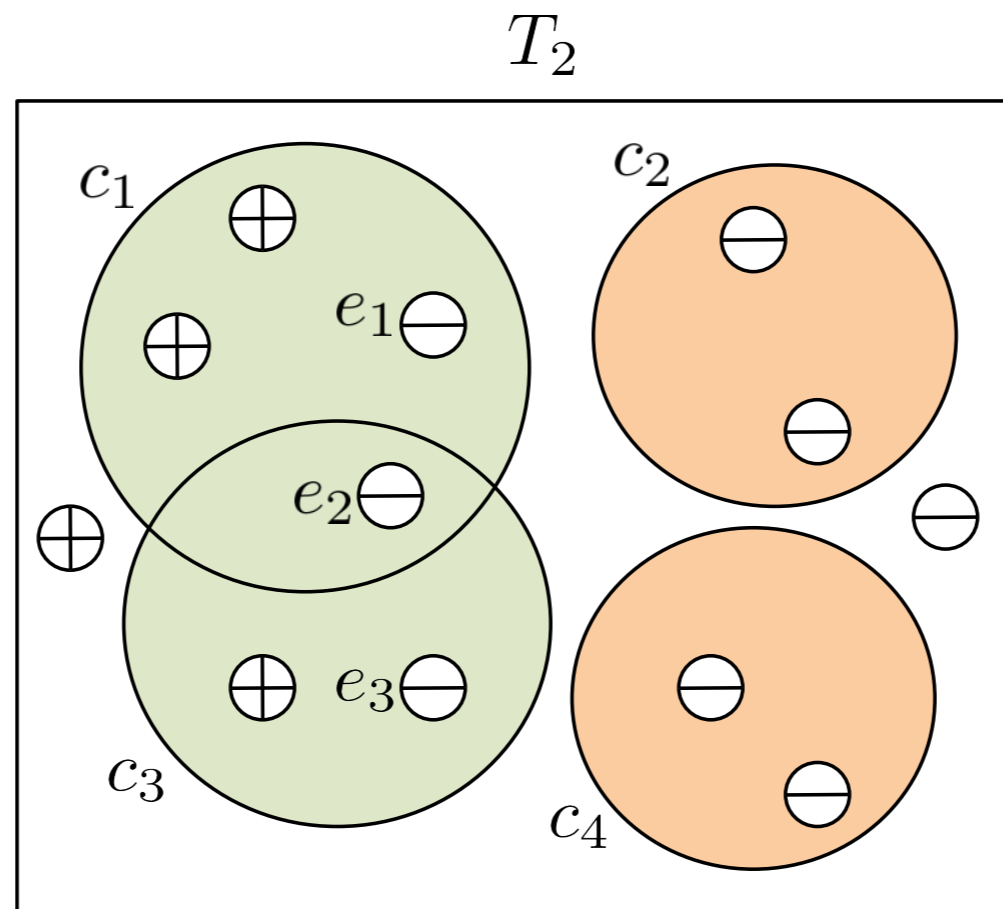
Argumentation in RADI

 H_1^0

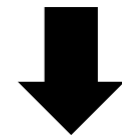
$$\begin{aligned} r_1 &= \langle c_1, + \rangle \\ r_2 &= \langle c_2, - \rangle \\ r_3 &= \langle c_3, + \rangle \\ r_4 &= \langle c_4, - \rangle \end{aligned}$$

 \downarrow
 \mathcal{R}^0

$$\begin{aligned} \alpha_1 &= \langle A_1, r_1 \rangle \\ \alpha_2 &= \langle A_1, r_2 \rangle \\ \alpha_3 &= \langle A_1, r_3 \rangle \\ \alpha_4 &= \langle A_1, r_4 \rangle \end{aligned}$$

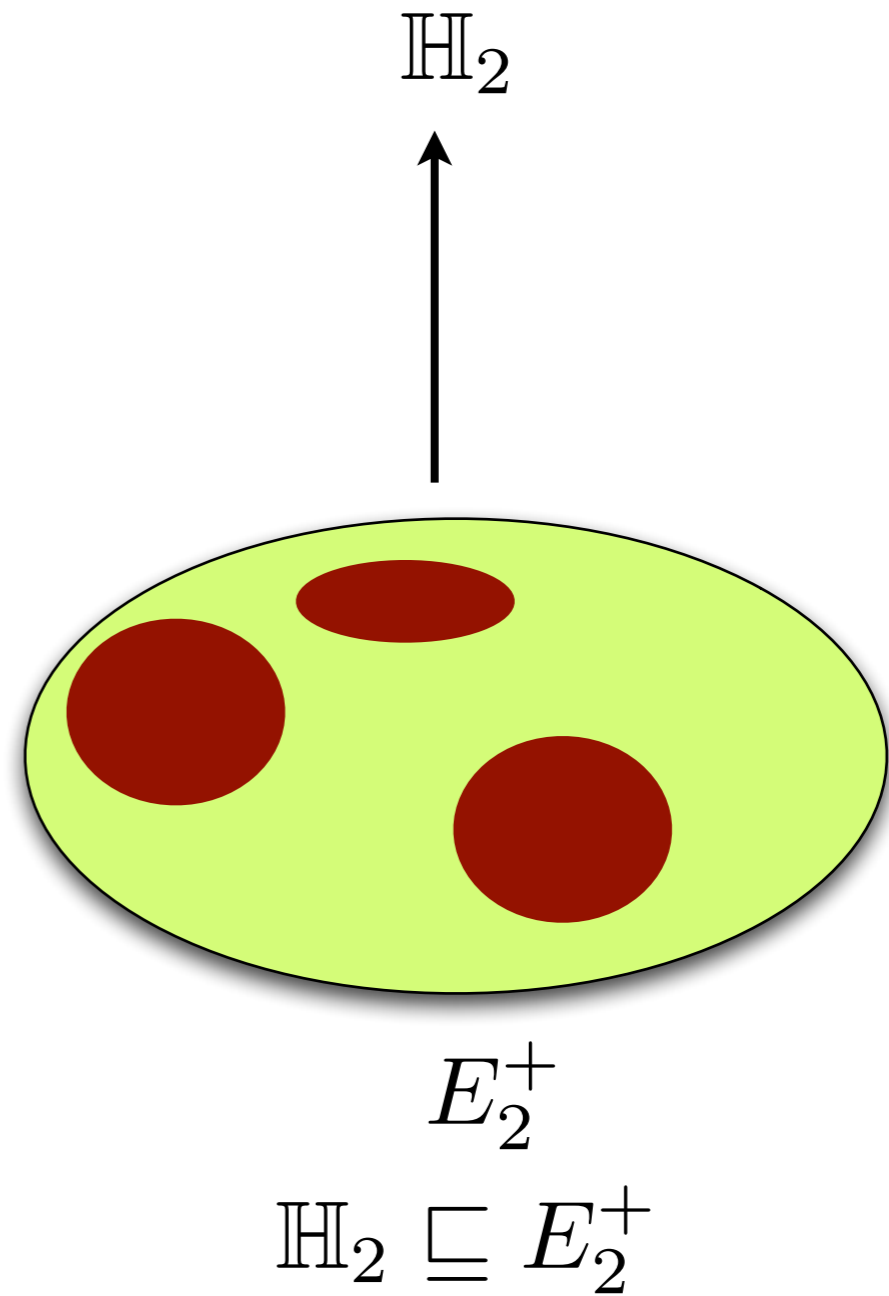
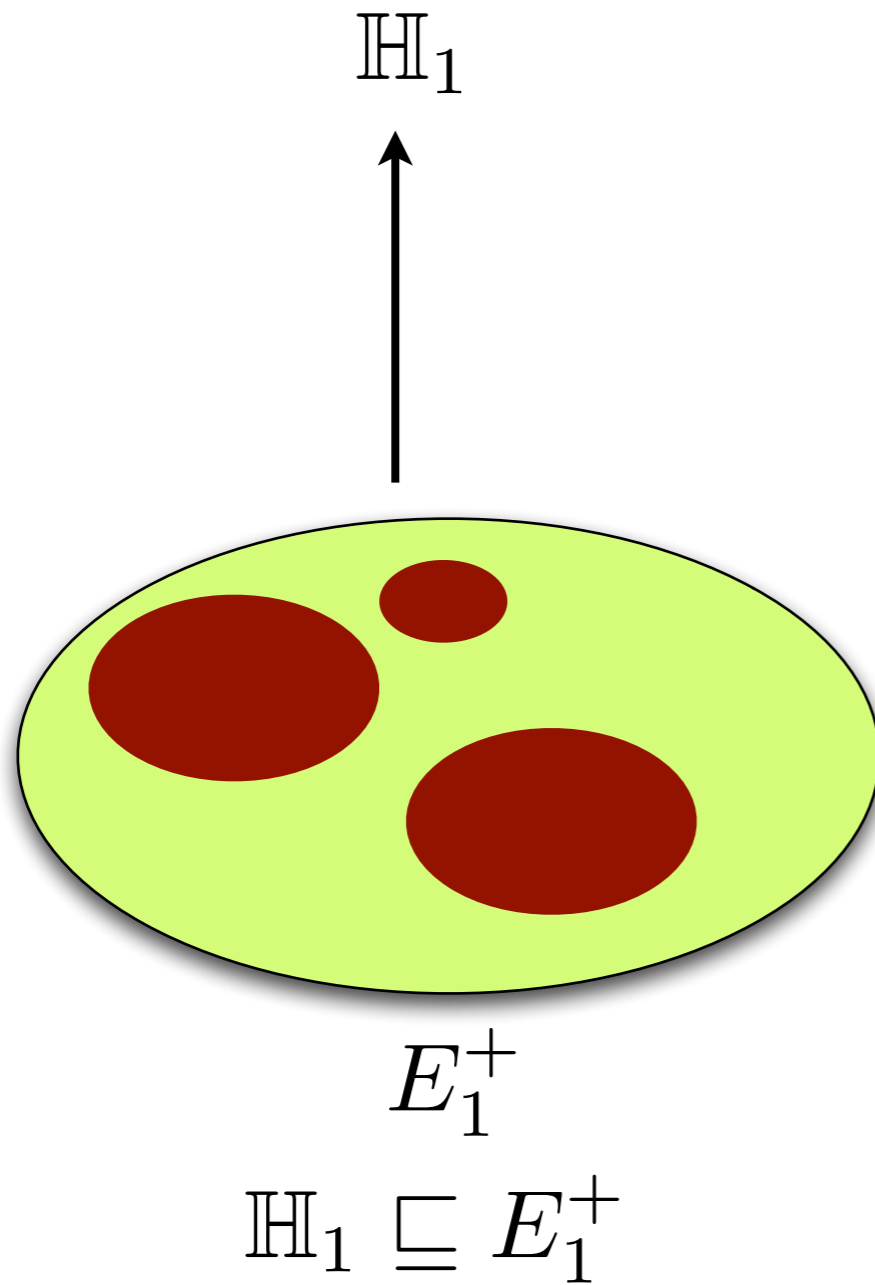


$$\begin{aligned} C(\alpha_1) &= \{e_1, e_2\} \\ C(\alpha_2) &= \emptyset \\ C(\alpha_3) &= \{e_2, e_3\} \\ C(\alpha_4) &= \emptyset \end{aligned}$$

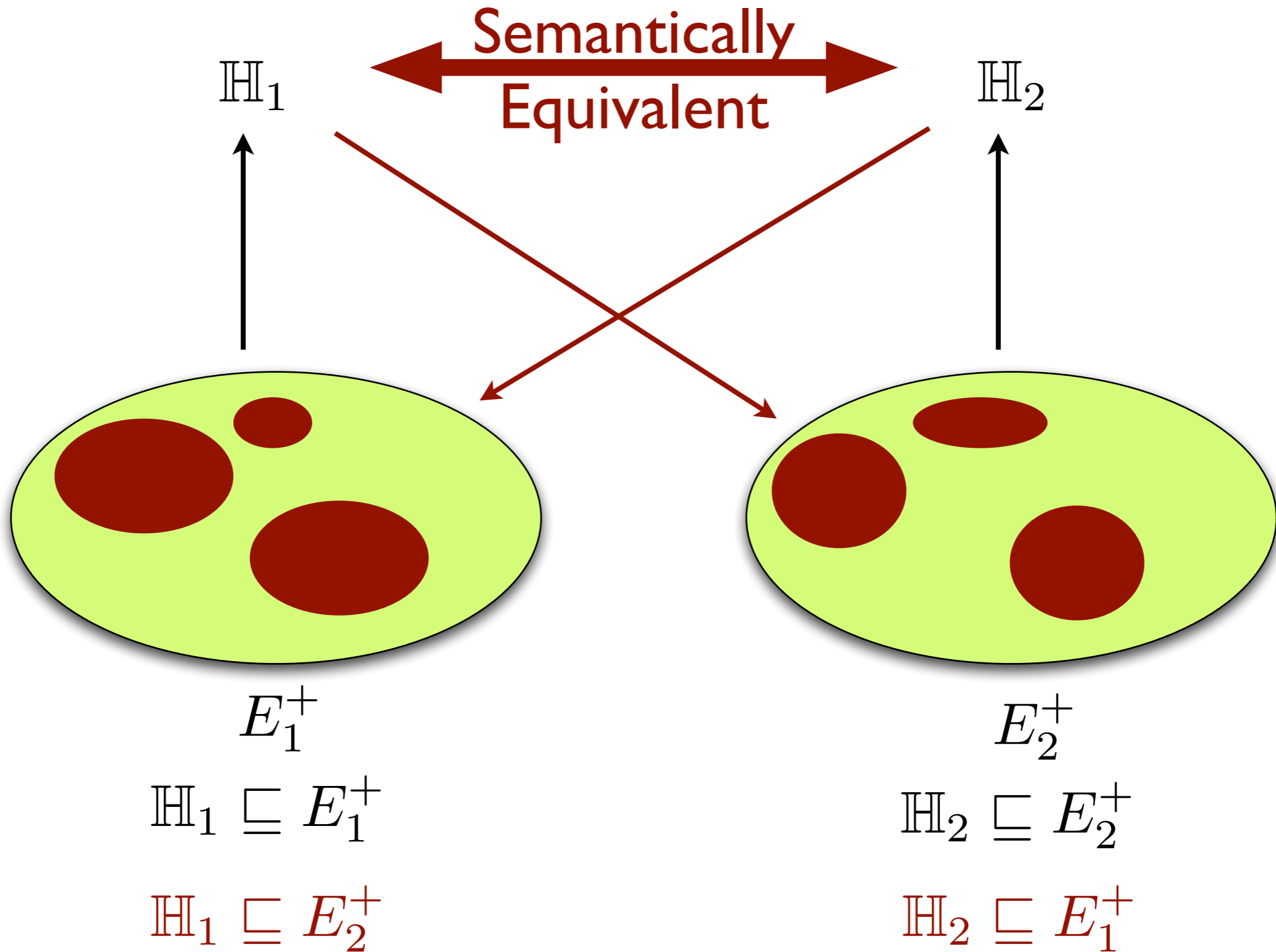


$$\begin{aligned} I^0 &= \{\alpha_1, \alpha_3\} \\ B^0 &= \{e_2\} \end{aligned}$$

Agreement



Agreement





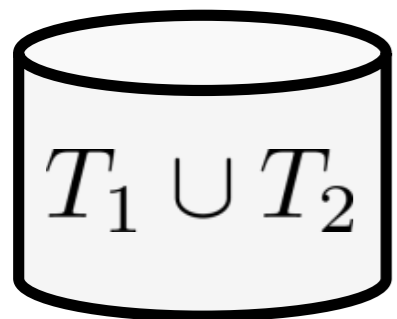
Evaluation of ADI & RADI

Distribution

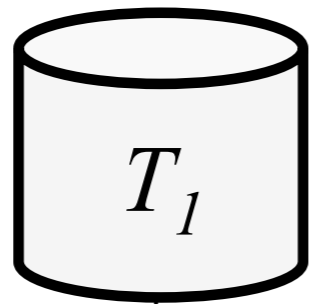
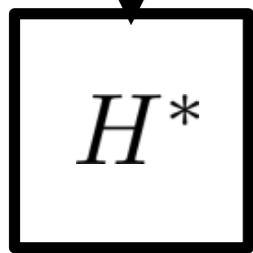
Centralized

Individual

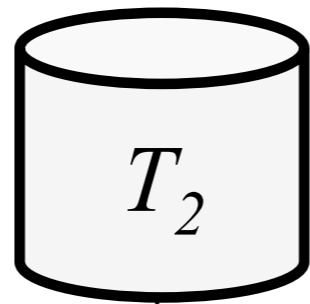
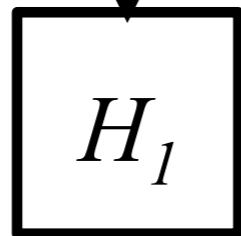
Union



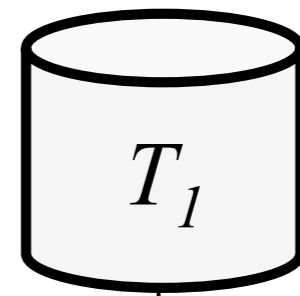
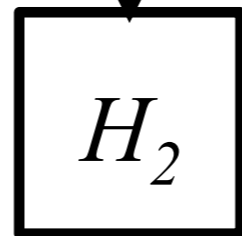
Induction



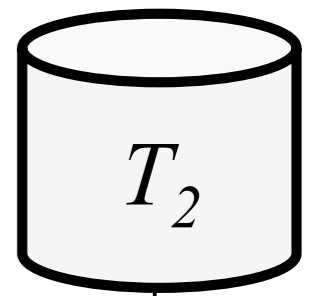
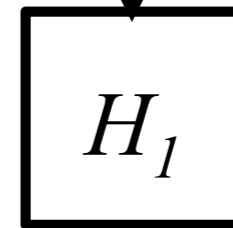
Induction



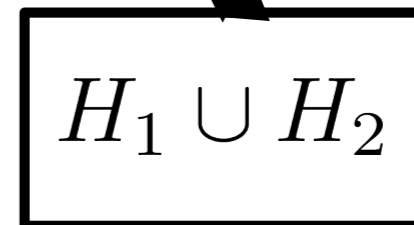
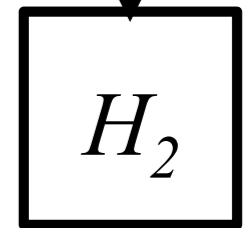
Induction

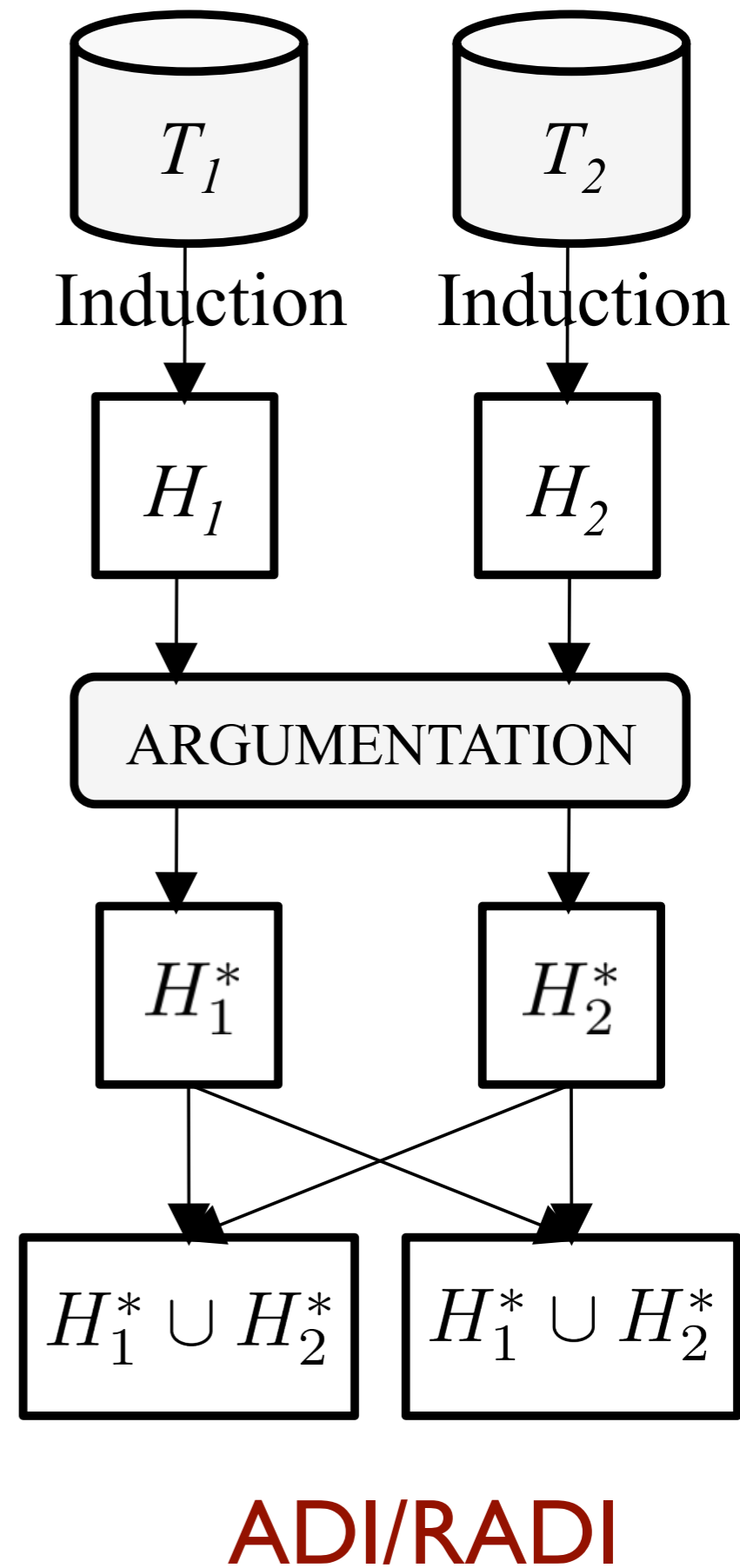
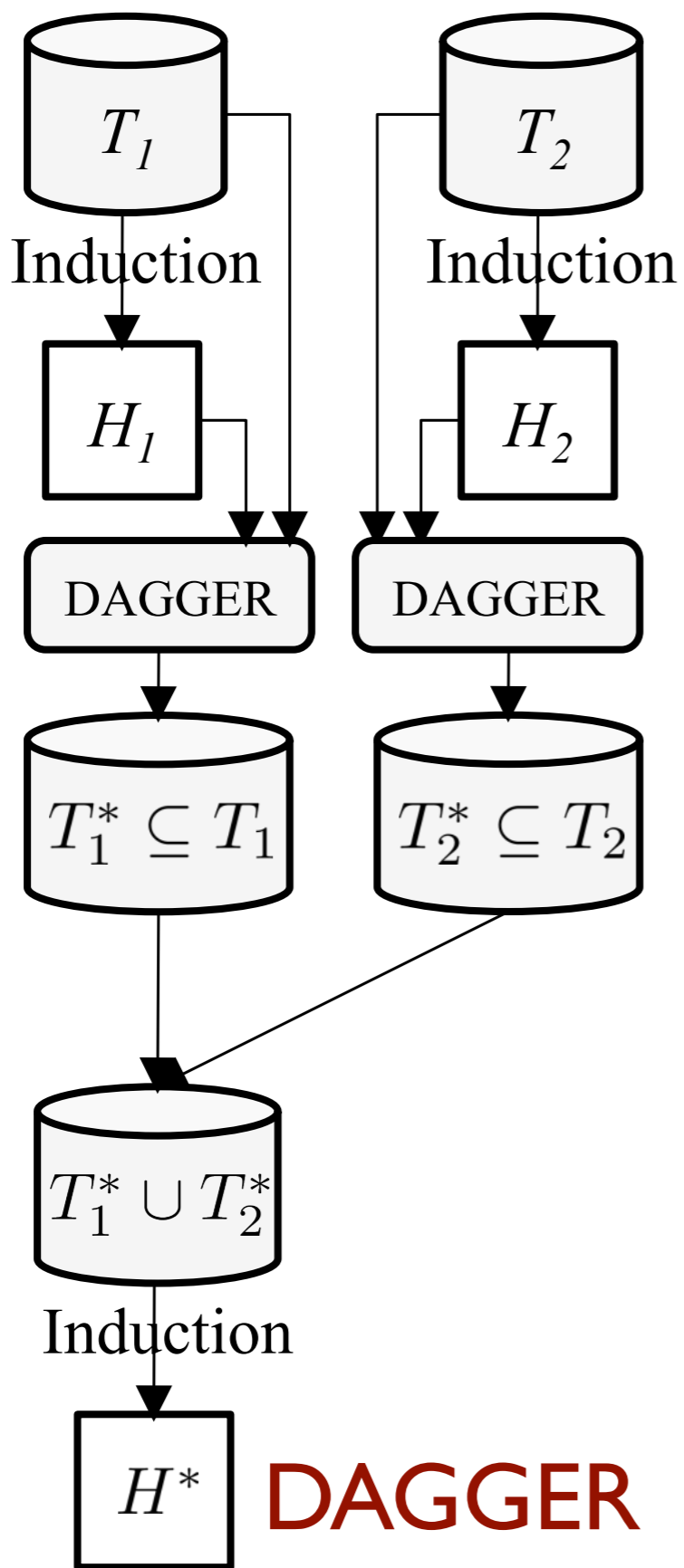


Induction



Induction





Evaluation

Accuracy	Training				Test			
	Soybean	Zoology	Cars	Sponges	Soybean	Zoology	Cars	Sponges
	ID3-centralized	100,00	100,00	100,00	99,44	85,00	99,00	88,95
ID3-Individual	85,67	93,85	93,84	80,20	76,50	90,00	86,83	55,54
ID3-union	90,25	94,73	97,73	94,05	81,00	94,00	90,99	60,36
ID3-DAGGER	99,57	100,00	76,36	99,76	80,67	92,50	68,95	62,50
ID3-ADI	100,00	100,00	100,00	99,70	88,50	99,00	88,95	58,21
ID3-RADI	100,00	100,00	100,00	99,74	87,67	99,00	89,24	58,21

Data set: 90% training; 10% test

2 Agents: 50% training set

Best results in bold (when not statistically significant more than one results are in bold)

Evaluation

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ID3-RADI	100,00	100,00	100,00	99,74	87,67	99,00	89,24	58,21

Training:

ADI & RADI indistinguishable results from Centralized
DAGGER good accuracy but not as Centralized

Evaluation

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ID3-RADI	100,00	100,00	100,00	99,74	87,67	99,00	89,24	58,21

Test:

**ADI & RADI accuracy equal or better than Centralized
DAGGER sometimes is better**

Union works very well only for Cars data set

ADI & RADI are less prone to overfitting

Evaluation

Accuracy	Training				Test			
	Soybean	Zoology	Cars	Sponges	Soybean	Zoology	Cars	Sponges
	CN2-centralized	100,00	100,00	100,00	100,00	84,66	94,00	80,64
CN2-Individual	87,82	94,62	89,90	88,29	77,83	87,50	80,84	74,46
CN2-union	54,91	91,65	80,41	70,71	53,66	86,00	80,00	68,20
CN2-DAGGER	99,49	99,65	95,86	99,88	79,33	92,50	75,34	78,93
CN2-ADI	100,00	100,00	100,00	100,00	84,90	93,50	80,61	79,11
CN2-RADI	100,00	100,00	100,00	100,00	84,66	93,50	80,17	78,93

Evaluation

Accuracy	Training				Test			
	Soybean	Zoology	Cars	Sponges	Soybean	Zoology	Cars	Sponges
	INDIE-centralized	99,64	100,00	100,00	100,00	83,00	94,00	91,80
INDIE-Individual	89,21	94,07	93,93	96,45	77,50	85,50	87,76	94,11
INDIE-union	91,44	96,48	97,42	97,90	78,00	90,00	91,80	94,29
INDIE-DAGGER								
INDIE-ADI	99,64	100,00	100,00	100,00	84,33	93,00	91,25	95,89
INDIE-RADI	99,64	100,00	100,00	100,00	84,50	94,00	91,37	94,11

DAGGER assumes propositional data sets, and is incompatible with INDIE that works only in relational data sets



Performance

	Time	Examples shared	Rules sent	Induction calls
Centralized	2,80	100,00%	0,00	1,00
Individual	1,50	0,00%	0,00	1,00
Union	1,50	0,00%	67,63	1,00
DAGGER	3,50	68,56%	64,75	1,00
ADI	155,40	19,04%	3.748,70	58,90
RADI	18,20	21,52%	679,34	5,77

*Results
averaged over
all data sets*



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Results averaged over all data sets

DAGGER requires exchanging more examples (68%) but few rules (only the final result, like Union)

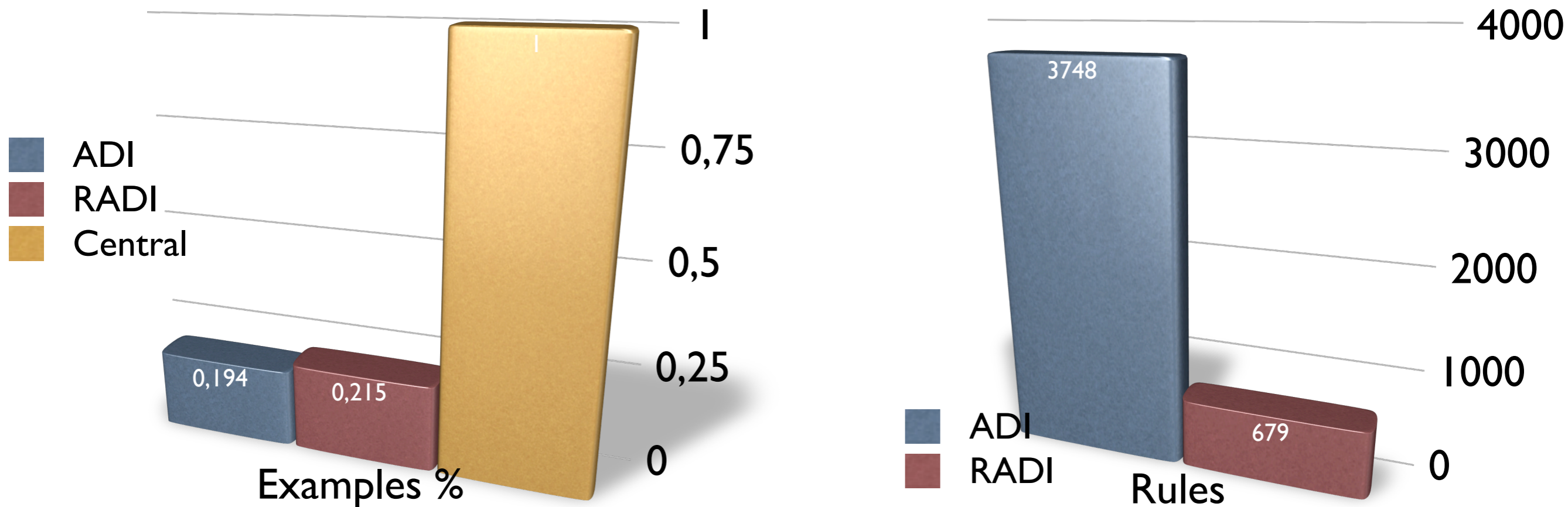
ADI & RADI requires exchanging more rules but fewer examples

RADI better than ADI: faster, less rules, less calls, (only requires to exchange slightly more examples)

Performance

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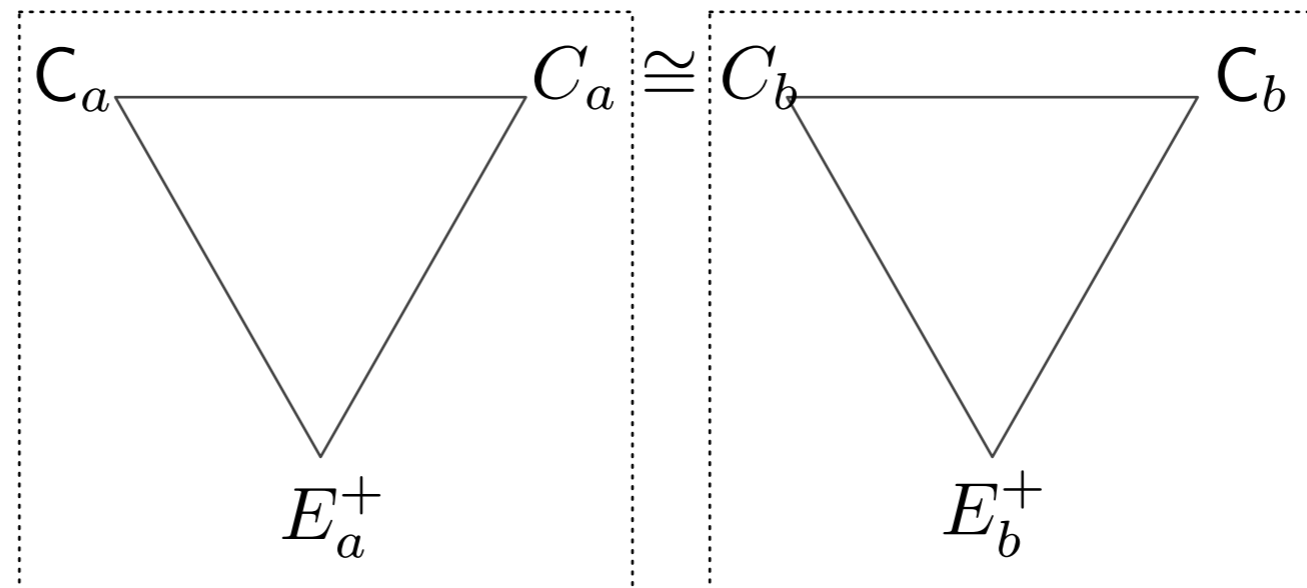


Conclusions

- General approach (w.r.t. induction methods)
 - counter-examples only (counter-arguments not used)
- Argumentation process allows a regulated interchange of information among learning agents about hypotheses, examples and their consistency
- ADI and RADI support distributed induction over existing ML inductive methods
 - less prone to overfitting

Future Work

- Concept Convergence
 - Counter-arguments require new inductive methods



- Argumentation among N agents (using induction)
 - What about convergence?
 - Majority rule problem?