Automated Negotiation: Challenges and Tools

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February 23rd, 2022

Outline

Why Now?

1. Industries are moving online.
2. Automation: Factory floor → The back office.
3. Human-Human Negotiation is cumpersome, and inefficient.
4. Automated Negotiation opens new possiblities:
   - Too fast for people: Repeated smart contracts.
   - Too large for people: complete supply chains

Negotiation in SCM Business

- Human negotiations lead to an estimated 17-40% *value leakage* in some estimates [1]
- A recent study suggests that at least 15 companies are working in *contracting support systems* [2].
- A recent UNECE UN/CEFACT proposal to standardize negotiation protocols for SCM and other applications [3]
- More to come [**?**].

[1] KPMG report: https://bit.ly/3kDRy6I
[2] Forrester report: https://bit.ly/3nwXEaY
[3] UN/CEFACT Project website: https://bit.ly/38LOsLX

The Automated Negotiation Challenge

Why is it hard?

Effectively building an agent for a large number of different yet related games with incomplete information.

Why is it interesting?

- Easy to state yet hard to solve.
- Can be tackled at different levels of abstraction and complexity.
- Several concrete open questions.
- Vibrant yet not saturated research space.

Outline

1. Introduction and Classic Results (45min)
2. Protocols, Strategies and Platforms (45min)
    1. Hands On Experience
3. Recent Advances (45min):
4. Supply Chain Management Competition (30min)
    1. Hands On Experience
5. Challenges and Open Problems (30min)

Materials

1. Tutorial Website: http://yasserm.com/aaai2022tutorial-automated_negotiation_challenges_and_tools/
2. Github Repository: https://github.com/yasserfarouk/Aaai2022AutomatedNegotiation
3. Handouts: https://github.com/yasserfarouk/Aaai2022AutomatedNegotiation/ra
4. Negmas Documentation: http://www.yasserm.com/negmas
5. SCML Documentation: http://www.yasserm.com/scml/scmldocs
6. SCML Competition: https://scml.cs.brown.edu

Automated Negotiation: Challenges and Tools

Introduction and Classic Results

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Outline

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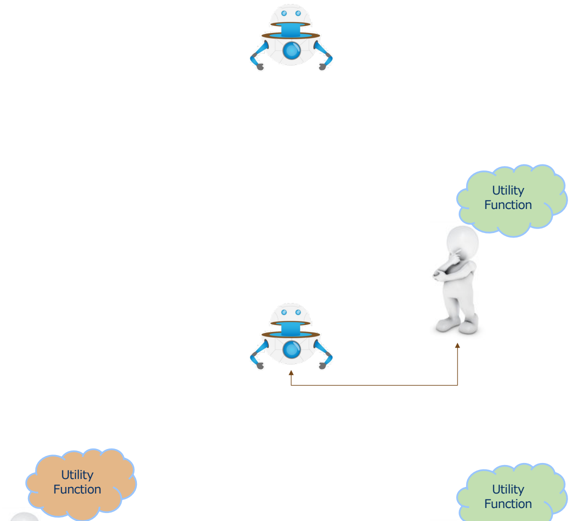
1. Negotiation
2. Classic Results
3. References


Utility
Function
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Function

Why not Auctions

or when to not use automated negotiation

Definition

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Negotiation

$$\Upsilon \equiv \left(A, T, N, \Omega, M, \left\{\tilde{P}_a, P_{ab}^n\ \forall 1 \le a, b \le A,\ 0 \le n \le N\right\}\right)$$

$A \in \mathbf{I}^+ - \{1\}$: Number of agents/actors.

$T \in \mathbf{R} \bigcup \infty$: The allowed time of the negotiation.

$N \in \mathbf{I} \bigcup \infty$: The allowed number of rounds of the negotiation.

$\Omega \equiv \{\omega_j\} \bigcup \phi$: Possible outcomes including ϕ signifying disagreement.

M The negotiation *mechanism* (protocol) defining rules of encounter for agents.

$\tilde{P}_a$: Preferences of **actor** a.

P_{ab}^n: Information available to **agent** a about preferences of **actor** b at the beginning of round n.

Known Preferences Assumption

Preference Representations

Preference Types

Partial Ordering $\succcurlyeq$ Defines preference as a partial ordering over Ω.

Ranking A total ordering over a subset of Ω.

Utility Function $\tilde{u}$ Defines a numeric value for every outcome in Ω.

$$\tilde{u} : \Omega \rightarrow \Re$$

Probabilistic Utility Function u Defines a distribution of values.

$$u : \Omega \times \Re \rightarrow [0, 1]$$

Known Ufun Assumption

$$u_a^t(\omega, x) = u_a^0(\omega, x) = \begin{cases} 1 & \tilde{u}(\omega) = x \\ 0 & otherwise \end{cases}$$

Components of the Negotiation Problem

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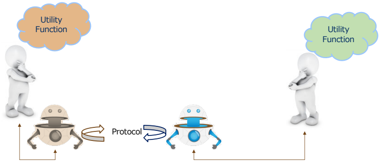


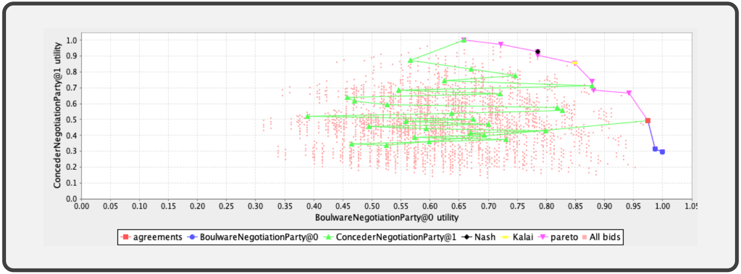
Negotiation Protocol Defines how negotiation is to be conducted [Mechanism Design Problem].

- Alternating Offers Protocol
- Single Text Protocol
- ...

Negotiation Strategy Defines how an agent behaves during the negotiation [Effective Negotiation Problem].

- Time-based strategies: Boulware, conceder, ...
- Tit-for-tat variations
- ...

Important Concepts



Pareto Frontier Outcomes that cannot be improved for one actor without making another worse off.

Welfare Total utility received by all actors.

Surplus utility Utility above disagreement utility.

Nash Equilibrium Strategies that are best responses to each other.

Sub-game Perfect Equilibrium A Nash Equilibrium in every sub-game.

Types of Automated Negotiation Problems

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Negotiator type

1. Agent-Agent negotiation
2. Agent-Human negotiation

Number of negotiators

1. Bilateral negotiation
2. Multilateral negotiation

Outcome Space

1. Single Issue: $\Omega = \{\omega_0, \omega_1, \ldots.\}$
2. Multiple Issues: $\Omega = \prod_{i=1}^{n_i} I_i$

Protocol Type

1. Mediated
2. Unmediated

Outline

Nash Bargaining Game: Solution

- Nash Point (1950): The point at which the product of surplus utility (above reservation value) of negotiators is maximized

$$\arg\max_{\omega_1,\omega_2} \prod_{i=1}^{2} \left(\tilde{u}_i(\omega_i) - \tilde{u}_i(\phi)\right)$$

- Kalai-Smorodinsky Point (1975): The Pareto outcome with equal ratios of achieved surplus utility and maximum feasible surplus utility

$$\arg\max_{\omega_1,\omega_2 \in F} (\omega_1 + \omega_2) \text{ s.t. } \left(\frac{\tilde{u}_1(\omega_1) - \tilde{u}_1(\phi)}{\tilde{u}_2(\omega_2) - \tilde{u}_2(\phi)} = \frac{\max_{v\in F}(\tilde{u}_1(v)) - \tilde{u}_1(\phi)}{\max_{v\in F}(\tilde{u}_2(v)) - \tilde{u}_2(\phi)}\right)$$

- Kalai Point (1977): The Pareto outcome maximizing the utility for the unfortunate player. Defining P as the Pareto front

$$\arg\max_{\omega_1,\omega_2 \in P} \min_{i\in\{1,2\}} \left(\tilde{u}_i(\omega_i) - \tilde{u}_i(\phi)\right)$$

Rubinstein's Bargaining Protocol: Description

The Game

- Two agents sharing a pie.
- Each agent is under a different time-pressure: $\tilde{u}_i^{t+\Delta}(\omega) < \tilde{u}_i^t(\omega)$. Examples of time-pressure:

  Exponential $\tilde{u}_i^{t+\Delta}(\omega) = \delta_i^\Delta u_i^t(\omega)$.

  Linear $\tilde{u}_i^{t+\Delta}(\omega) = u_i^t(\omega) - \Delta c_i$
- Actor's initial utility is the assigned part of the pie: $\tilde{u}_i^0 = \omega_i$.
- Time pressure and utility information are common knowledge.
- No externally imposed time-limit.
- Zero reservation value: $u_i^\tau(\phi) = 0 \ \forall \tau$.

Main Result

There is a unique *sub-game perfect equilibrium* that requires a single negotiation step in most cases.

Rubinstein's Bargaining Protocol: Equilibrium

Exponential Discounting

The negotiation ends in **one step** with the first agent proposing and the second agent accepting *for asymmetric cases*:

$$(\omega_1^*, \omega_2^*) = \left(\frac{1-\delta_2}{1-\delta_1\delta_2}, \frac{\delta_2\left(1-\delta_1\right)}{1-\delta_1\delta_2} \right)$$

Linear Discounting

The negotiation ends in **one step** with the first agent proposing and the second agent accepting:

$$(\omega_1^*, \omega_2^*) = \begin{cases} (c_2, 1-c_2) & c_1 > c_2 \\ (x, 1-x)\ \forall x \in [c_1, 1] & c_1 = c_2 \\ (1, 0) & c_1 < c_2 \end{cases}$$

Negotiation With Full information

Hick's Paradox

Why do rational parties negotiate when they have full information?

Becuase the world exists!! [Fernandez and Glazer, 1989]

- A union negotiating with management about a wage raise in rounds.
- The union *can* strike.
- Both parties are perfectly rational and fully informed.

Main Findings:

- Sub-game perfect equilibria exist in which there is some finite striking time followed by agreement.
- That happens in real time even when round length goes to zero.

Negotiation With Incomplete Information

Impossibility Result

Define a good mechanism as:

- Incentive compatible.
- No external subsidy.

Assuming rationality, there is *no* good mechanism that can guarantee agreement when it is dominant [Myerson and Satterthwaite, 1983].

Example

- A buyer values a product at v.
- A seller can create the product at cost c.
- $v > c$.
- There is no way to design a good mechanism that results in agreement for all v, c values.

Outline

References I

Fernandez, R. and Glazer, J. (1989). Striking for a bargain between two completely informed agents. Technical report, National Bureau of Economic Research.

Myerson, R. B. and Satterthwaite, M. A. (1983). Efficient mechanisms for bilateral trading. *Journal of economic theory*, 29(2):265–281.

Automated Negotiation: Challenges and Tools

Protocols and Strategies

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Outline

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Unmediated Protocols

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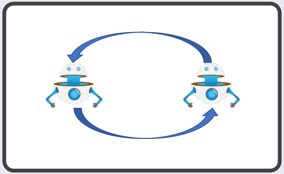
Main Features

- No central coordinator.
- Agents negotiate by exchanging *messages*.
- All proposals come from negotiators.



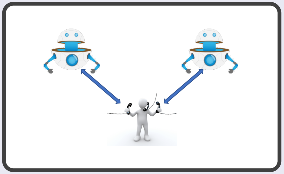
Examples

Nash Bargaining Game	Single iteration, single issue, bilateral protocol with complete information.
Rubinstein Bargaining Protocol	Infinite horizon, single issue, bilateral protocol with complete information [Rubinstein, 1982].
Alternating Offers Protocol	Finite horizon, multi-issue,

Mediated Protocols

Main Features

- Has A central *mediator*.
- Agents negotiate by exchanging *messages* with the *mediator*.
- Proposals can come from the mediator or the negotiators.



Examples

Single Text Protocol: The mediator proposes a single hypothetical agreements, gets feedback about it and modifies it based on this feedback.

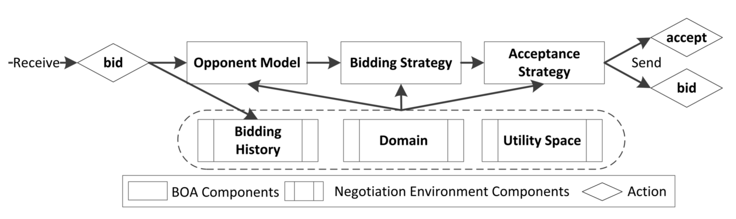
Stacked Alternating Offers Protocol

```
n_agreed, current = 0, randint(0, n_agents)
offer = agents[current].offer()
while not timeout()
        current = (current + 1) % n_agents
        response = agents[current].respond(offer)
        if response == 'accept':
                n_agreed += 1
        if n_agreed == n_agents:
                return offer
        elif response == 'end_negotiation':
                return 'failed'
        elif response == 'reject':
                offer = agents[current].offer()
return "timedout"
```

Outline

Outline

Negotiator Components [Baarslag et al., 2014][1]



OBA Atchitecture

Model(s) Learns about the partner, and negotiation state.

Bidding Strategy Generates new bids.

Acceptance Strategy Decides when to accept.

[1] Supported by Genius

Bidding Strategy

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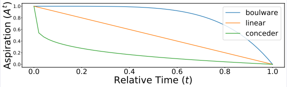
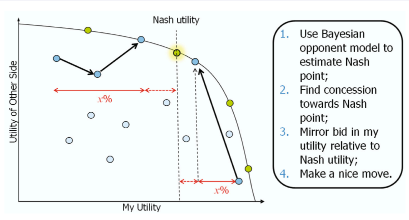
Time-based strategies

The negotiator's offers and decisions (acceptance, ending) depend **only** on the relative negotiation time.



(Nice) Tit-for-Tat (bilateral) [Baarslag et al., 2013]

Concede as much as the opponent and do not retaliate.



Opponent Modeling

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What is being modeled?

- Opponent preferences.
- Opponent strategy.
- Acceptance probability.
- Future offers.
- Opponent Type.

When is it modeled?

- Before the negotiation.
- During the negotiation.

Data

- This negotiation vs. past negotiations.
- This opponent vs. this opponent group vs. others.
- Exchanged offers vs. agreements

Opponent Model: Example

Bayesian Learning

Hypothesis A hypothesis about the opponent's behavior.

Evidence Behavior of the agent (e.g. its offers/rejections).

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

Example

Hypothesis space: Utility function as a weighted sum of basis functions

$$u(\omega) = \sum_{i=1}^{n} \alpha_i f_i(\omega_i; \sigma_i)$$

Evidence: Rejection and offers (assuming a strategy).

Acceptance Strategy

Examples

Accept if the utility of the offer $\succ$

- **Previous** my last offer.
- **Current** what I am about to offer.
- **Expected** the best offer I expect to receive (needs an opponent model).
- **Threshold** an offer with the current utility threshold (τ).
  - **Constant** May be a fraction of maximum utility.
  - **Time-based** Monotonically decreasing with time.
  - **Predictive** Predicts the expected/max utility on rejection (e.g. Gaussian Process).

Outline

Platforms [Used in this tutorial]

Genius [Lin et al., 2014]

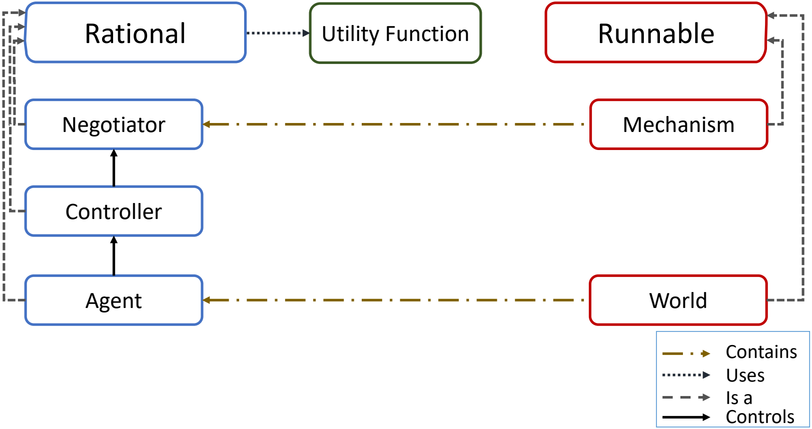
a Java-based negotiation platform to develop general negotiating agents and create negotiation scenarios. The platform can simulate negotiation sessions and tournaments and provides analytical tools to evaluate the agents' performance.

NegMAS [Mohammad et al., 2019]

a Python-based negotiation platform for developing autonomous negotiation agents embedded in simulation environments.The main goal of NegMAS is to advance the state of the art in situated simultaneous negotiations.

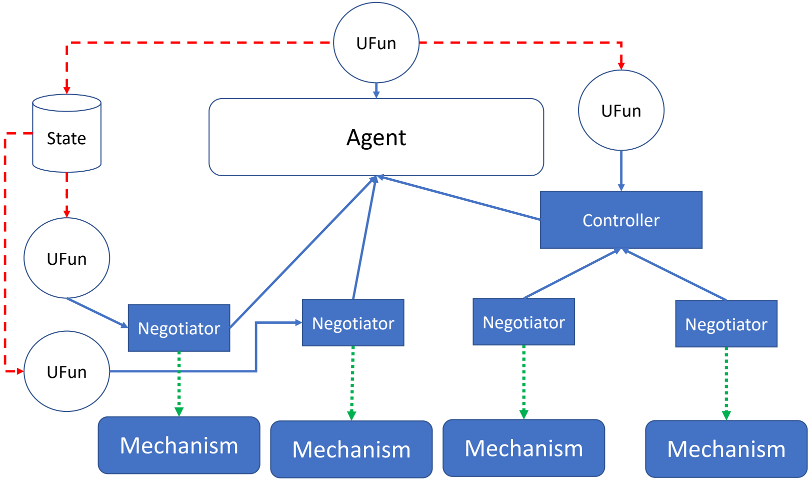
Outline

NegMAS[2] in two slides

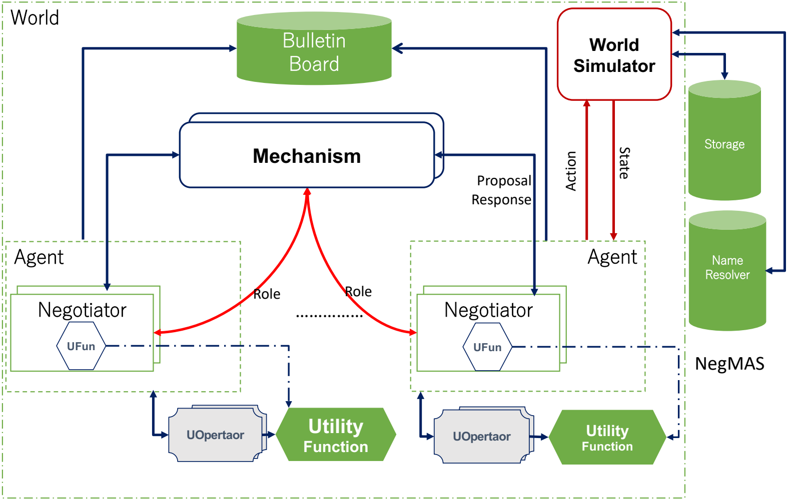


[2] https://www.github.com/yasserfarouk/negmas

NegMAS in two slides



NegMAS in two slides (... OK 3)



NegMAS in two slides (... really!!!)

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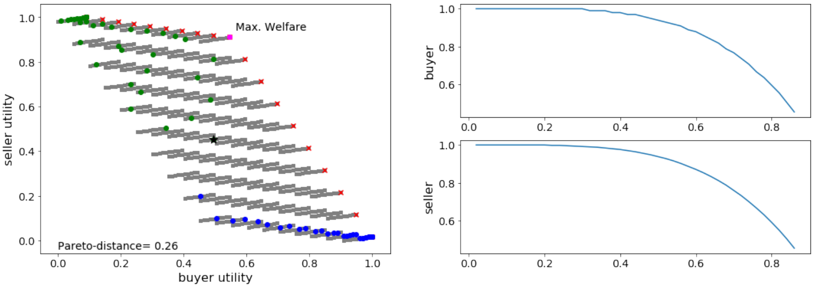

- An Example negotiation.
- Can you spot a problem?

Outline

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Recent Advances

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1. Negotiation With Incomplete Information
    - Negotiation with Known Acceptance Model
    - Greedy Concession Algorithm
    - Speeding up GCA
    - Extending GCA
2. Supervised Learing in Automated Negotiation
3. Reinforcement Learing in Automated Negotiation

Outline

Negotiation with Known Acceptance Model

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Scenario

$T \in \mathbb{I}$: The round-limit.

$\Omega \equiv \{\omega\}$: Possible outcomes.

- $\phi \in \Omega$ represents disagreement.

$u : \Omega \to [0, 1]$ Agent Utility Function.

$a : \Omega \times [0, T] \to [0, 1]$ The acceptance model.

Policy (Υ)

A deterministic time-dependent policy $\pi : [1, T] \to \Omega$ is simply a **sequence** of outcomes

Problem

Find the **optimal** deterministic time-dependent policy π^* such that:

$$\pi^* = \arg\max \mathcal{EU}(\pi|\Upsilon)$$

Acceptance Model Progression

General AM $a(\omega) = f(\omega, t, \pi, x)$

Dynamic AM $a(\omega) = f(\omega, t, \pi)$

Time Dependent AM $a(\omega) = f(\omega, t)$

Monotonic AM

$$\big(f(\omega, t+1) - f(\omega, t)\big)\big(f(\omega, t+2) - f(\omega, t+1)\big) \geq 0$$

Homogeneous AM

$$f(\omega_1, t+1) - f(\omega_1, t) = f(\omega_2, t+1) - f(\omega_2, t)$$

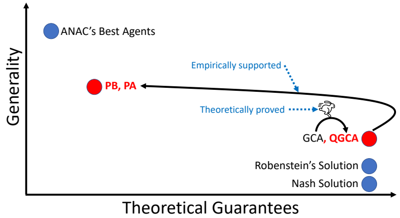
Fixed Rate AM

$$f(\omega, t+2) - f(\omega, t+1) = f(\omega, t+1) - f(\omega, t)$$

Static AM $f(\omega, t+1) = f(\omega, t)$

Positioning this work

Why is this worth doing?



Why are we trying this?

- You cannot argue with .
  - Faster calculation of π^* opens new .
- Advance our Fundamental Understanding.
  - When **exactly** is GCA optimal?
  - Why **exactly** is GCA optimal?
- Provide ideas and inspiration for new strategies to advance the state of the art.

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Greedy Concession Algorithm

Applicability

Designed and proved optimal for negotiations **static** acceptance models, and **no-repetition** of offers [?].

Main Idea

- The optimal policy of length one is known: $\arg\max_{\omega} a(\omega)u(\omega)$
- Optimal policy of length N contains *scrambled* version of the optimal policy of length $N-1$ $\rightarrow$ Optimality of greediness theorem.
- The optimal policy is a **conceding** policy $\rightarrow$ the concession lemma.

Understanding Optimality of GCA

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GCA

1: $\pi \leftarrow <>$ ▷ Empty policy
2: **for** $k \leftarrow 1 : T$ **do**
3: $\omega^* \leftarrow \arg\max_{\omega \in \Omega - \pi} \mathcal{EU}(sort_{\mathcal{EU}}(\pi \circ \omega))$
4: $\pi \leftarrow sort_{\mathcal{EU}}(\pi \circ \omega^*)$ ▷ Operator *o* inserts an element in a set

Time Complexity

$$O(TK^2)^a$$

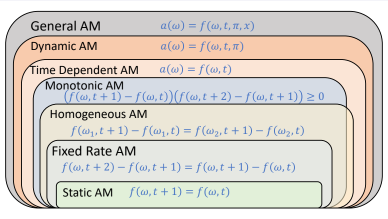
- Linear in negotiation time.
- **Quadratic** in outcome space size.

[a] trees do not help here 😱

Understanding Optimality of GCA

Can it be extended without modifications?

- Allowing repetition $\rightarrow$ **YES.**
- Extension **keeping optimality** to more AMs?
    - General TDAM $\rightarrow$ **NO.**
    - Monotonic AM $\rightarrow$ **NO.**
    - Homogeneous AM $\rightarrow$ **NO.**
    - Fixed Rate AM $\rightarrow$ **NO.**



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Quick GCA

Applicability

Static Acceptance Models.

Main Idea

90% of CS is caching ... [a]

- Calculating the $\mathcal{EU}$ of a policy **repeats** many calculations of shorter policies.
- Let's **cache** those.
- Allows us to calculate the effects of various operations on the expected utility in **O(1)** time (and space).

[a] this is not a quote. Just invented it.

QGCA Details

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Cached Quantities

$P : [0, T] \rightarrow [0, 1]$ The aggregate multiplication of probability of rejection used in the evaluation of $\mathcal{EU}$.

$$P_i = \prod_{j=0}^{i-1} 1 - a(\pi_j) \tag{1}$$

$S : [0, T] \rightarrow [0, 1]$ The cumulative sum of the expected utility value.

$$S_i = \sum_{j=0}^{i} u(\pi_j)a(\pi_j)P_j = S_{i-1} + u(\pi_i)a(\pi_i)P_i \tag{2}$$

Calculating $\mathcal{EU}$ using $\uparrow$

$\mathcal{EU} = S_T$

Operations on Policies

Static AM

Operation	Symbol	Effect on $\mathcal{EU}(\pi)$
Replacing π_i with ω	π_i^{ω}	$P_i(u(\omega)a(\omega,i) - u(\pi_i)a(\pi_i)) + (S_T - S_i)\frac{a(\omega,i)-a(\pi_i,i)}{1-a(\pi_i,i)}$
Swapping π_i, π_j	$\pi_{i\leftrightarrow j}$	$u_i\left(a_i^jP_j\frac{1-a_j^i}{1-a_i^i} - a_i^iP_i\right) + u_j\left(a_j^iP_i - a_j^jP_j\right) + (S_{j-1} - S$
Swapping π_i, π_{i+1}	$\pi_{i\rightarrow 1}$	$u_i\left(a_i^{i+1}P_i(1 - a_{i+1}^i) - a_i^iP_i\right) + u_{i+1}\left(a_{i+1}^iP_i - a_{i+1}^{i+1}P_{i+}$

General TDAM

Replacing π_i with ω	π_i^{ω}	$P_i(u(\omega)a(\omega) - u(\pi_i)a(\pi_i)) + (S_T - S_i)$
Swapping π_i, π_j	$\pi_{i\leftrightarrow j}$	$u_ia_i\left(P_j\frac{1-a_j}{1-a_i} - P_i\right) + u_ja_j\left(P_i - P_j\right) + (S_{j-}$
Swapping π_i, π_{i+1}	$\pi_{i\rightarrow 1}$	$P_ka(\pi_i)a(\pi_{i+1})\left(u(\pi_{i+1}) - u(\pi_i)\right)$
Inserting outcome ω at location t	$\pi_{\omega @ i}$	$u(\omega)a(\omega)P_i - a(\omega)(S_T - S_{i-1})$

Quick GCA

$\pi \leftarrow <>$ ▷ Empty *linked* list

$\mathcal{L}_\omega = 0 \forall \omega \in \Omega$ ▷ Initialize location of all outcomes

$S_{-1}, P_{-1} \leftarrow 0, 1$

for $k \leftarrow 1 : T$ **do**

  $d^*, \omega^* \leftarrow -\infty, \phi$

  for $\omega \in \Omega$ **do**

    $i \leftarrow \mathcal{L}_\omega$ ▷ Lookup location of insertion

    $d_\omega \leftarrow S_{i-1} + (1 - a(\omega))(\mathcal{EU}(\pi) - S_{i-1}) + P_i \mathcal{EU}(\omega) a(\omega)$

    if $d_\omega \geq d^*$ **then**

      $d^*, \omega^* \leftarrow d_\omega, \omega$

  $\pi \leftarrow \pi \circ_{\mathcal{L}_{\omega^*}} \omega^*$ ▷ Insert best outcome in its correct place

  Update $S, P, \mathcal{L}$

  if no-repetition **then**

    $\Omega \leftarrow \Omega - \{\omega^*\}$

Time Complexity

$$O(TK)$$

- Linear in negotiation time

Outline

1. Negotiation With Incomplete Information
   - Negotiation with Known Acceptance Model
   - Greedy Concession Algorithm
   - Speeding up GCA
   - Extending GCA
2. Supervised Learing in Automated Negotiation
3. Reinforcement Learing in Automated Negotiation

Extending GCA to General TDAM

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Why cannot we use GCA as it is?

- The concession lemma does not hold.
  - The optimal policy may **NOT** be conceding.
- The greedy-is-optimal theorem does not hold.
  - The optimal policy may **NOT** contain shorter optimal policies (even scrambled).

What to do

- Start by running QGCA $\rightarrow$ a conceding policy.
  - Use the mean as the SAM.
- Use fast operations to permute this policy for a better one.
  - Policy Bubbling (PB).
- Starting from PB, search for a better policy (i.e. using simulated annealing)
  - Policy Annealing (PA).

Policy Bubbling

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```
π ← π^c                                  ▷ Start from the result of QGCA+
for r ← 1 : T do
    π^- ← π
    for k ← 1 : T − 1 do
        if EU(π_{k→1}) − EU(π) > 0 then
            π ← π_{k→1}
    if π^- = π then
        return π^b = π
return π^b = π
```

Time Complexity

$$O(T^2)$$

Policy Annealing

$\pi \leftarrow \pi^b$ ▷ Start from the result of PBS
for $r \leftarrow 1 : R$ **do**
  Randomly select a site s and an outcome $\omega \in \Omega - \{\pi_s\}$
  $\delta \leftarrow \mathcal{EU}(\pi_s^\omega) > \mathcal{EU}(\pi)$
  if $\delta > 0 \vee rand() > \exp^{-\delta/\tau(r)}$ **then**
    $\pi \leftarrow \pi_s^\omega$
  for $i \leftarrow 1 : T$ except s **do** ▷ Find the best permutation
    if $\mathcal{EU}(\pi_{i \leftrightarrow s}) > \mathcal{EU}(\pi)$ **then**
      $\pi \leftarrow \pi_{i \leftrightarrow s}$
return $\pi^a = \pi$

Time Complexity

$$O(TR)$$

Outline

Supervised Learing in Automated Negotiation

Outline

1. Negotiation With Incomplete Information
2. Supervised Learing in Automated Negotiation
3. Reinforcement Learing in Automated Negotiation

Reinforcement Learing in Automated Negotiation

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Automated Negotiation: Challenges and Tools

Automagted Negotiation is SCM

Yasser Mohammad[1,2,3] and **Amy Greenwald**[4]

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[2] National Institute of Advanced Industrial Science and Technology (AIST)

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[4] Brown University

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Outline

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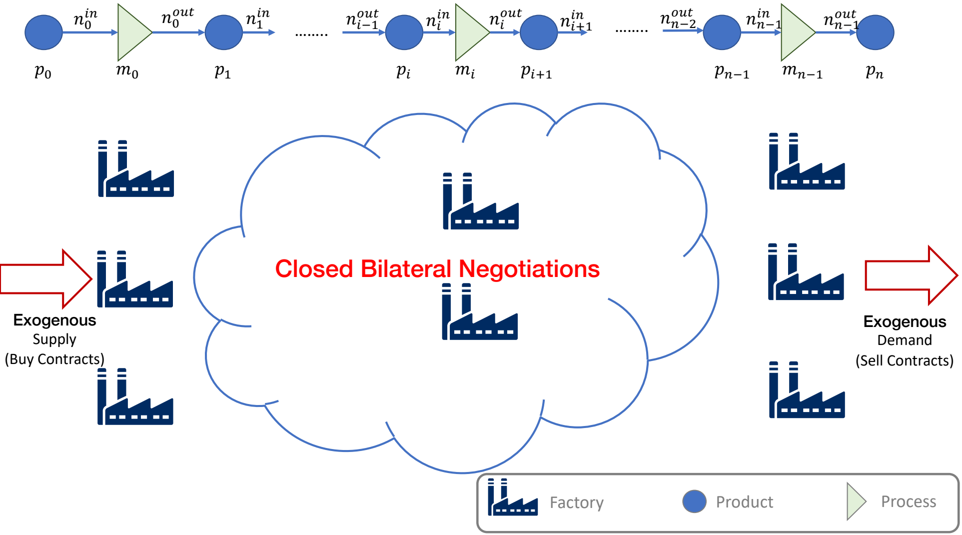
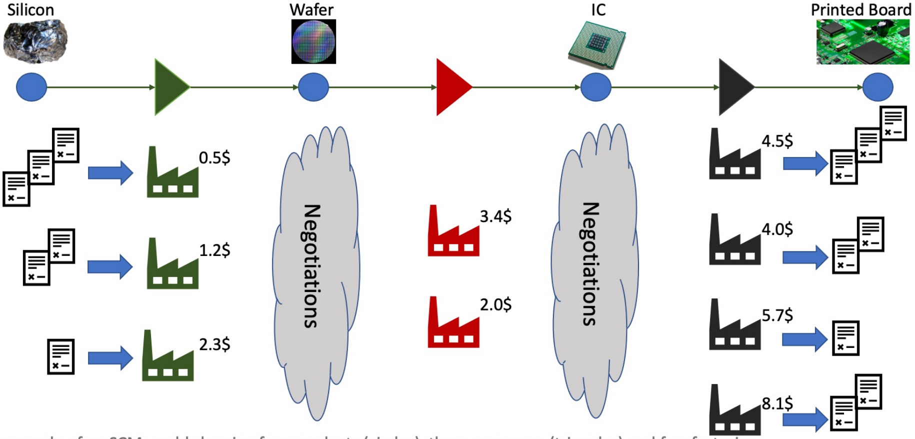
SCML Competition [Mohammad et al., 2019]



Example Configuration



An example of an SCM world showing four products (circles), three processes (triangles) and few factories.
Each process consumes one item of its input and generates one output of its output in one day.
Each factory requires a different cost to run its process (shown in its top right).
Factories in the first level have exogenous contracts to buy raw material (silicon) and factories at the last level have exogenous contracts to sell the final product (printed boards). These contracts drive the market.

SCML World

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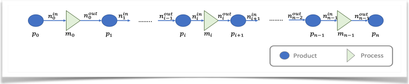
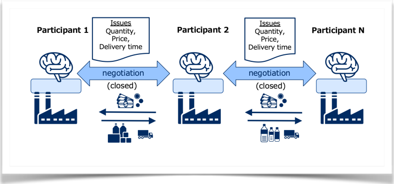
Challenge

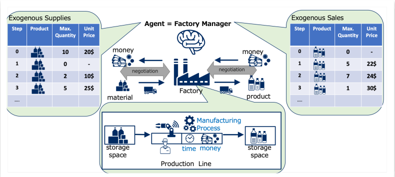
- Turn maximize profit into a ufun!!
- Dynamic interdependent ufuns.
- Sequential negotiations.
- Concurrent Negotiations.
- Negotiation under uncertainty.
- Adaptation and learning.
- Trust management.

Information

- **Website** https://scml.cs.brown.edu/







SCML Competition

Competition Details

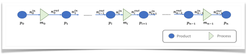
- Runs as part of ANAC IJCAI.
- You control one or more factories.
  - **Standard track** $\rightarrow$ one factory.
  - **Collusion track** $\rightarrow$ multiple factories (3).

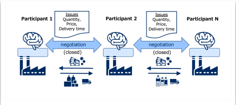
Score Evaluation

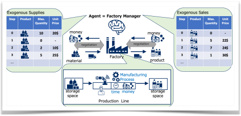
- **Per instantiation**: Total profit counting inventory at half the trading price.
- **Total**: median of per-instantiation scores.

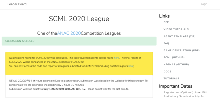
Flavors

- Online competition at https://scml.cs.brown.edu





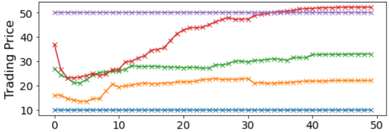


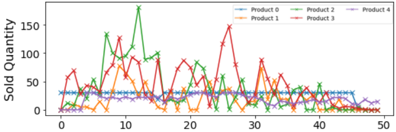


Simulation Steps

Simulation Steps

Trading prices





What is trading price and why is it calculated?

- A value calculated by the system for each product.
- Represents some estimate of the current price.
- Never revealed to agents.
- Usages:
  - Used at the end to value inventory.
  - Used when calculating spot-market price. during breach processing.

How does the system calculate it?

$$\mathrm{tp}(p, s) = \frac{\beta^{s+1}\ Q_{-1}(p)\ \mathrm{cat}(p) + \sum_{i=0}^{s} \beta^{s-i}\ Q_i(p)\ \mu_i(p)}{\beta^{s+1} \cdots + \sum^{s} \cdots \beta^{s-i} \cdots},$$

Trading prices: The details

Quantities and prices

$$Q_i(p') = \sum_{\{c \in C^i | c.p = p'\}} c.\bar{q}$$

$$\mu_i(p') = \frac{\sum_{\{c \in C^i | c.p = p'\}} c.\bar{q} \times c.u}{Q_i(p')}$$

How does the system calculate it?

$$\mathrm{tp}(p, s) = \frac{\beta^{s+1}\; Q_{-1}(p)\; \mathrm{cat}(p) + \sum_{i=0}^{s} \beta^{s-i}\; Q_i(p)\; \mu_i(p)}{\beta^{s+1} + \sum_{i=0 | Q_i(p) > 0}^{s} \beta^{s-i}} \quad ,$$

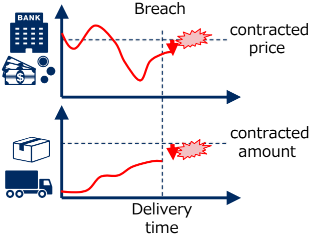
When things go wrong

What is a breach

- Insufficient funds or insufficient inventory.

Breach Processing

- A breach report is **always** published.
  - who and fraction.
- Insufficient products → **forced to** buy from the spot market.
- Insufficient funds → bankruptcy.
  - bankruptcy → liquidation.



Outline

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Automated Negotiation: Challenges and Tools

Future Challenges and Open Problems

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Outline

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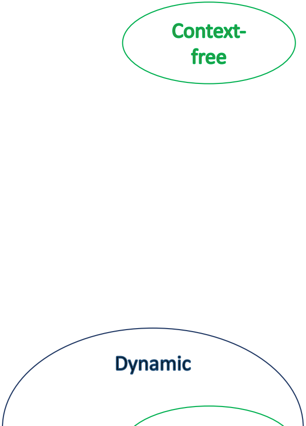
Situated Negotiation



Outline

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Negotiation Under Uncertainty

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The challenge

How to negotiate when you have *partial* information about your actor's utility function?

The Game

- ANAC 2019 agent game @ IJCAI introduced the first competition in this domain.
- Input is a ranking of a subset of the outcomes.

Example Solutions

- Regress the utility of all outcomes using a polynomial model.
- Use a GP to create a probabilistic ufun.

Outline

1. Situated Negotiation
2. Optimality Results
   - Against Known Opponents
   - In Specific Settings
3. Preference Elicitation During Negotiation
4. Concurrent Negotiation
5. References

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Preference Elicitation

The challenge

How to reduce Uncertainty in user preferences:

- before negotiation (offline preference elicitation).
- while negotiating (online preference elicitation).

Types of questions

Utility Value what is $\tilde{u}(\omega)$?

Utility Constraint Is $\tilde{u}(\omega) \geq x$? Usually implemented as a standard gamble.

Utility Comparison Is $\omega_1 \succ \omega_2$?

Elicitation Procedures

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1. Long history in the decision support and economics research community.
2. Take away message: Do not ask about the utility directly..
3. Practical elicitation uses a **series** of comparisons between outcomes to assess utilities.

A Gamble

(ω^*, ω_*, p) : Getting ω^* with probability p otherwise ω_*

Example query

Do you prefer to get ω for certain over (ω^*, ω_*, p)?

Elicitation Procedures/Strategies

Probability Equivalence

find p so that $\omega = (\omega^*, \omega_*, p)$

Certainty Equivalence

find ω so that $\omega = (\omega^*, \omega_*, p)$

- Both require *normalized* utilities.
- Both require knowledge of $\omega^* \succ \omega \succ \omega_*$.
- Lead to different biases.

Comparison-only Procedures

1. Titration-down: $p_k = 1 - s \times k$
2. Titration-up: $p_k = s \times k$
3. Ping-pong: $p_k = \begin{cases} s \times \lfloor k/2 \rfloor & \text{k is odd} \\ 1 - s \times k/2 & \text{k is even} \end{cases}$

Importance of Elicitation

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Negotiation with Elicitation

$m,\ \Omega,\ R,\ \tilde{U}_i\ \forall 1 \leq i \leq m\ ,\ \hat{U}_i^0\ \forall 1 \leq i \leq m$

m Number of agents/actors

$\Omega = \{\omega_j\}$ Possible outcomes (assumed countable)

n Number of outcomes $|\Omega|$

$R(i) \equiv r_i$ Reserved value for agent i

$\tilde{U}_i : \Omega \to [0, 1]$ Utility of outcomes to **actor** i

$\hat{U}_i^0 : \Omega \to P$ Probability distribution of utility values for **agent** i
$\hat{U}_{ij}^0 \equiv \hat{U}_i^0(\omega_j)$

$P : \{[0, 1] \to [0, 1]\}$ A probability distribution on the closed interval $[0, 1]$

What is Elicitation Doing?

Reduces uncertainty in $\hat{U}$

State of the Art

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- Lots of work on preferences/utility elicitation in decision making domain.
- Some work on incremental utility elicitation.
- Few works on incremental utility elicitation during negotiations

Why Is Negotiation Different

1. The acceptance model changes over time $\rightarrow$ environment dynamics are not static.
2. Exploration is extremely costly.
3. Usually negotiations are not repeated much.
4. Cannot train on a simulator (in most cases).

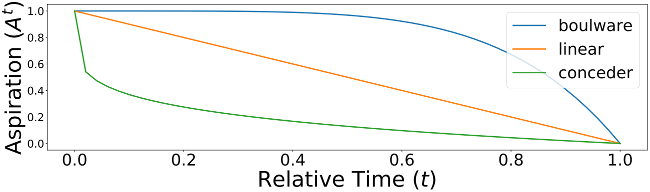
Outline

Pandora's Problem [Economics]

1. A set of n boxes ($\{\omega_j\}$).
2. Opening a box j gives a reward between 0 and ∞ according to distribution p_j after t_j time-steps, and costs c_j.
3. Future rewards are discounted with a known factor β.
4. Pandora's Problem:
   1. What is the optimal order to open the boxes?
   2. When should she stop?
5. Similar to elicitation (boxes = outcomes, open = query) but assumes that uncertainty is completely removed.

Optimal Elicitation [Baarslag and Gerding, 2015]

Adapts Pandora's Rule to the negotiation context:



1. $\beta = 1.0$
2. Define aspiration level as: $A^t \equiv r_i + \left(A^0 - r_i\right) \times \left(1 - \frac{t}{N}^{1/e}\right)$
   $e > 1 \rightarrow$ Boulware, $e = 1 \rightarrow$ Linear, $e < 1 \rightarrow$ Conceder
3. $p_j = \Lambda_i^t(\omega_j) \times \mathbb{E}\left(\hat{U}_{ij}^t\right) + (1 - \Lambda_i^t(\omega_j)) \times A^t(\omega_j)$
4. Assume that there is an open box giving r_i with outcome index 0.
5. End the negotiation once the best box is 0.

Why is OE sub-optimal?

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Main Issue

Assuming that all uncertainty is removed by elicitation.

1. Assuming that $\hat{U}_{ij} \rightarrow \delta\left[u = \tilde{U}_i(\omega_j)\right]$
2. Consider any practical strategy (e.g. titration-down):
   - After the first question: $\hat{U}^t_{ij} \rightarrow \hat{U}^{t+1}_{ij}$
   - z_j was calculated using $\hat{U}^t_{ij}$ and must be recalculated.

Take-away message

Avoid deep-elicitation.

Extensions to Pandora's algorithm

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Closed-form Calculation of z-index[Mohammad and Nakadai, 2018b]

$$z_j = \begin{cases} \frac{a+b}{2}\beta - c_j & z_j \leq a \\ \frac{-\lambda \pm \sqrt{\lambda^2 - 4\zeta}}{2} & a < z_j \leq b \end{cases}$$

λ $-2\left(b + \frac{a-\beta}{\beta}(b-a)\right)$

ζ $b^2 - \frac{2c_j}{\beta}(b-a)$

The balanced expectation operator

$$\mathcal{E}(\hat{U}_{ij}^t) = \frac{t}{N} \times Min\left(\hat{U}_{ij}^t\right) + \left(1 - \frac{t}{N}\right) \times Max\left(\hat{U}_{ij}^t\right)$$

Min/*Max* a *biased* estimator that exaggerate the lower/upper part of its input. For $U(a,b)$, $Min, Max = a, b$.

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Value of Information Algorithm

- Based on [Chajewska et al., 2000] in decision-support context.
- Adapted to the negotiation context.

Main Idea

- Assume an accurate opponent model (acceptance probability)
- Given a set of queries $Q \rightarrow$ find the one with the maximum difference between the expected expected utility before and after asking it[Baarslag and Kaisers, 2017, Mohammad and Nakadai, 2018a].

VOI Based Elicitation

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Policy

$$\pi^{t} = \left(\omega^{t}, \omega^{t+1}, \omega^{N}\right) \text{ where } \omega^{x} \in \Omega$$
$$K\left(\omega|\pi\right) \equiv \text{index of } \omega \text{ in } \pi$$
$$\pi\left(k\right) = \omega \text{ where } K\left(\omega|\pi\right) = k$$

Probability of Agreement

$$Pa^{t}\left(\omega|\pi\right) = \begin{cases} \Lambda^{t}\left(\omega\right)\prod_{k=1}^{K_{\pi}\left(\omega\right)-1}\left(1-\Lambda^{t}\left(\pi\left(k\right)\right)\right) & \omega \in \pi \\ 0 & \textit{otherwise} \end{cases}$$

Expected Expected Utility [Boutilier, 2003]

$$EEU^{t}\left(\pi, \left\{\hat{U}^{t}_{\omega}\right\}\right) = \sum_{\omega\in\Omega} Pa\left(\omega|\pi\right)\mathbb{E}\left(\hat{U}^{t}_{\omega}\right)$$

Optimal Policy

$$\pi^{t*} = \arg\max_{\pi} EEU^{t}\left(\pi, \left\{\hat{U}^{t}_{\omega}\right\}\right)$$

VOI Based Elicitation II

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Questions and Answers

$$Q \equiv \{q_l\}$$
$$q_l \equiv \left\{\left(Ans_s^l, p_s\right)\right\}$$
$$Ans_s^l \equiv \left\{\hat{U}_\omega^{t+1}\right\}$$
$$\sum_s p_s = 1$$

Expected value of information

$$EVOI\left(q^l, \left\{\hat{U}_\omega^t\right\}\right) =$$
$$\mathbb{E}_s\left(\max_\pi EEU\left(\pi, Ans_s^l\right)\right) - \max_\pi EEU\left(\pi, \left\{\hat{U}_\omega^t\right\}\right)$$

Elicitation

Ask q^* where

$$q^* = \arg\max_q \left(EVOI\left(q^l, \left\{\hat{U}_\omega^t\right\}\right) - c_q\right)$$

VOI main Issues

Accurate Agreement Model Assumption

- Everything depends on the probability of agreement (Pa)
- Pa depends on the **product** of probabilities in the acceptance model (Λ^t)

$$Pa^t(\omega|\pi) = \begin{cases} \Lambda^t(\omega) \prod_{k=1}^{K_\pi(\omega)-1} \left(1 - \Lambda^t(\pi(k))\right) & \omega \in \pi \\ 0 & otherwise \end{cases}$$

Speed: Complexity $= O(nN|Q||Ans|)$

- Too many *argmax* and $\mathbb{E}$ operations.
- Every policy extends to the end of the negotiation.

$$q^* = \arg\max_q \left(EVOI\left(q^l, \left\{\hat{U}^t_\omega\right\}\right) - c_q \right)$$

$$EVOI\left(q^l, \left\{\hat{U}^t_\omega\right\}\right) =$$

$$\mathbb{E}_s\left(\max_\pi EEU\left(\pi, Ans^l_s\right)\right) - \max_\pi EEU\left(\pi, \left\{\hat{U}^t_\omega\right\}\right)$$

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Concurrent Negotiation

Generality

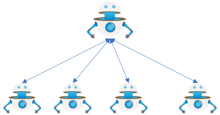
- Specific scenario (buyer-seller).
- General domain

Decommitment

- Symmetric de-commitment.
- Asymmetric de-commitment.
- No de-commitment.

Timing

- Synchronous.
- Any-time.



Outline

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Conclusion

- Automated negotiation can enhance societal welfare.
- Genius and NegMAS as open-ended platforms for research in automated negotiation.
- Classical automated negotiation research in economics focused on simplified situations and provided performance guarantees.
- Many open questions:
    - General environment and unknown opponents.
    - Incomplete information about self.
    - Concurrent negotiations.
    - Negotiations with non-stationary utilities.
    - When to use negotiation?