Self-adaptation in Autonomic Electronic Institutions through Case-Based Reasoning

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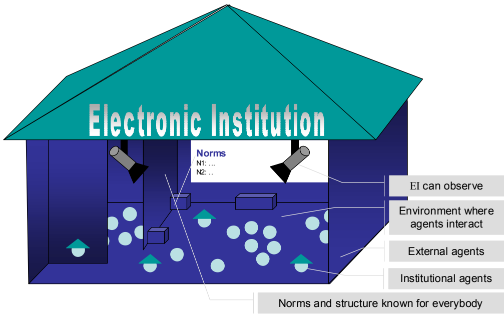
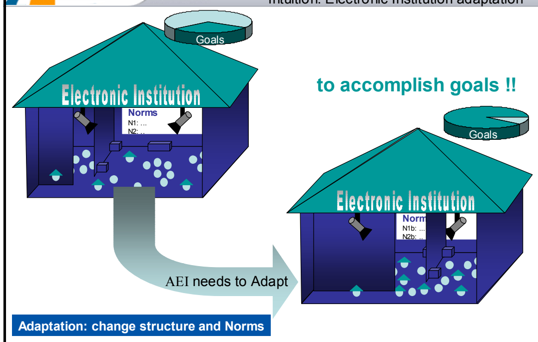
Introduction

Electronic Institution (EI) intuition



Introduction

Intuition: Electronic Institution adaptation

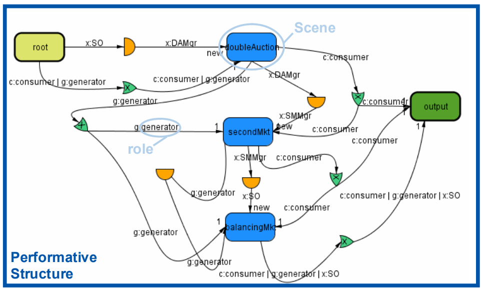


Introduction

- Electronic Institutions (EI):
  - Regulated virtual environments where agents interact:
    - EIs structure dialogic activities (agent interactions)
    - Participating agents play different roles.
  - Composed of:
    - **Dialogical framework**: establishes agents' common language and ontology.
    - **Performative structure**: agents' activities and relationships
      - Scenes, agent roles.
    - **Norms**: define the consequences of agents' actions.

Introduction

EI example: Electricity Market



Norm: Power stations are obliged to keep 10% of extra production to eventually cover shortages.

Introduction

From EI to AEI

- We aim at studying how to endow Electronic Institutions with autonomic capabilities to dynamically adapt to changing circumstances
  - different agent behaviors
  - Notion of:
    - Institutional goal to comply with
    - Adaptation mechanisms
  - To define **Autonomic Electronic Institutions**

Outline

- Introduction
- **Autonomic Electronic Institutions**
- Learning Model
- Case Study: Traffic Control
- Empirical Evaluation
- Conclusions & Future Work

AEI
Definition

- We define an Autonomic Electronic Institution as a tuple:

$$\langle \underbrace{PS, N, DF}, G, P_i, P_e, P_a, V, \delta, \gamma \rangle$$

- PS: Performative Structure,
- N: set of Norms,
- DF: Dialogical Framework,
- $G = \{c_1, \ldots, c_p\}$ set of institutional Goals

  defined as constraints: c_i is an expression $g_i(V) \triangleleft [m_i, M_i]$

AEI
Definition

- We define an Autonomic Electronic Institution as a tuple:

$$\langle PS, N, DF, G, \underbrace{P_i, P_e, P_a, V}, \delta, \gamma \rangle$$

- $V = \langle v_1, \ldots, v_q \rangle$ *reference* values: $v_j = h_j(P_a, P_e, P_i)$.
- $P_i = \langle i_1, \ldots, i_s \rangle$ *institutional property* values,
- $P_e = \langle e_1, \ldots, e_r \rangle$ *environment property* values,
- $P_a = \langle a_1, \ldots, a_n \rangle$ *institutional state* of agents in A

  $\mathbf{a_j} = \langle a_{j_1}, \ldots, a_{j_m} \rangle$ institutional state of agent A_j

AEI
Definition example: electricity market

- We define an Autonomic Electronic Institution as a tuple:

$$\langle PS, N, DF, G, \underbrace{P_i, P_e, P_a, V}, \delta, \gamma \rangle$$

- P_i = <market_price> *institutional property* value,
- P_e = <current_date> *environment property* value,
- $P_a = \langle [demand_1],..,[demand_n], [offer_1],..,[offer_m] \rangle$ *agent institutional state* values
- V_1 = <sum(offer)-sum(demand)> *reference* value
- $G = \{ 50 < V_1 < 200\}$ institutional goal

AEI
Definition

- We define an Autonomic Electronic Institution as a tuple:

$$\langle PS, N, DF, G, P_i, P_e, P_a, V, \underbrace{\delta, \gamma} \rangle$$

- $\delta : N \times G \times V \rightarrow N$ *normative transition function*,

  norm N_i has a set of parameters $\langle p^N_{i1}, \ldots, p^N_{im_i} \rangle$ (i.e., var's in δ)

- $\gamma : PS \times G \times V \rightarrow PS$ *performative transition function*,

  scene S_i has $\langle p^R_{i1}, \ldots, p^R_{iq_i} \rangle$, p^R_{ij} = #agents playing role r_j in S_i

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Learning Model
General Process

- Adapt δ, γ to $\mathbf{A}$

1st step: Genetic Algorithms (GA)

Lean best parameters for **prototypical** agent populations

2nd step: Case-Based Reasoning (CBR)

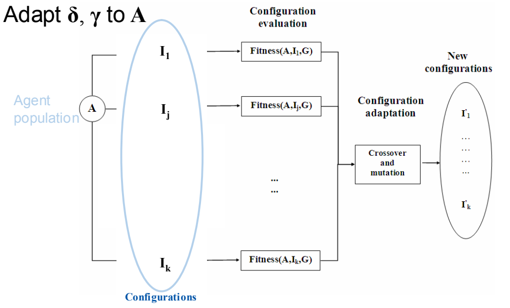
Adapt to **any** agent population

- CBR: Solves new problems reusing past experiences:
  - uses solutions from similar problems previously learnt (cases).

Problem: given the current agent population, provide the best AEI's parameters so to accomplish institutional goals

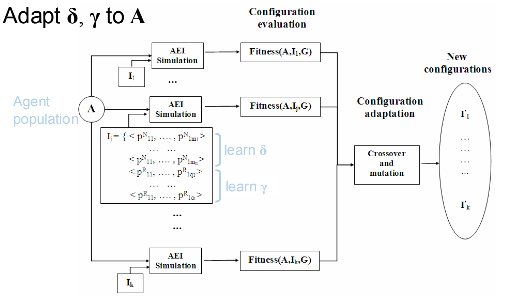
Learning Model
Genetic Algorithm

- Adapt δ, γ to $\mathbf{A}$

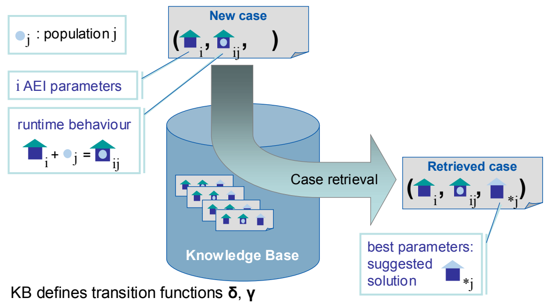


Learning Model
Genetic Algorithm

- Adapt δ, γ to $\mathbf{A}$



Learning Model
CBR



KB defines transition functions δ, γ

Learning Model
CBR: Case Definition

- Case definition:

<N^p, PS^p, V, pop, N^{p*}, PS^{p*}>

i
- N^p : current norm parameters' values;
- PS^p: current performative structure parameters' values

ij
- V: current reference values
- pop: statistic data about agent population's behaviour

*j
- N^{p*}: norm parameters' best values
- PS^{p*}: best values of performative structure parameters

Learning Model
CBR: Case Retrieval

- Case similarity function: (distance)
  - Aggregated function:

$$S(C^i,C^j) = w_1 \cdot s\_AEI(C^i,C^j) + w_2 \cdot s\_V(C^i,C^j) + w_3 \cdot s\_pop(C^i,C^j)$$

  - attribute distance:

$$sim(attr^i, attr^j) = \frac{|attr^i - attr^j|}{max(attr) - min(attr)}$$

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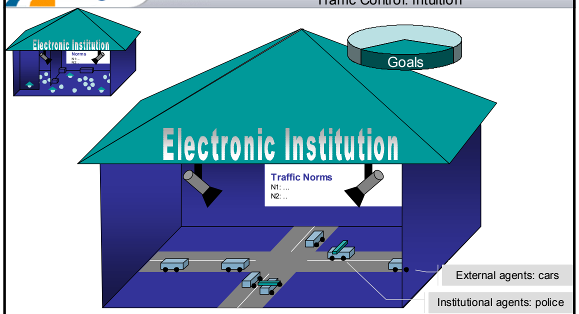
Case Study

Traffic Control: intuition



Case Study

Traffic Control

- Traffic Regulation Authority as an AEI.
  - Simulation: Simma MAS tool
  - We focus on a two-road junction (traffic scene)
    - Cars: external agents
    - Agents' institutional state:

      $P_a = <a_1, \ldots, a_n>$,

      a_j represents A_j

      $a_j = <x_j, y_j, h_{jx}, h_{jy}, speed_j, indicator_j, offenses_j, accidents_j, distance_j, points_j>$

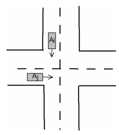
Traffic AEI

Norms I

- Norms:
  - related to actions performed by cars
  - have associated penalties (point reductions).

Right priority norm

Action	$in(a_i, J_{BE}, t-1) \wedge$ $in(a_i, (x_i^{t-1} + h_{ix}^{t-1}, y_i^{t-1} + h_{iy}^{t-1}), t) \wedge$ $\neg indicator(a_i, right, t-1)$
Pre-conditions	$right(a_i, a_j, t-1)$
Consequence	$points_i^t = points_i^t - fine_{right}$



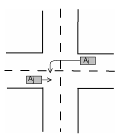
Traffic AEI III

Norms II

- Norms:
  - related to actions performed by cars
  - have associated penalties (point reductions).

Front priority norm

Action	$in(a_i, J_{BE}, t-1) \wedge$ $in(a_i, (x_i^{t-1} + h_{ix}^{t-1}, y_i^{t-1} + h_{iy}^{t-1}), t) \wedge$ $indicator(a_i, left, t-1)$
Pre-conditions	$in(a_j, J_{BE}, t-1) \wedge$ $front(a_i, a_j, t-1)$
Consequence	$points_i^t = points_i^t - fine_{front}$



Traffic AEI

Agents & Norms

- Car agents decide whether to comply with a norm based on four parameters:

  <fulfill_prob, high_punishment, inc_prob, police>

$$final\_prob = \begin{cases} police \cdot fulfill\_prob & fine \leq high\_punishment \\ police \cdot (fulfill\_prob + inc\_prob) & fine > high\_punishment \end{cases}$$

- Institutional agents in the traffic scene represent Traffic Authority employees (police agents).

Traffic AEI
Reference Values

- Reference values

  V = <*col, crash, off, block, expel, police*>

  - *col*: number of collisions,
    $$col = \sum_{t=t_{now}-t_w}^{t_{now}} \sum_{e \in P_e^t} f(e_{\alpha^t}) \quad f(e_{\alpha^t}) = \begin{cases} 1 & if\ |e_{\alpha^t}|>1 \\ 0 & otherwise \end{cases}$$
  - *crash*: #cars involved on accidents
  - *off*: # offences
    $$off = \sum_{t=t_{now}-t_w}^{t_{now}} \sum_{i=0}^{|A|} offenses_i^t$$
  - *block*: # cars being blocked by other cars
  - *expel*: # cars being expelled out of the environment
  - *police*: percentage of deployed police agents

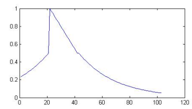
Traffic AEI
Goals I

- Goals:
  - constraints upon a combination of reference values:

$$G = \langle\, g(col) \in [0, maxCol],\ g(off) \in [0, maxOff],\ g(crash) \in [0, maxCrash],\ g(block) \in [0, maxBlock],\ g(expel) \in [0, maxExpel],\ g(police) \in [0, maxPolice]\,\rangle$$

  - g_i function over the reference values
  - degree of satisfaction of a goal $f(x,[m,M],\mu)$

$$f(x,[m,M],\mu) = \begin{cases} \dfrac{\mu}{e^{k\frac{m-x}{M-m}}} & x < m \\ 1-(1-\mu)\dfrac{x-m}{(M-m)} & x \in [m,M] \\ \dfrac{\mu}{e^{k\frac{x-M}{M-m}}} & x > M \end{cases}$$



m=20, M=40, μ=0.5, k=0.75

Traffic AEI
Goals II

- Fitness function to combine multiple goals:

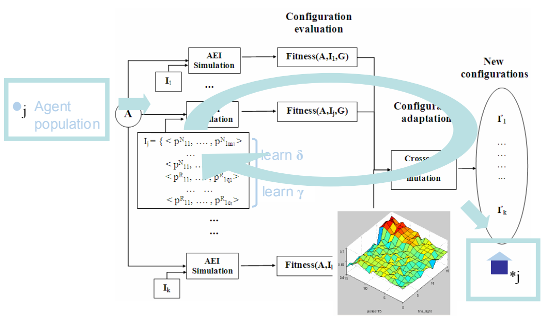
$$O(V) = \sum_{i=1}^{|G|} w_i \sqrt{f(g_i(V),[m_i,M_i],\mu_i)}$$

  - w_i weighting factors

$$O(V) = \frac{4}{10}\cdot\sqrt{f(g(col),[0,maxCol],\frac{1}{2})} + \frac{4}{10}\cdot\sqrt{f(g(off),[0,maxOff],\frac{1}{2})} +$$

$$\frac{1}{10}\cdot\sqrt{f(g(expel),[0,maxExpel],\frac{3}{4})} + \frac{1}{10}\cdot\sqrt{f(g(police),[0,maxPolice],0)}$$

Traffic AEI
Learning: Genetic Algorithm



Traffic AEI
Learning: Case Base Reasoning

- Case definition
  - N^p : norm parameters ($fine_{right}$, $fine_{front}$)
  - PS^p: performative structure parameter (*police*)
  - V: reference values (*col, crash, off, block, expel*)
  - pop: statistic data about agent population's behaviour (*meanOff, medianOff, ...*)
  - N^{p*}: norm parameters' best values ($fine^*_{right}$, $fine^*_{front}$)
  - PS^{p*}: performative structure parameter's best value ($police^*$)

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Empirical Evaluation
Building the Knowledge Base

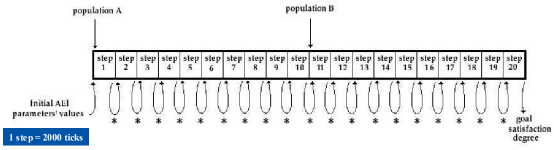
- Case generation:
  - 7 prototypical populations
  - AEI's 108 (=6x6x3) different parameters:
    - $fine_{right}, fine_{front} \in \{0, 3, 6, 9, 12, 15\}$
    - $police \in \{ 0.8, 0.9, 1 \}$

756 cases
2000 ticks each

Populations	Pop. 1	Pop. 2	Pop. 3	Pop. 4	Pop. 5	Pop. 6	Pop. 7
$fulfill\_prob$	0.5	0.5	0.5	0.5	0.5	0.5	0.5
$high\_punishment$	0	3	5	8	10	12	14
inc_prob	0.4	0.4	0.4	0.4	0.4	0.4	0.4
$fine^*_{right}$	2	5	8	11	13	14	15
$fine^*_{front}$	1	4	6	9	12	13	15
$police^*$	1	1	1	1	1	1	1

Empirical Evaluation
Case Retrieval

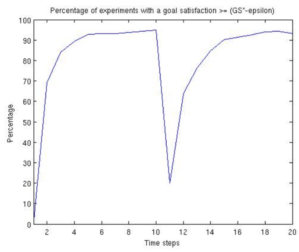
- Can the AEI adapt to any agent population?
  - Experimental setting:
    - Initially: $fine_{right} = fine_{front}$=0 and $police$=0.8
    - Population A = Pop1 ….Pop15 , Population B = Pop7
    - Every step AEI checks if adaptation is required
      - If Goals are not satisfied (G<G*-Ɛ) → Retrieve a case from the KB



1 step = 2000 ticks

Empirical Evaluation
Case Retrieval Evaluation

- Can the AEI satisfy its goals?
  - G ≥ G*- Ɛ
  - 750 experiments:
    - 15 pop x 50 runs



1 step = 2000 ticks

Empirical Evaluation
Case Retrieval Evaluation

- Can the AEI satisfy its goals?
  - Most times YES
    - Number of experiments stabilized in first 10 steps (population A = Pop1 …Pop15):

Steps	1	2	3	4	5	6	7	8	9	10	Not stabilized
Stabilized	0	518	153	36	19	9	5	2	1	1	6
Percentage stabilized	0	69	20.4	4.8	2.5	1.2	0.7	0.3	0.1	0.1	0.8

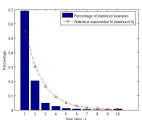
    - Number of experiments stabilized in last 10 steps (change to population B = Pop7):

Steps	11	12	13	14	15	16	17	18	19	20	Not stabilized
Stabilized	157	332	102	70	46	15	15	8	4	1	0
Percentage stabilized	20.9	44.2	13.6	9.3	6.1	2	2	1	0.5	0.1	0

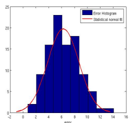
1 step = 2000 ticks

Empirical Evaluation
Case Retrieval Evaluation

- Statistical analysis
  - Chi-square test (exponential percentage)
    - 95% pop is stable at step 5
    - 95% pop becomes stable again at step 16
    - significance level 0.01



  - Frequentist method of replicated error measurements
    - maximum error is 11.01
    - with confidence 97.5%



1 step = 2000 ticks

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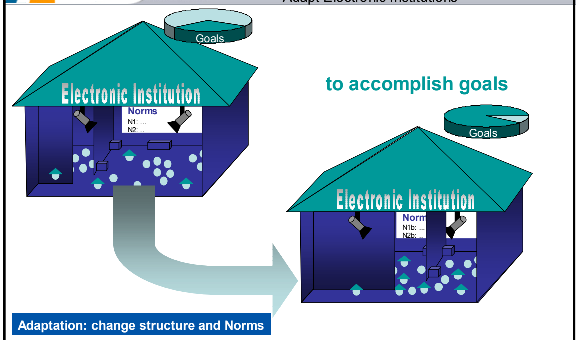
Conclusions

- AEI proposed as an extension of the current EIs:
  - Autonomic capabilities.
- Adaptation by CBR approach:
  - Case definition,Retrieval process: distance measure
- Implementation of a traffic AEI case study:
  - AEI learns traffic norms and the percentage of institutional agents needed to fulfill its goals
  - adapting to different agent populations.
- Empirical evaluation (statistical analysis)
  - AEI is able to adapt to new and changing populations
  - In a short time and with low error.

Conclusions

Adapt Electronic Institutions



Future Work

- Study adaptation capabilities to heterogeneous populations.
- Develop a more complex traffic network:
  - decentralized approach where different areas (i.e., junctions) are regulated by different institutions.

Thank you
for your attention