The Third
Automated Negotiating
Agent Competition

4th July 2012

Background

- Started in 2010, as a joint project of the universities of Delft (group of Prof. Catholijn Jonker, Dr. Koen Hindriks, Dr. Dmytro Tykhonov, Tim Baarslag) and Bar-Ilan (Prof. Sarit Kraus, Dr. Raz Lin)
- In 2011, organised by Nagoya Institute of Technology (Prof. Takayuki Ito, Dr. Katsuhide Fujita)
- In 2012, organised by University of Southampton (Colin Williams, Dr. Valentin Robu, Dr. Enrico Gerding, Prof. Nick Jennings)

- Aim: to provide a platform to compare and benchmark different state-of the-art heuristics developed for automated, bilateral negotiation

Competition Setup

- Bi-lateral Negotiation
- Alternating Offers Protocol
- Real-time, 3-Minute Deadline
- Discounting Factor

Domains and Preferences

- Each domain consists of pair of preference profiles.
- Each preference profile specified as linearly additive utility function.

- Between 1 and 8 issues.
- Domains with between 3 and 390,625 possible outcomes.

Example Domain

- Property Rental
  - Rent Price per month
    - $1,800, $2,000, $2,400, $2,700
  - Number of Payments
    - 1, 2, 3
  - Advance Payment
    - 0.5%, 1%, 2%, 2.5%
  - Contract Period
    - 3 months, 6 months, 9 months, 12 months

Example Preferences

Rent Price per month	Landlord	Tenant
weight	*0.350*	*0.353*
$1,800	20	80
$2,000	40	60
$2,400	60	40
$2,700	80	10

Number of Payments	Landlord	Tenant
weight	*0.2*	*0.129*
1	20	5
2	15	8
3	10	12

Previous Competitions

- 2010
  - 7 Entries
- 2011
  - 18 Entries (6 institutions)
- 2012
  - 17 Entries (8 institutions)

New Feature

- Reservation Value
  - Utility of conflict, which each party receives if no agreement is formed.
  - Affected by discounting factor.

Participants

- 17 Teams Entered
- 8 Institutions
- 5 Countries
  - China, Israel, Netherlands, Japan, United Kingdom

ANAC 2012

Qualifying Round

Qualifying Round

- Negotiations carried out for every combination of:
  - 17 Agents
  - 17 Opponents
  - 18 Domains
    - (17 submitted this year, plus *Travel* from 2010)
- Each repeated 10 times to establish statistical significance.
- Total of 52020 negotiations.

Qualifying Round - Rankings

- Welch's T-test for statistical significance
  - Extension of Student's T-test
- All i, j in A, compute $w(\mu_i, \sigma_i, \mu_j, \sigma_j)$
- Determine lower bound on rank by calculating how many opponents beat the agent.
- Determine upper bound on rank by calculating how many opponents the agent beats.

Qualifying Round - Rankings

Rank	Agent	Mean Score	Variance
1-2	CUHKAgent	0.597	0.000058
1-2	OMACagent	0.590	0.000106
3-5	TheNegotiator Reloaded	0.572	0.000073
3-7	BRAMAgent2	0.568	0.000045
3-7	Meta-Agent	0.565	0.000104
4-7	IAMhaggler2012	0.564	0.000029
4-8	AgentMR	0.563	0.000136
7-9	IAMcrazyHaggler2012	0.556	0.000016
8-10	AgentLG	0.550	0.000090
9-11	AgentLinear	0.547	0.000071
10-11	Rumba	0.542	0.000064
12	Dread Pirate Roberts	0.521	0.000068
13-14	AgentX	0.469	0.000034
13-14	AgentI	0.465	0.000071
15-16	AgentNS	0.455	0.000063
15-16	AgentMZ	0.447	0.000064
17	AgentYTY	0.394	0.000018

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Qualifying Round - Rankings

http://anac2012.ecs.soton.ac.uk

Hosted by:
UNIVERSITY OF Southampton

- Home
- Instructions
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- Submission
- Domains
- Results
- FAQ

Previous Competitions
ANAC2011 | ANAC2010

Sponsored by:
Makoto Lab., Inc

Selected domain:	Music Collection	Show all domains | Show details
Selected agent:	CUHKAgent, The Chinese University of Hong Kong	
Selected opponent:	OMACagent, Maastricht University	Show all opponents

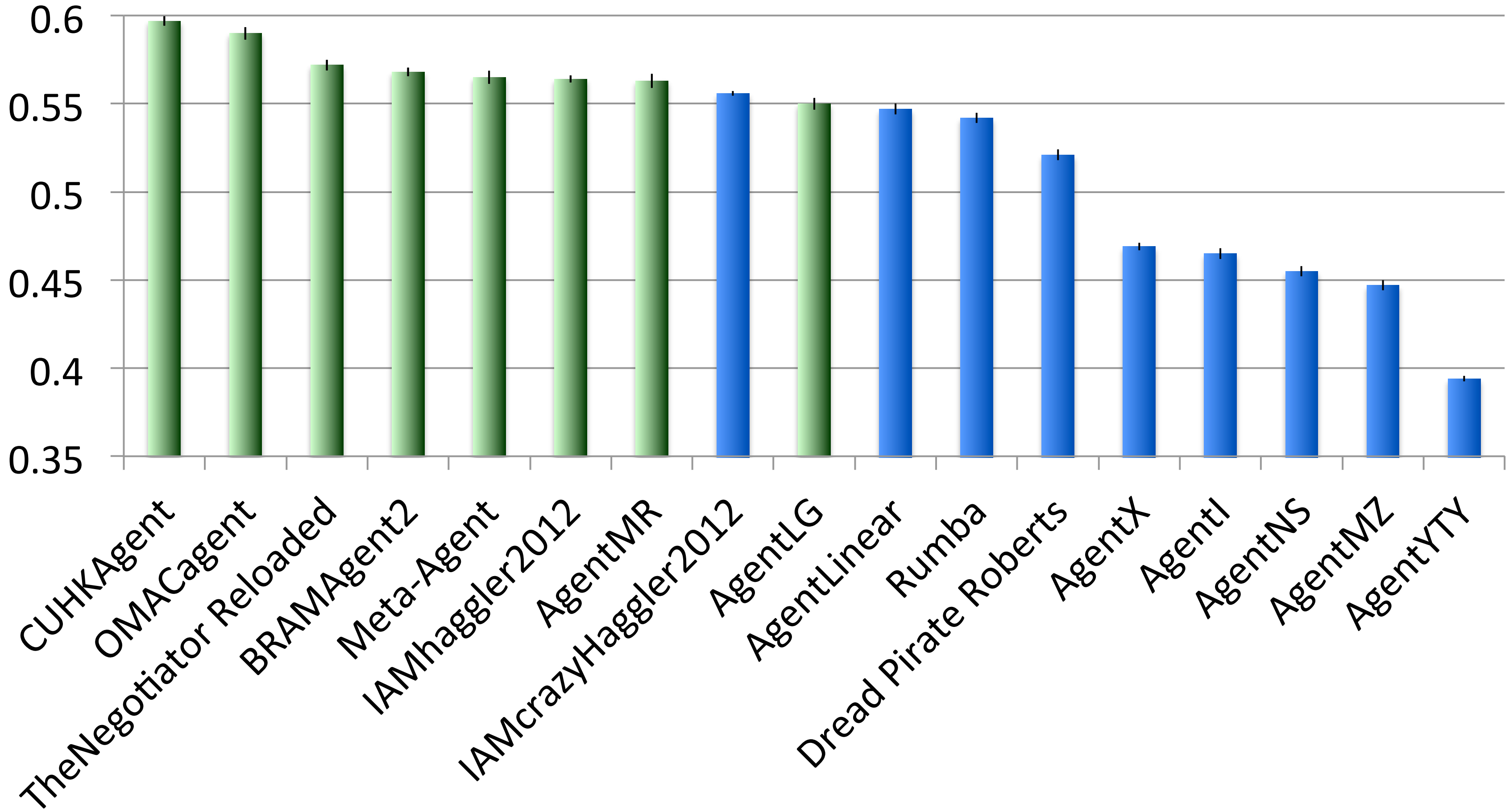
Profile 1

Agent Score	repetition
0.943	00
0.894	01
0.922	02
0.922	03
0.963	04
0.922	05
0.922	06
0.943	07
0.963	08
0.873	09

Profile 2

Agent Score	repetition
0.924	00
0.924	01
0.921	02
0.865	03
0.924	04
0.896	05
0.910	06
0.910	07
0.875	08
0.910	09

Qualifying Round



Agent Presentations

AgentLG

Bar-Ilan University

Luba Golosman

(presented by **Assaf Frieder**)

First Stage

- **0.0 - 0.6 of the total time**
  - Bids are offered in order of agent's utility until the lower bound
  - Decrease threshold based on discount factor
  - Up to 25% of the difference between first bids
  - Learn opponent's preference profile

Second Stage

- **0.6 - 0.9 of the total time**
  - Estimate opponent's compromise based on utility profile
  - Decrease threshold based on opponent's compromise and utility profile

Last Stages

- **Time 0.9- 0.9995 :**
  - Maximal compromise is half of the utility difference
- **Time >0.9995:**
  - Offers opponent's best bid if higher than the reserve value
- **Acceptance:**
  - Opponent's bid utility is higher than 99% of the agent's bid
  - After 0.999 of time, 90% of the agent's bid utility

AgentMR

Nagoya Institute of Technology

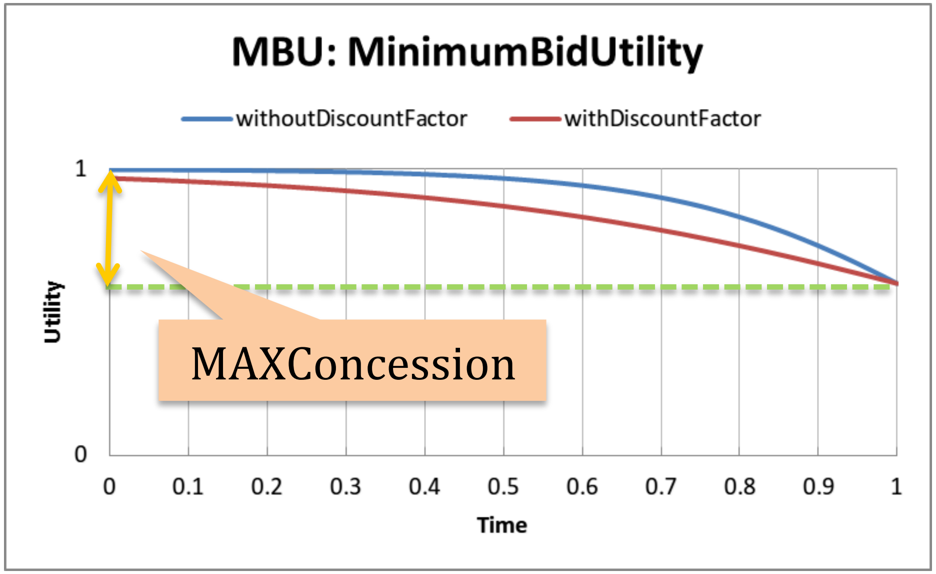
Shota Morii

AgentMR has the following features:

Concedes slowly

Makes “acceptable” bids

Concede slowly



- MBU is threshold value.
- Our bid > MBU

$MBU=1-1/1+e^{-a(t-b)}$ t:time

a: constant
b: MBU(t=1) = 1− MAXConcession

MAXConcession $\propto$ *(ourMaximumUtility− OpponentFirstBid)*

- In Win-Win domains we don't need to concede much to make deal.
- In Win-Lose domains we need to concede more in order to make deal.

We assume, *OpponentFirstBid* = Opponent's best bid

If MAXConcession > 0.3, make it 0.3

Make ‘acceptable’ bid

Heuristic

- *Bids “similar” to opponent bid have high utility for the opponent and hence are more ‘acceptable’ .*

Opponent bid

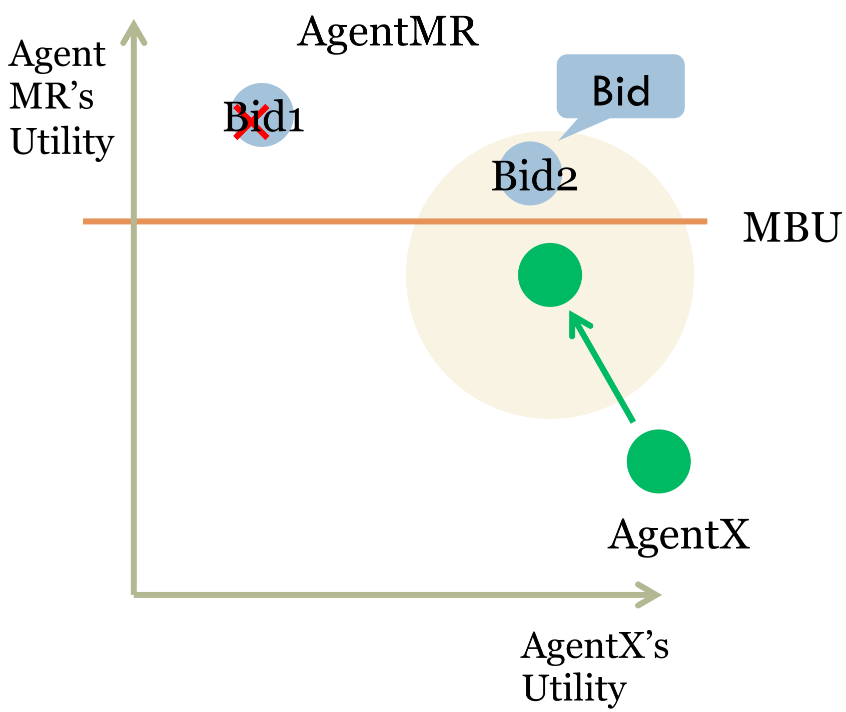
OS	Display	HDD	Mem	Utility
Mac	22	320GB	2GB	75%

Generate “Similar” bids by changing only one issue value at a time

My bid

OS	Display	HDD	Mem	Utility
Mac	22	320GB	4GB	80%

Make 'acceptable' bid



1. *Bid1 and Bid2 have utility grater than MBU*
2. *The circle region represents location of bids which are close to AgentX's recent bid*
3. *Since Bid2 is in this region we choose to offer it to AgentX*

✓ *Generally our strategy is to concede slowly and make bids which are acceptable.*

BRAMAgent2

Department of Information Systems Engineering
and
Deutsche Telekom Laboratories
Ben-Gurion University of the Negev, Beer-Sheva, Israel

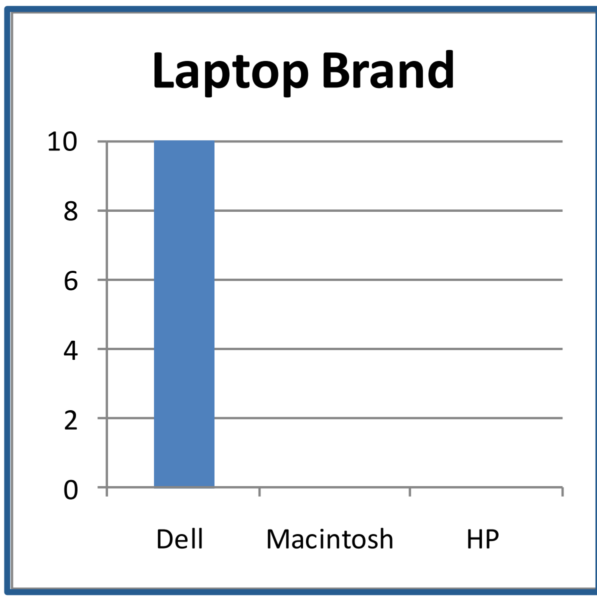
Radmila Fishel, Maya Bercovitch

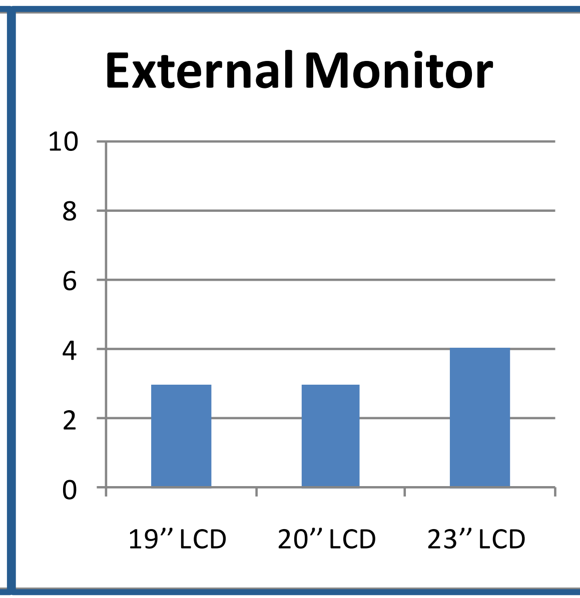
BRAM's Characteristics

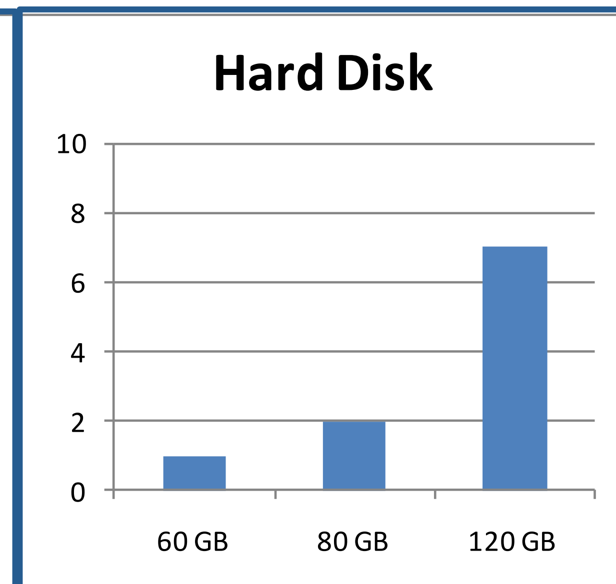
- Simple and fast
- Compromise as time elapses
- Interrupt modeling attempts by other
- Seek a Win-Win agreement

Seek a Win-Win Agreement

- BRAM creates a histogram for each issue according to the last 10 offers received from the other agent and create a new offer with as many "top required" values as possible







Improved Version of BRAM

- BRAM ends the negotiation if it is willing to offer a bid with utility lower than the reservation value

- BRAM is more tough and stubborn

Thank you!

BercovitchMaya@gmail.com
Rada.fishel@gmail.com

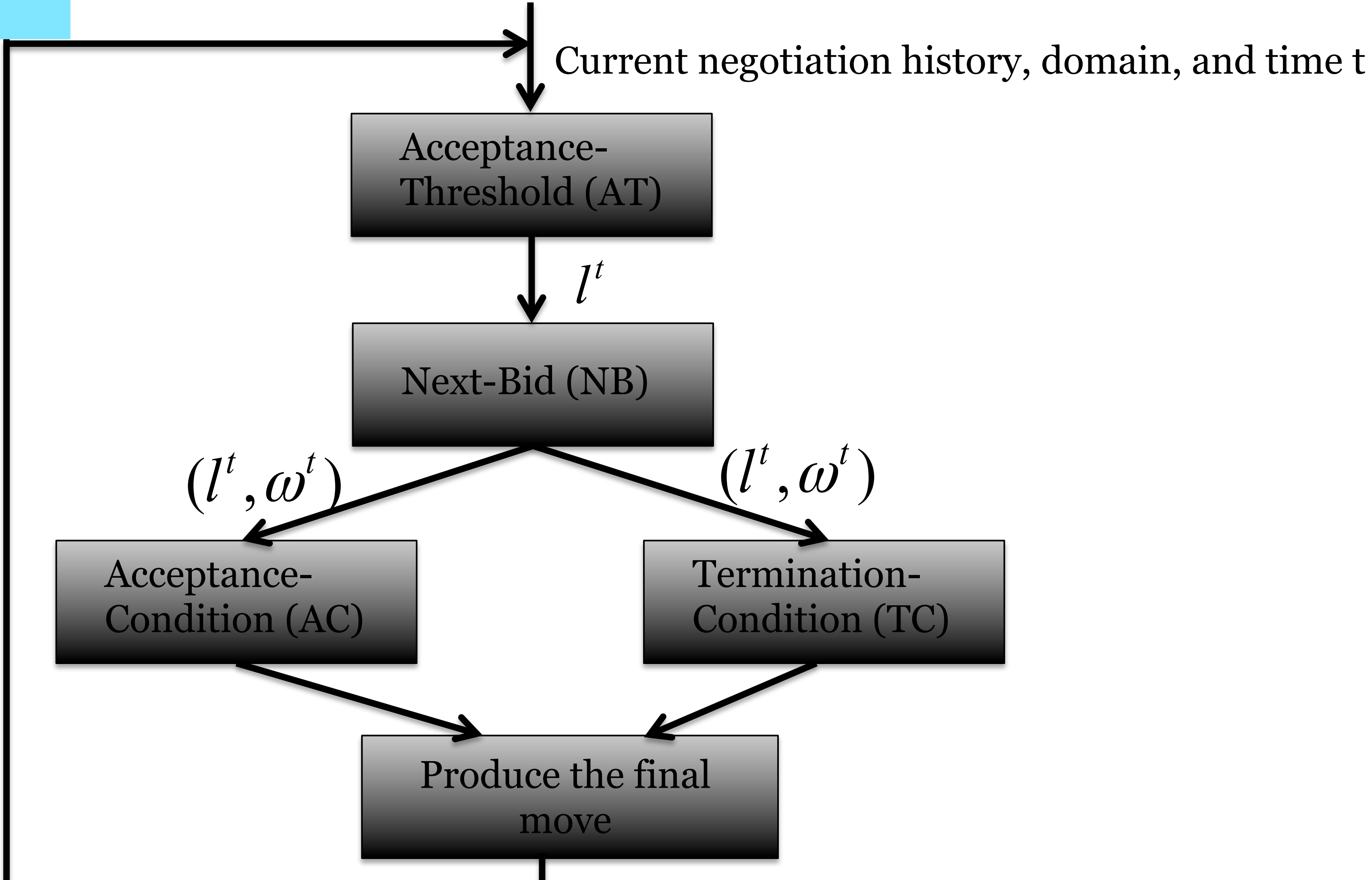
CUHKAgent

The Chinese University of Hong Kong

Jianye Hao, Ho-fung Leung

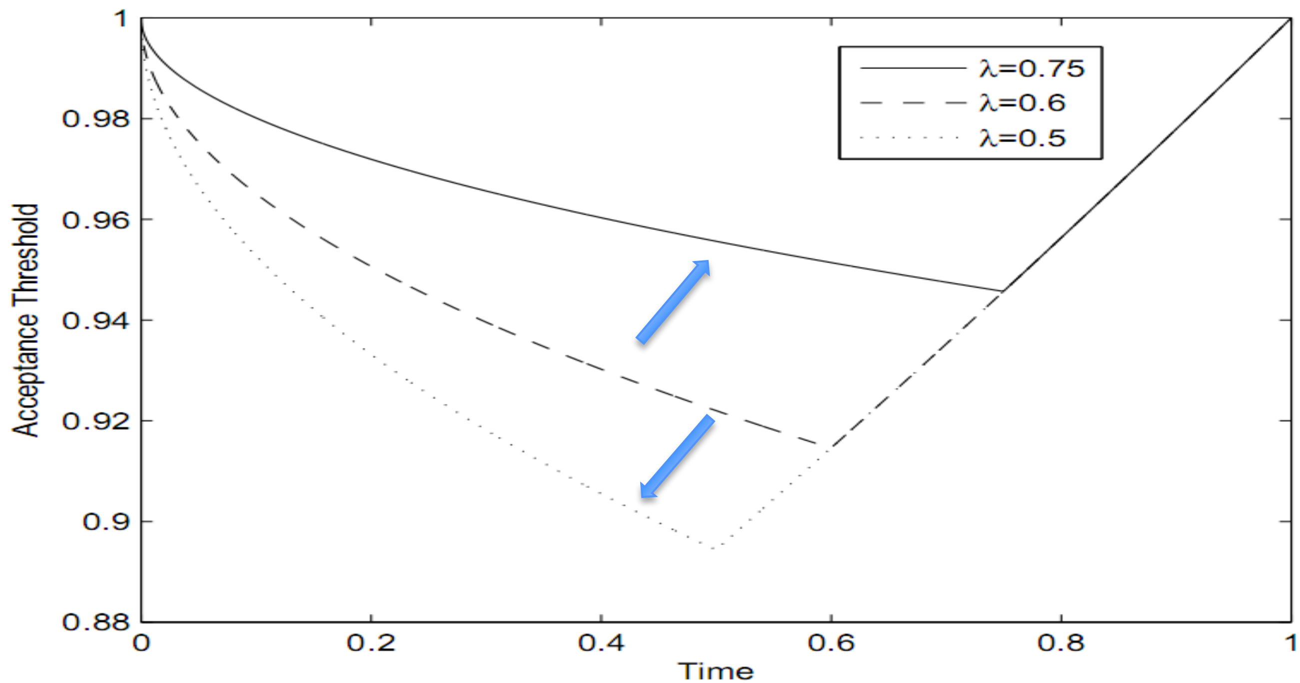
Automated Negotiating Agent Competition 2012

Strategy Design



Component Description

- Acceptance-Threshold (AT) component
  - Non-exploitation point λ
  - Adaptively adjusting Non-exploitation point λ
    - Domain-dependent, e.g., discount factor, domain size.
    - Behavior-dependent, e.g., Concession degree of the opponent



Component Description (cont.)

- Next-Bid (NB) component
  - Select the estimated best one for opponent from the set of candidate negotiation outcomes
- Acceptance-Condition (AC) component
  - Acceptance conditions
    - Our agent's utility of the opponent's offer > our acceptance threshold

      OR
    - Our agent's utility of the opponent's offer >its utility of our offer to be proposed
- Termination-Condition (TC) component
  - Treating the reservation value simply as an **alternative offer** proposed by the opponent
  - Termination conditions

Thank you!
Q&A

IAMhaggler2012

University of Southampton

Colin R Williams, Valentin Robu,
Enrico H Gerding, Nicholas R Jennings

Our Approach

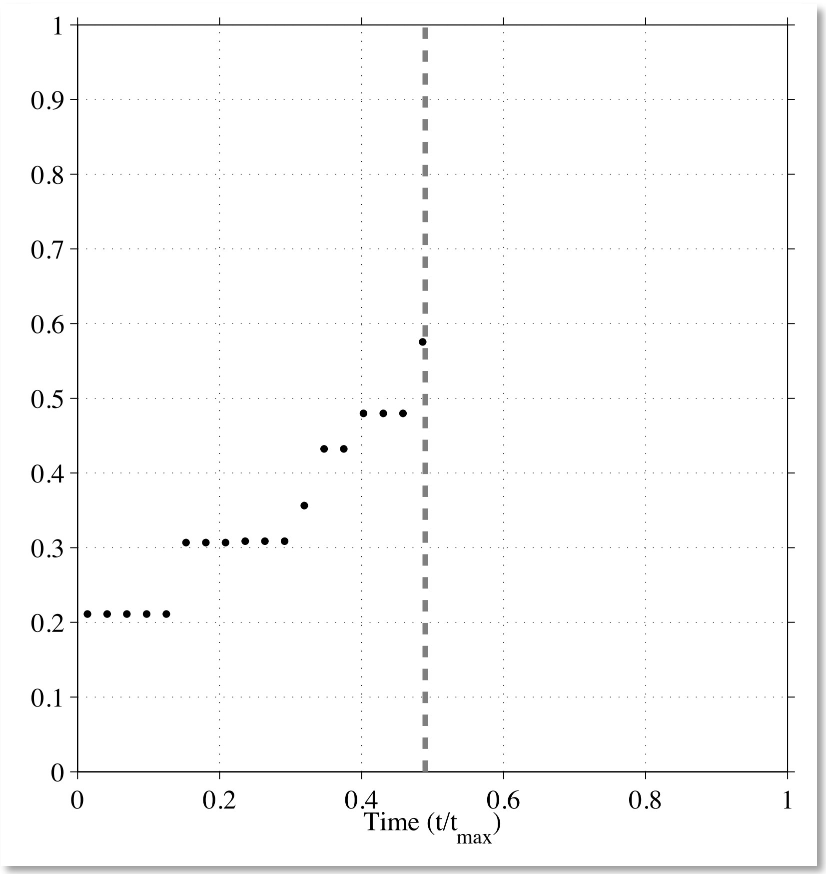
- Principled, decision-theoretic approach
  - Sets behaviour as best response to negotiation environment and opponent behaviour.
- Considers
  - The **discounting factor**
  - The **remaining time**
  - The effect of the opponent's **future concession** on our utility

Gaussian Process Regression

- Use a Gaussian process regression technique in an attempt to learn the opponent's concession.
  - Mean prediction
  - Confidence measure
- Set concession rate according to this prediction.

Gaussian Process Regression

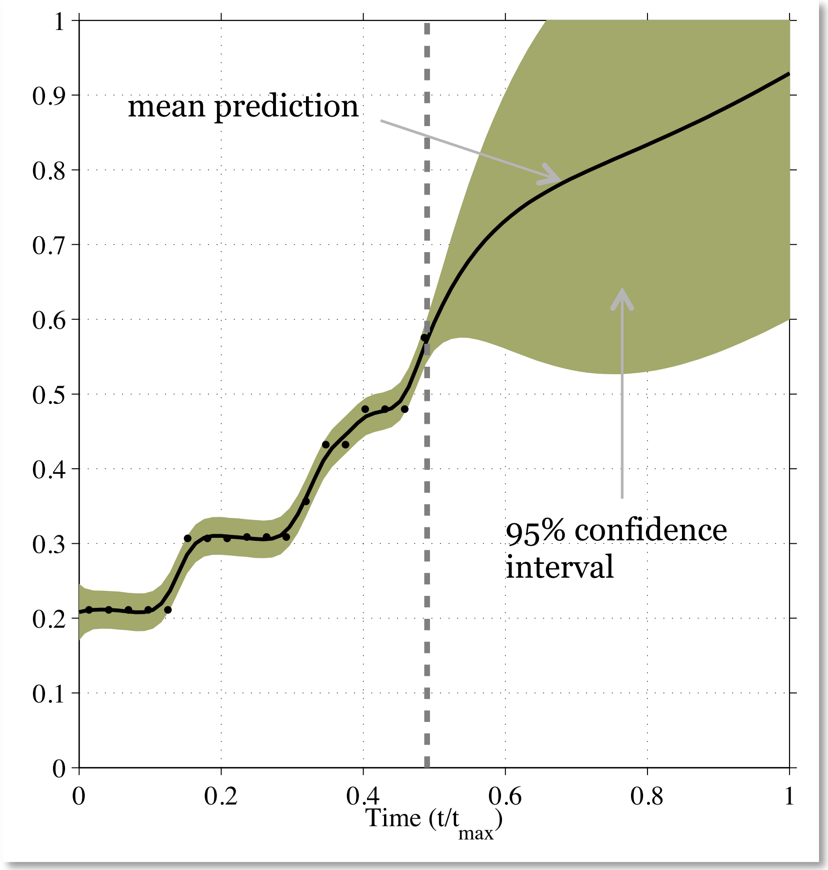
- Use a Gaussian process regression technique in an attempt to learn the opponent's concession.



Observed data points at time t_c

Gaussian Process Regression

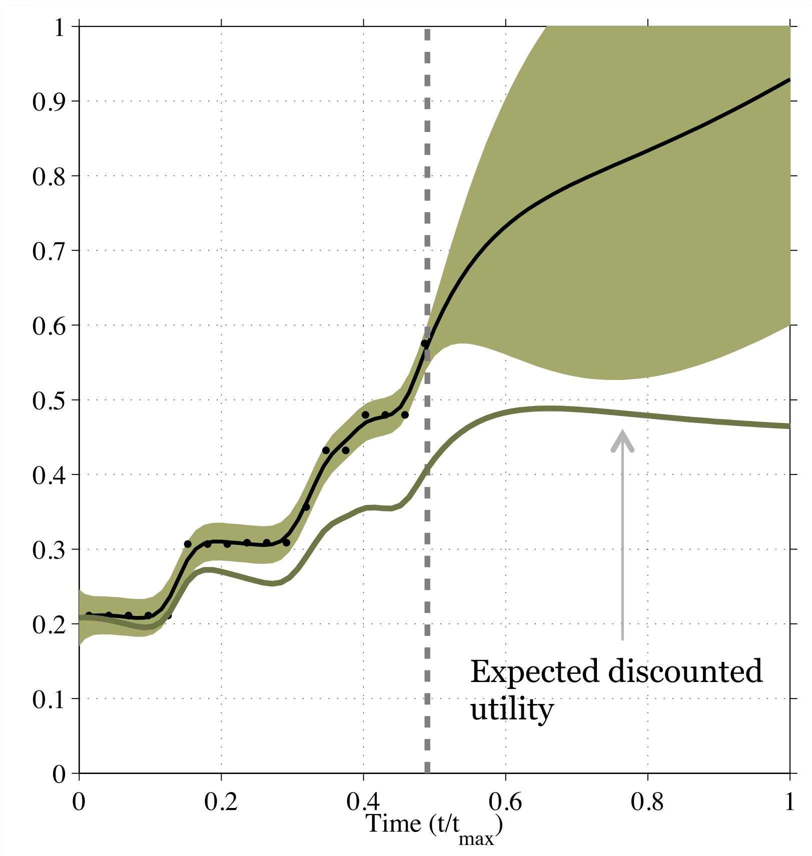
- Predict future concession by opponent.



Completed Gaussian Process Regression
(showing mean and 95% confidence interval)

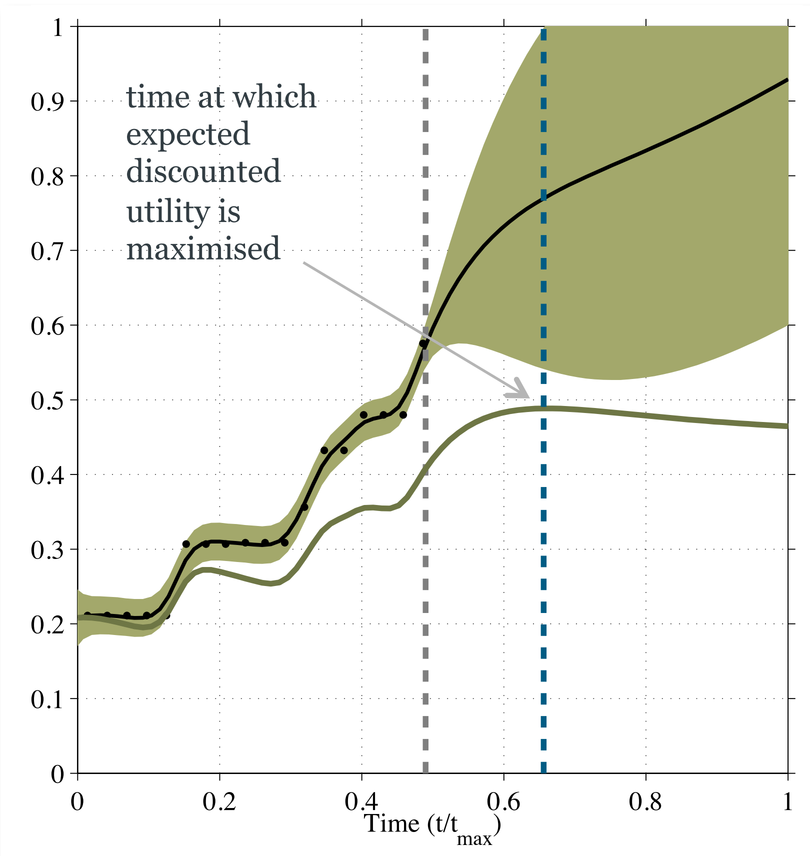
Maximise Expected Utility

- Apply discounting to determine expected discounted utility of our opponent's offer at time t.



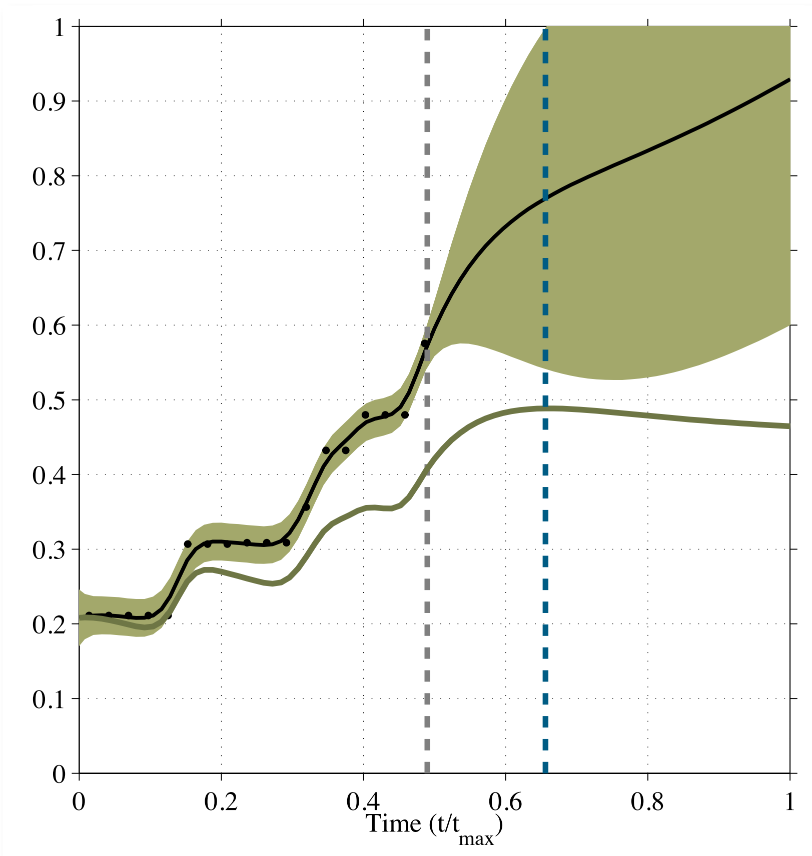
Maximise Expected Utility

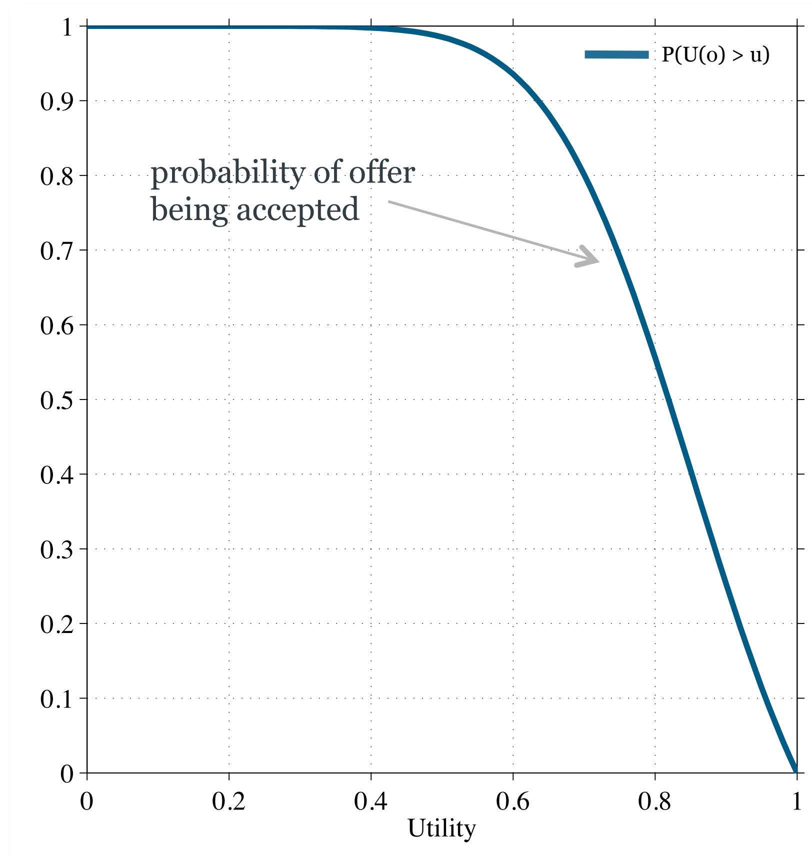
- Find the **time**, t^*, at which expected discounted utility of our opponent's offer is maximised.



Maximise Expected Utility

- Find the best **utility**, u^* to offer at time t^*





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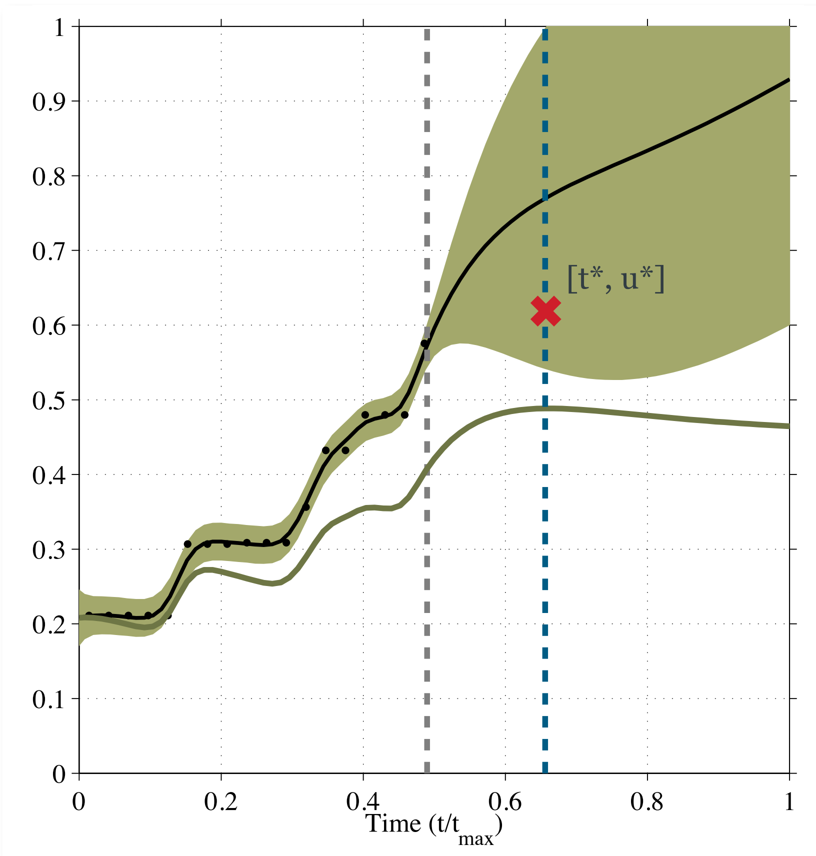
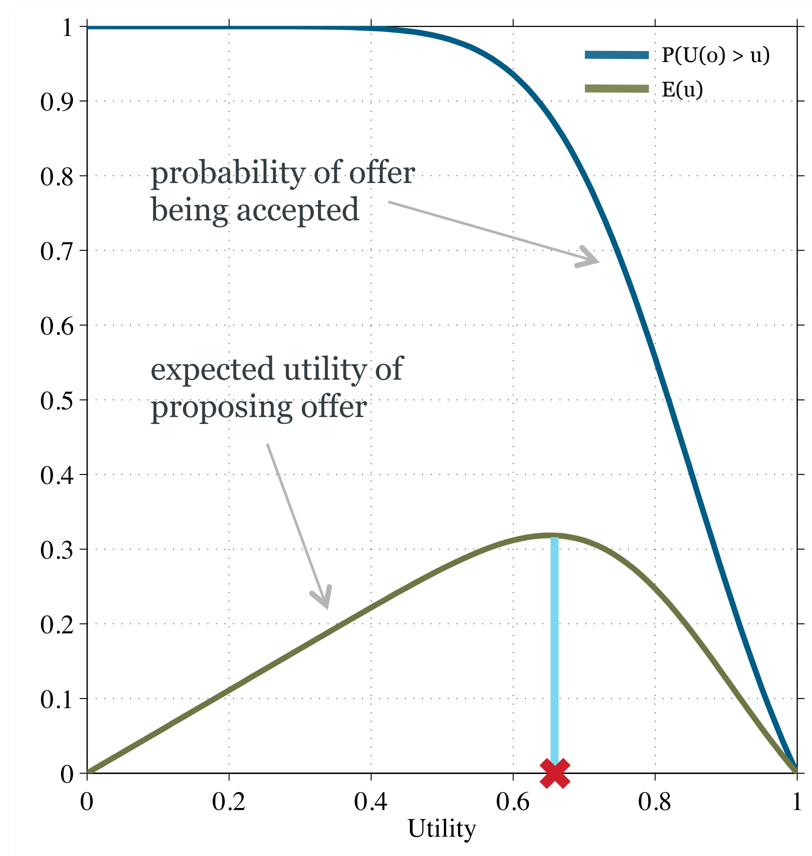
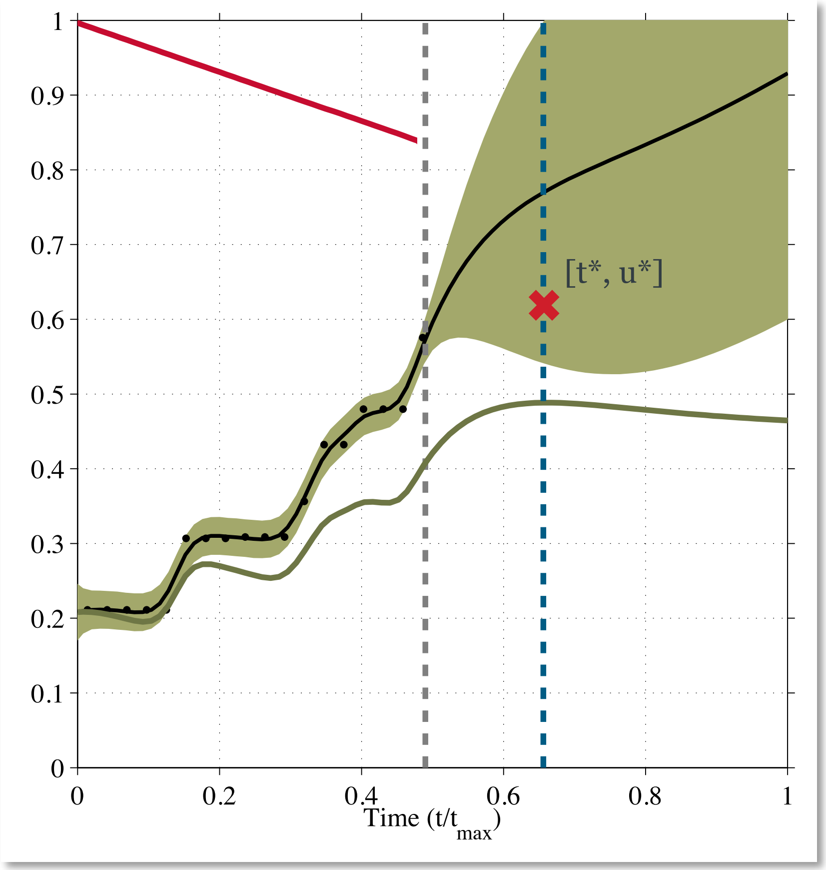
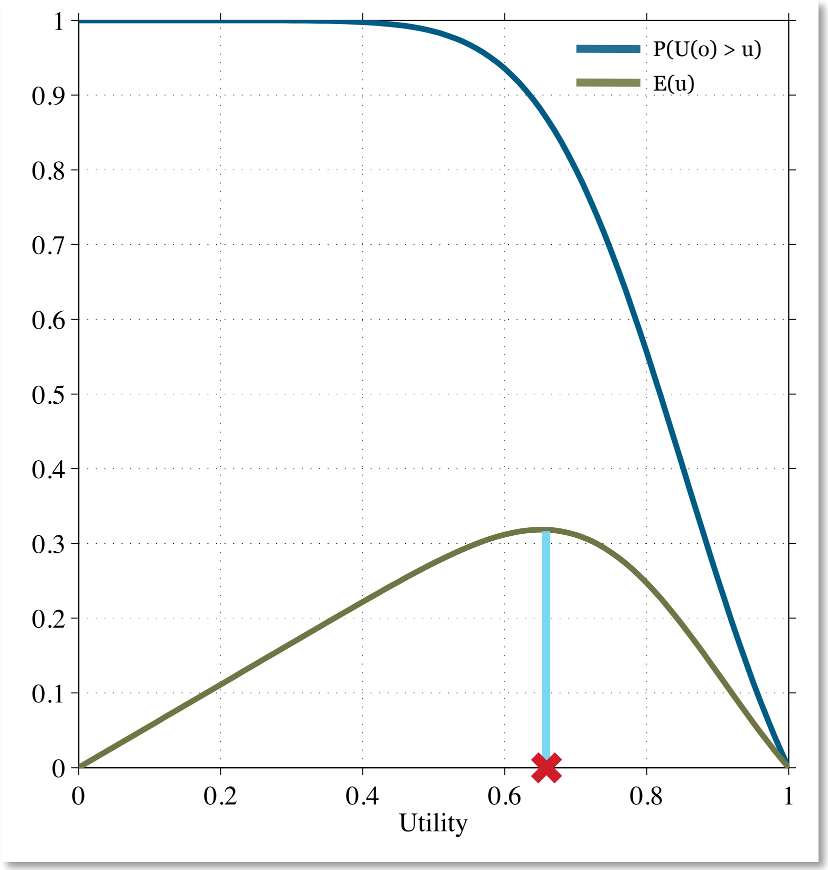




Choose Target Utility

- Concede towards [t*, u*].





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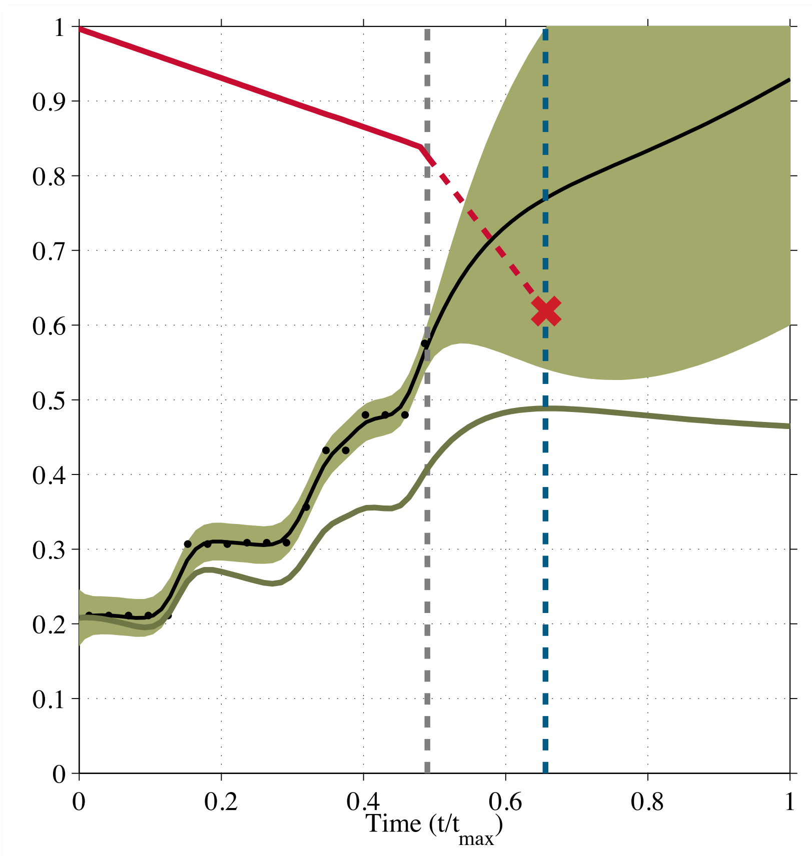

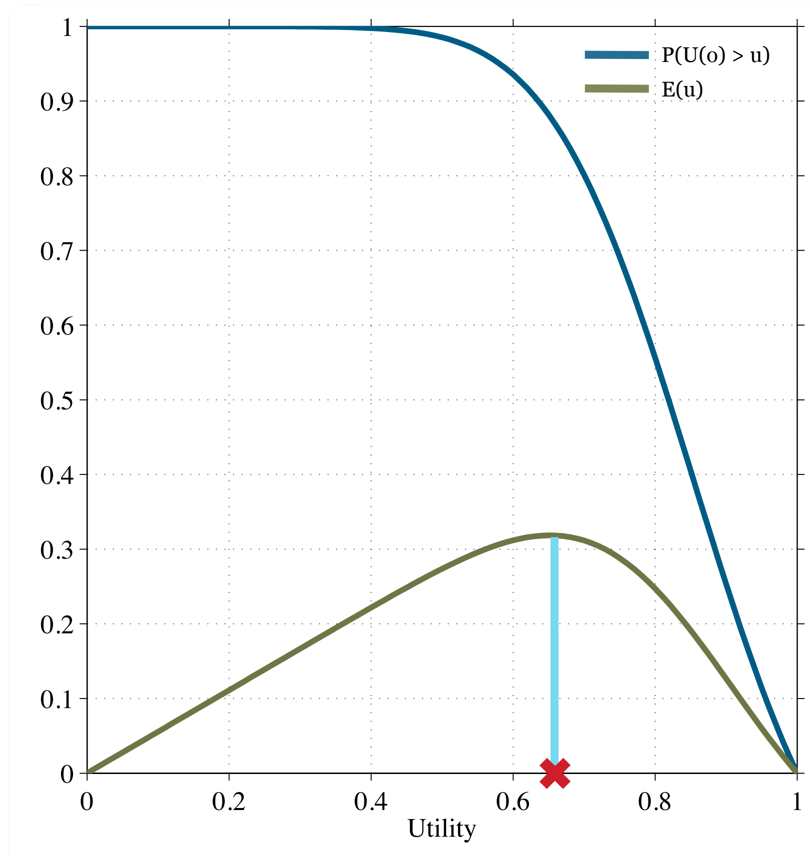

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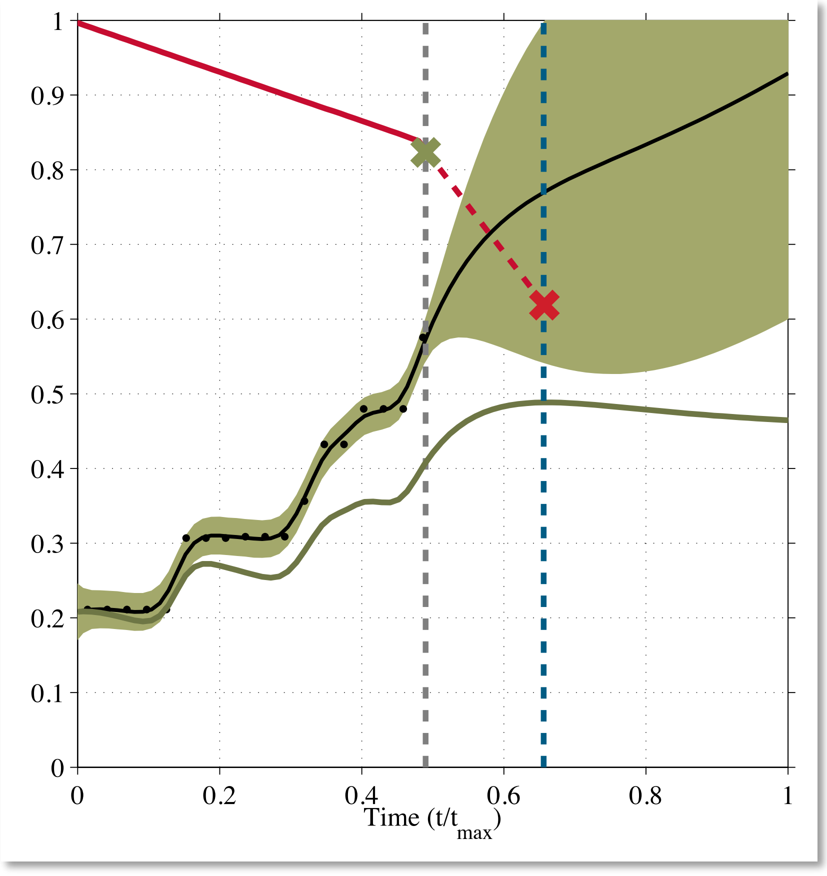
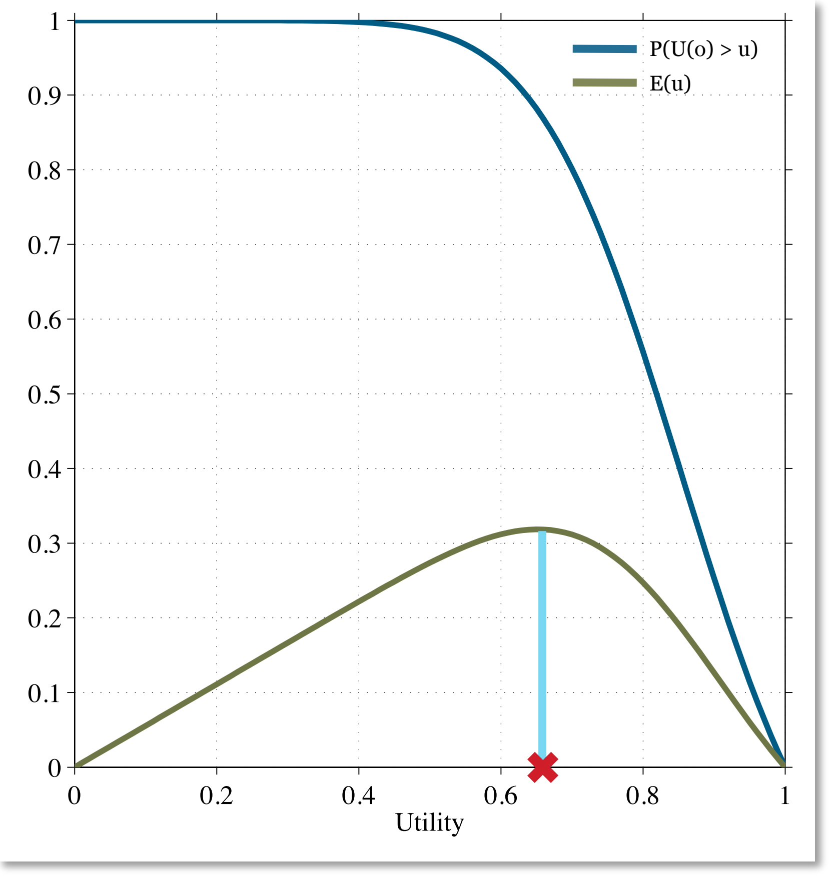




Dealing with Multiple Issues

- Select a random package, with utility close to target (according to concession strategy).
  - Fast process allows many offers to be made.
  - Encourages exploration of outcome space.

Meta-Agent

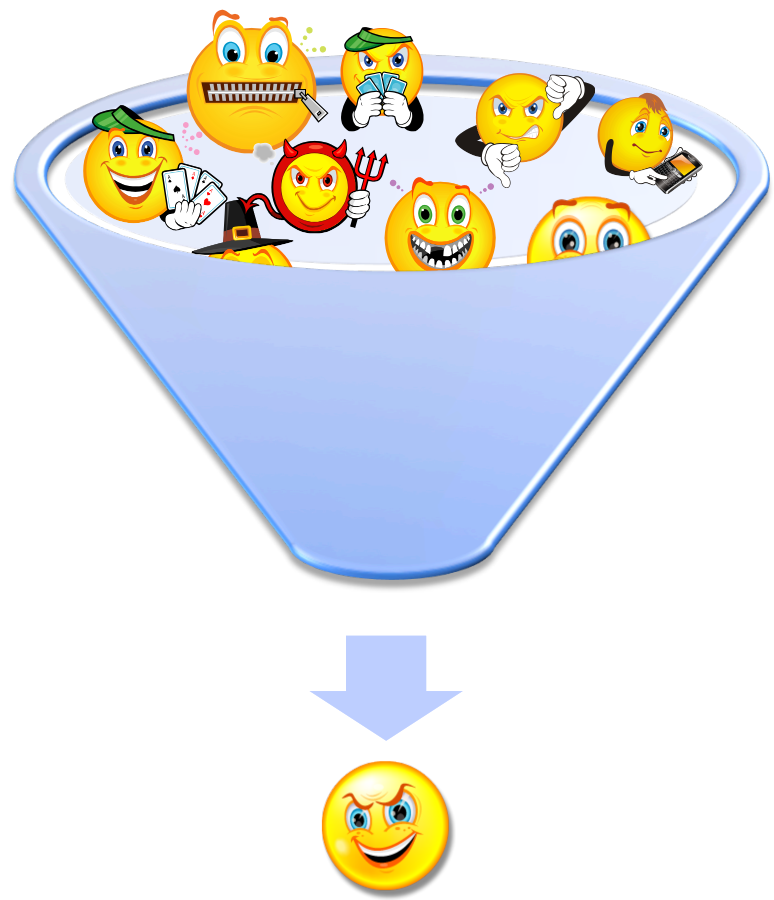
Ben-Gurion University of the Negev

Litan Ilany, **Ya'akov (Kobi) Gal**

ANAC 2012

Not a regular agent…

- Based on "Wisdom of the Crowd" theory.
- Combined all publicly available ANAC 2011 strategies.
- **Not a single line of strategic code.**
(except reservation-value adding)



AI@BGU

ANAC 2012

Methodology

- Used publicly available ANAC qualifying results as training set.
- Used Linear Regression to predict the best agent.
- Designed Meta agent that chooses the best agent for each role in each domain.

OMACagent

Maastricht University, The Netherlands

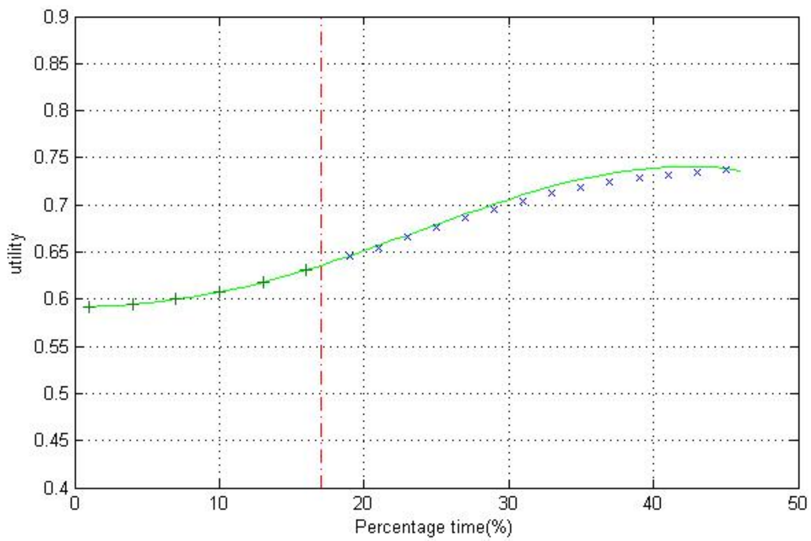
Siqi Chen, Gerhard Weiss

Introduction

- OMAC = "Opponent Modeling + Adaptive Concession-making"
- OMACagent = a basic implementation of OMAC
- Following two slides about the two main components (OM + AC)

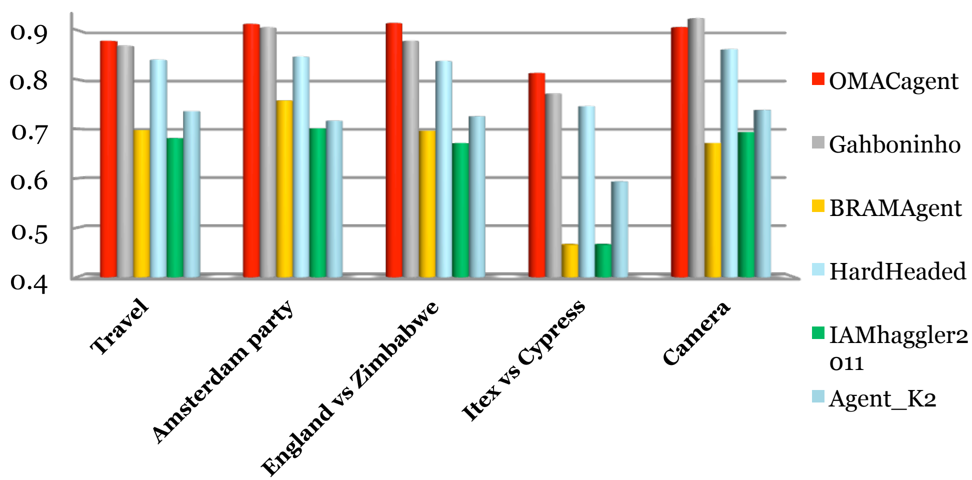
Modeling opponent's negotiation strategy

- Discrete wavelet transform (DWT)
- Cubic smoothing spline



Adaptive concession-making mechanism

- Estimation function of future opponent concession
- Dynamic conservative utility function



TheNegotiator Reloaded

Delft University of Technology

Mark Hendrikx, Alex Dirkzwager

Contents

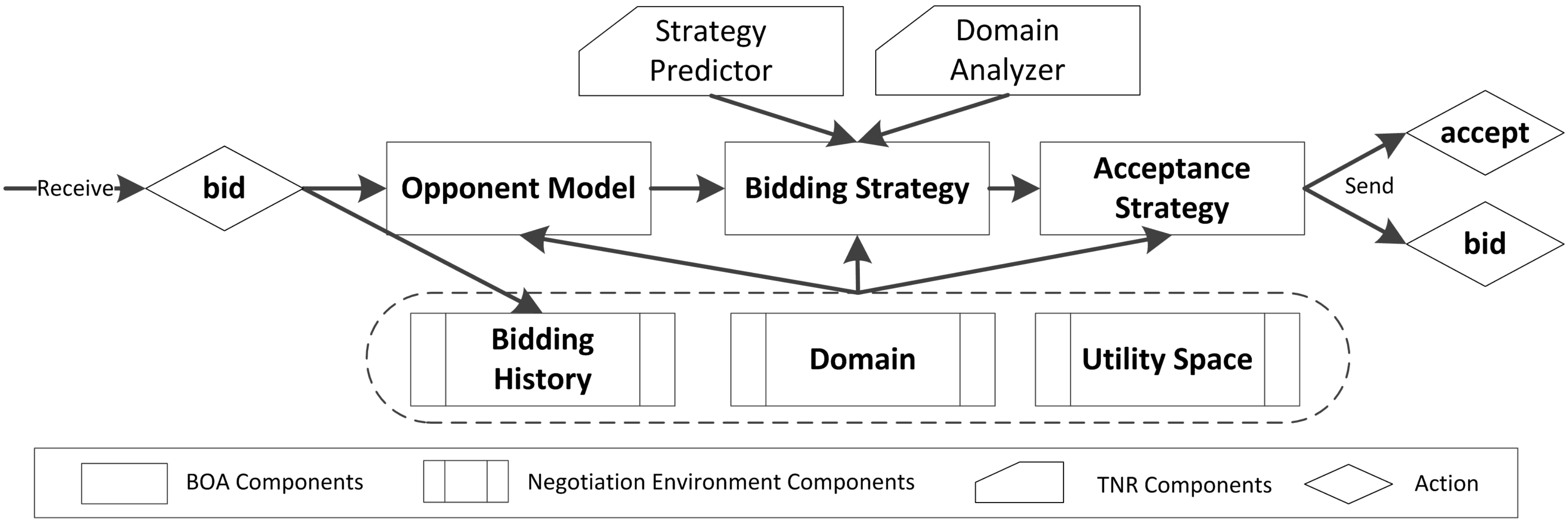
1. BOA Framework

2. Implementation BOA Components
   - Bidding strategy
   - Acceptance Strategy

3. Optimization of Agent

4. Conclusion

BOA Framework



Baarslag, T.; Hindriks, K.; Hendrikx, M.; Dirkzwager, A. & Jonker, C.

Decoupling Negotiating Agents to Explore the Space of Negotiation Strategies

ANAC 2012

Implementation BOA Components

Bidding Strategy

Start of window

Estimate Kalai-point

Discount Kalai-point (DK)

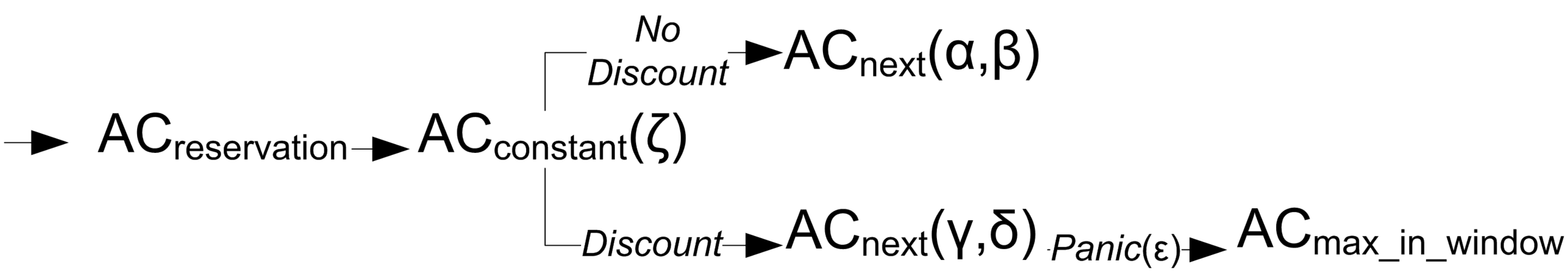
Determine opponent strategy type (OS)

Determine TDT parameters using DK, OS, and discount

End of window

Implementation BOA Components

Acceptance Strategy



Optimization of Agent

- Basic components → Database of BOA
- Bidding strategy → Distributed Genius
- Opponent model → Model analyzer of BOA
- Acceptance condition → MAC of BOA

Conclusion

- First ANAC agent using the BOA framework
- Optimized using new methods
- Dynamic domain- and opponent-based strategy

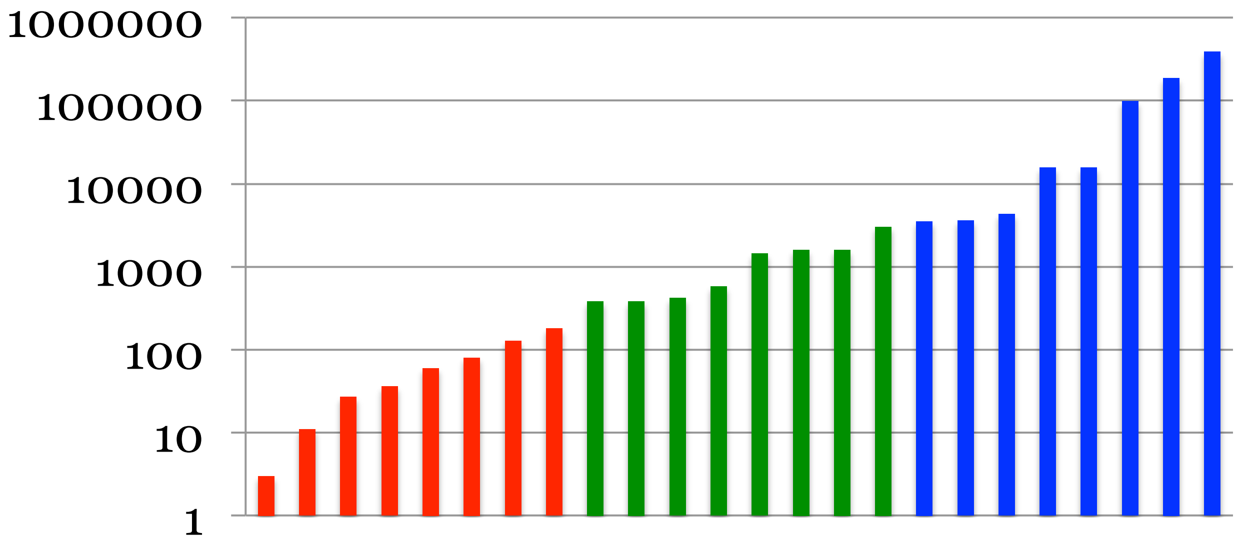
Final Round

Final Round

- 8 Agents
- 8 Opponents
- 24 Base Domains
  - (17 submitted this year, 5 from 2011, 2 from 2010)
- 3 Discounting factors:
  - 1.00, 0.75, 0.50
- 3 Reservation values:
  - 0.00, 0.25, 0.50

Final Round

- 24 base domains of varying size



- Split into small, medium, large.

ANAC 2012

Final Round

- From each base domain, generated three domains with different values of *df* and *rv*
  - These three domains covered all three values of *df* and all three values *rv*.

		rv		
		0.00	0.25	0.50
df	1.00	S	M	L
	0.75	L	S	M
	0.50	M	L	S

Final Round

- 8 Agents
- 8 Opponents
- 72 Domains
- Entire setup repeated 10 times to establish statistical significance.
- Total of 46080 negotiations.

ANAC 2012

Prizes

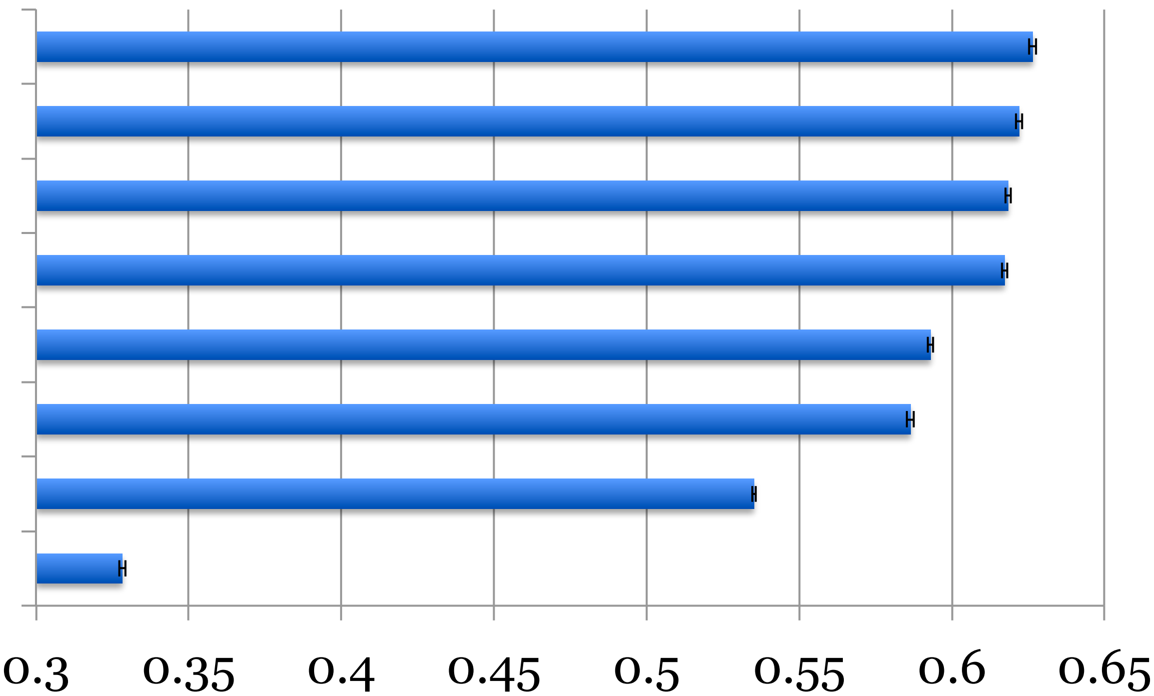
1st Place	$500
2nd Place	$400
3rd Place	$300
Best in Discounted Domains	$100
Best in Undiscounted Domains	$100
Most Social Agent	$100

With thanks to our sponsors:

Prof. Dr. Catholijn Jonker
Prof. Dr. Sarit Kraus
Prof. Dr. Takayuki Ito / Makoto Lab., Inc.

Overall Rankings

- Agent which achieves best average score across all domains.



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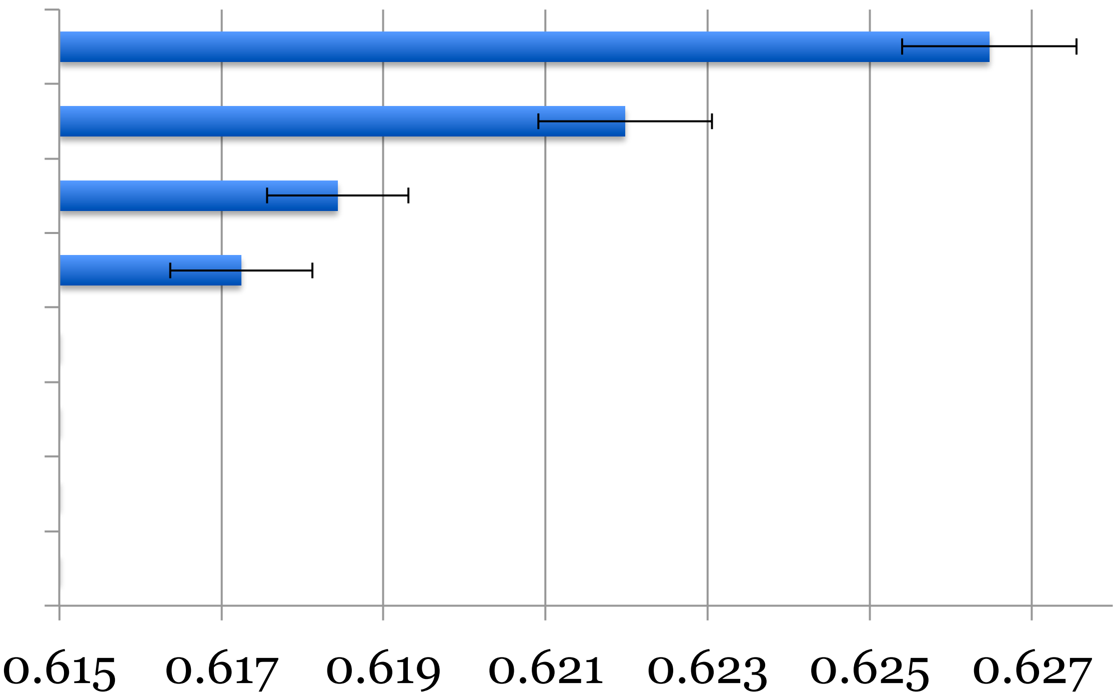


ANAC 2012

3rd Place

3rd

0.618

OMACagent

Maastricht University

Siqi Chen, Gerhard Weiss

and

0.617

TheNegotiator Reloaded

Delft University of Technology

Mark Hendrikx, Alex Dirkzwager

ANAC 2012

2nd Place

2nd

0.622

AgentLG

Bar-Ilan University

Luba Golosman

ANAC 2012

1st Place

1st

0.626

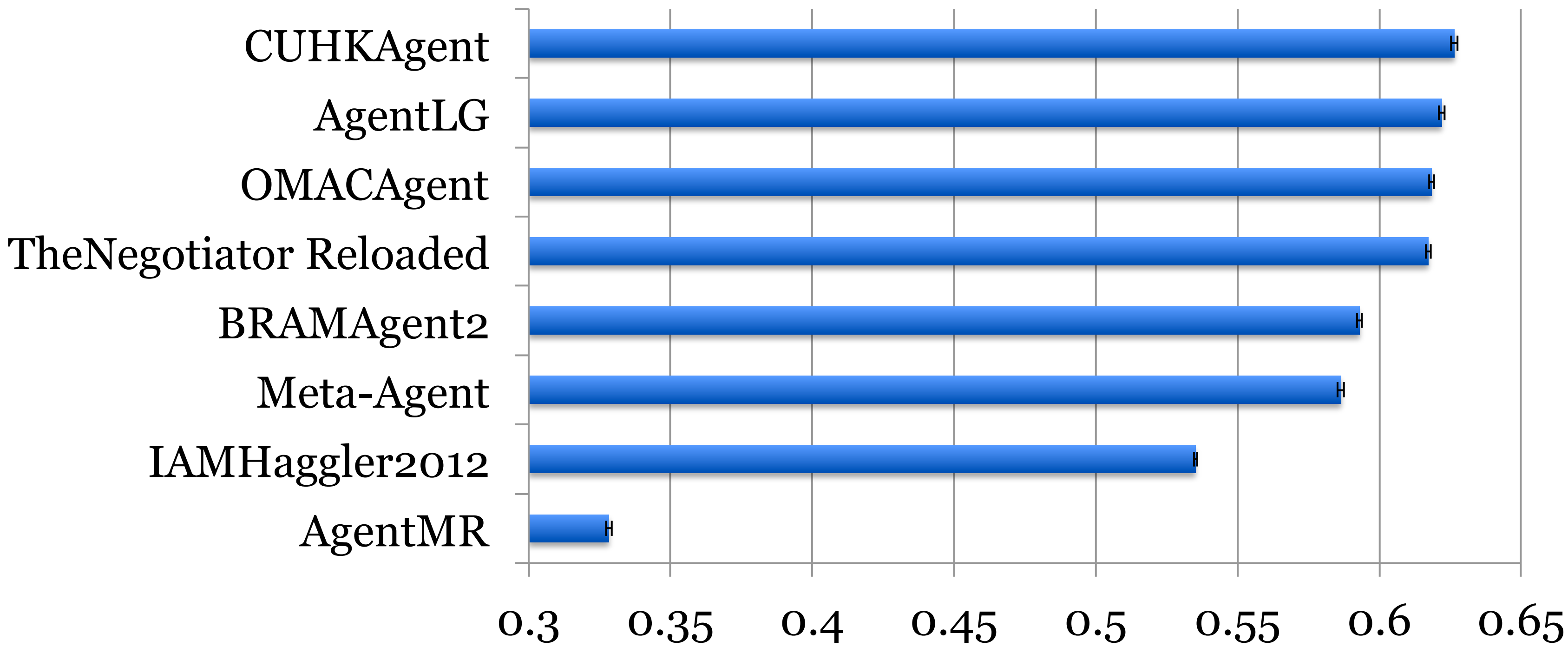
CUHKAgent

The Chinese University of Hong Kong

Jianye Hao, Ho-fung Leung

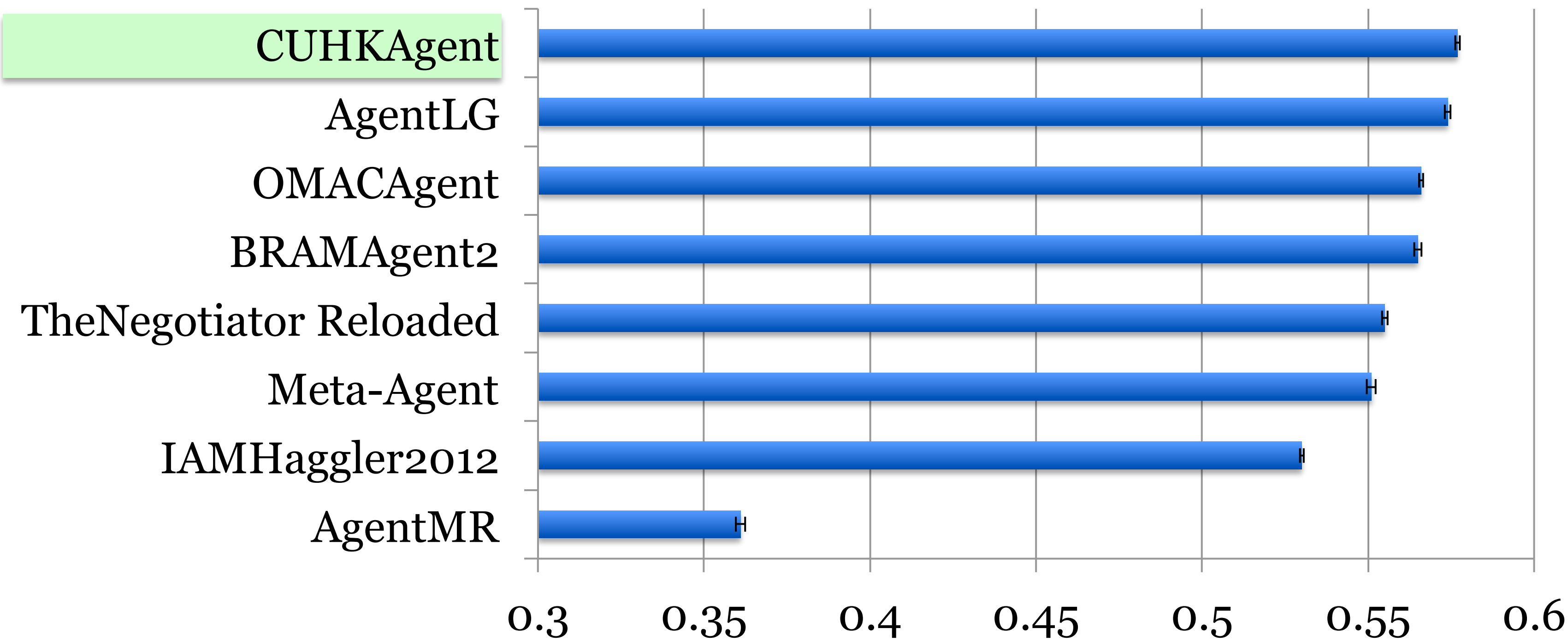
Overall Rankings

- Agent which achieves best average score across all domains.



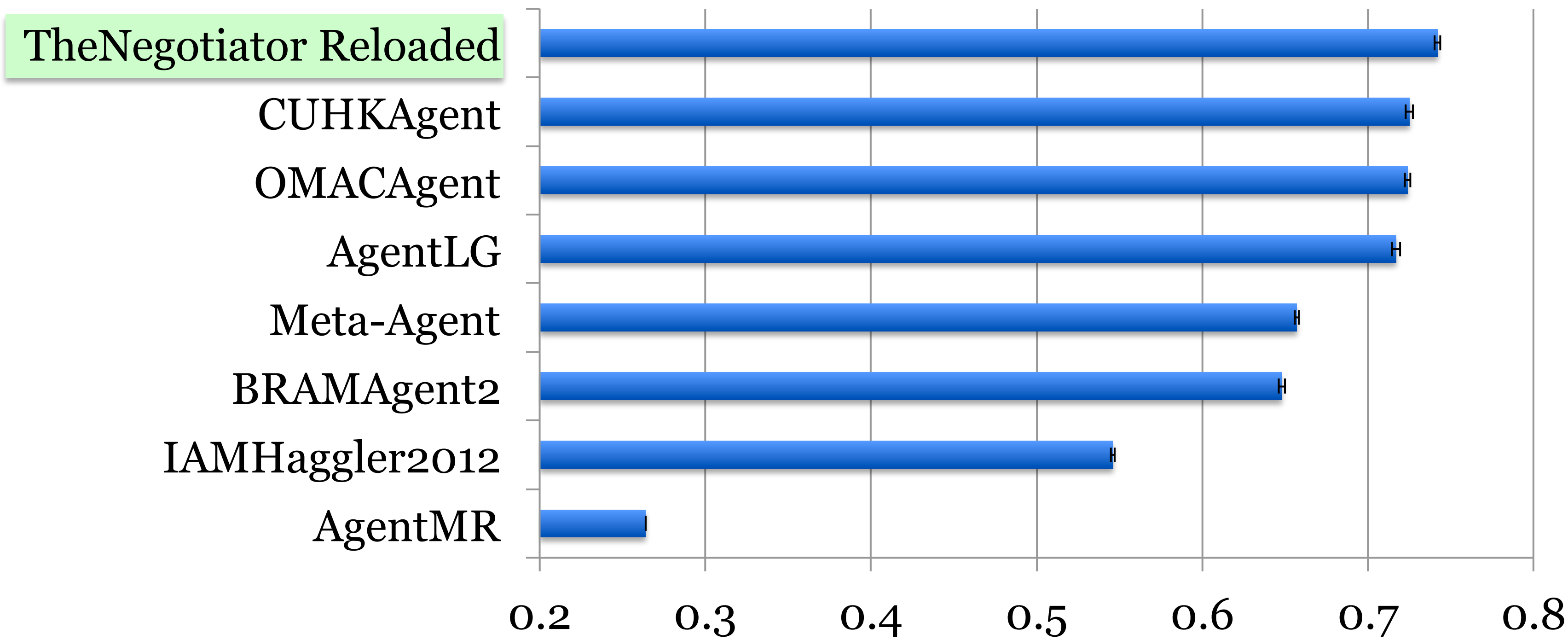
Best in Discounted Domains

- Agent which achieves best average score over discounted domains.



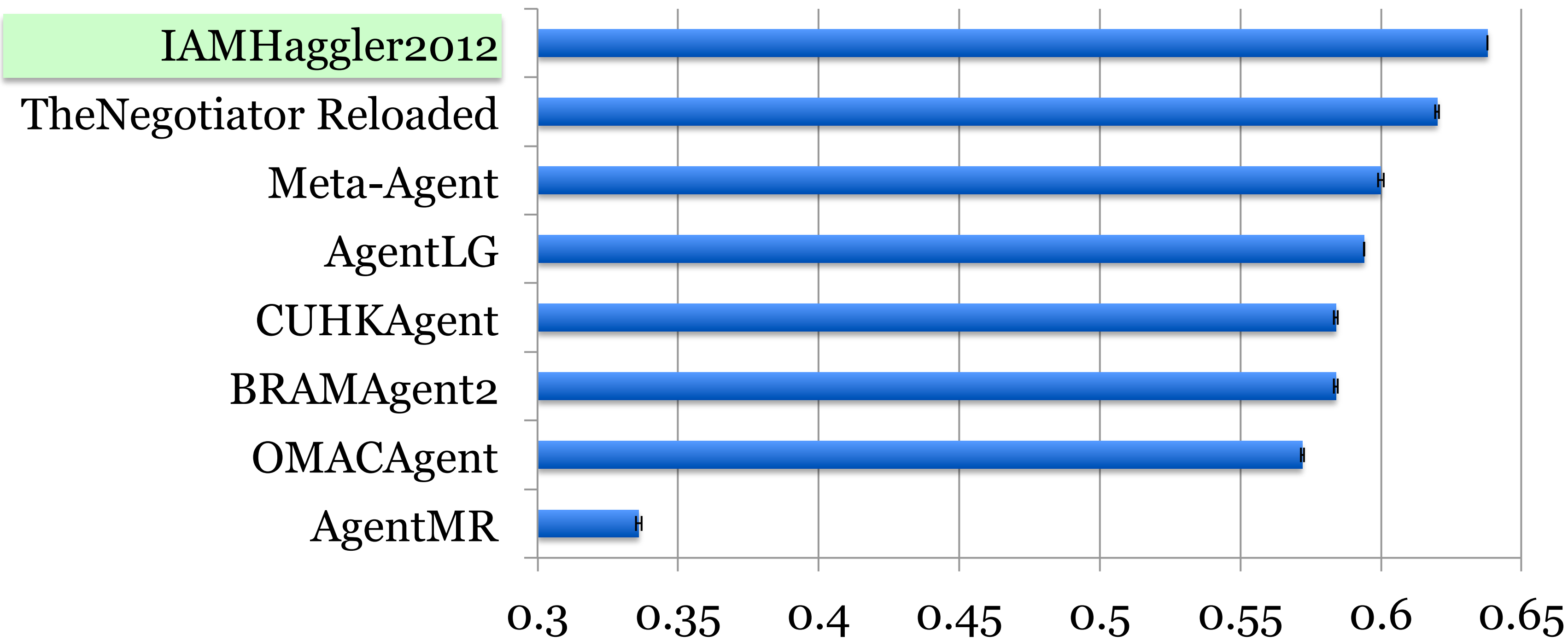
Best in Undiscounted Domains

- Agent which achieves best average score over undiscounted domains.

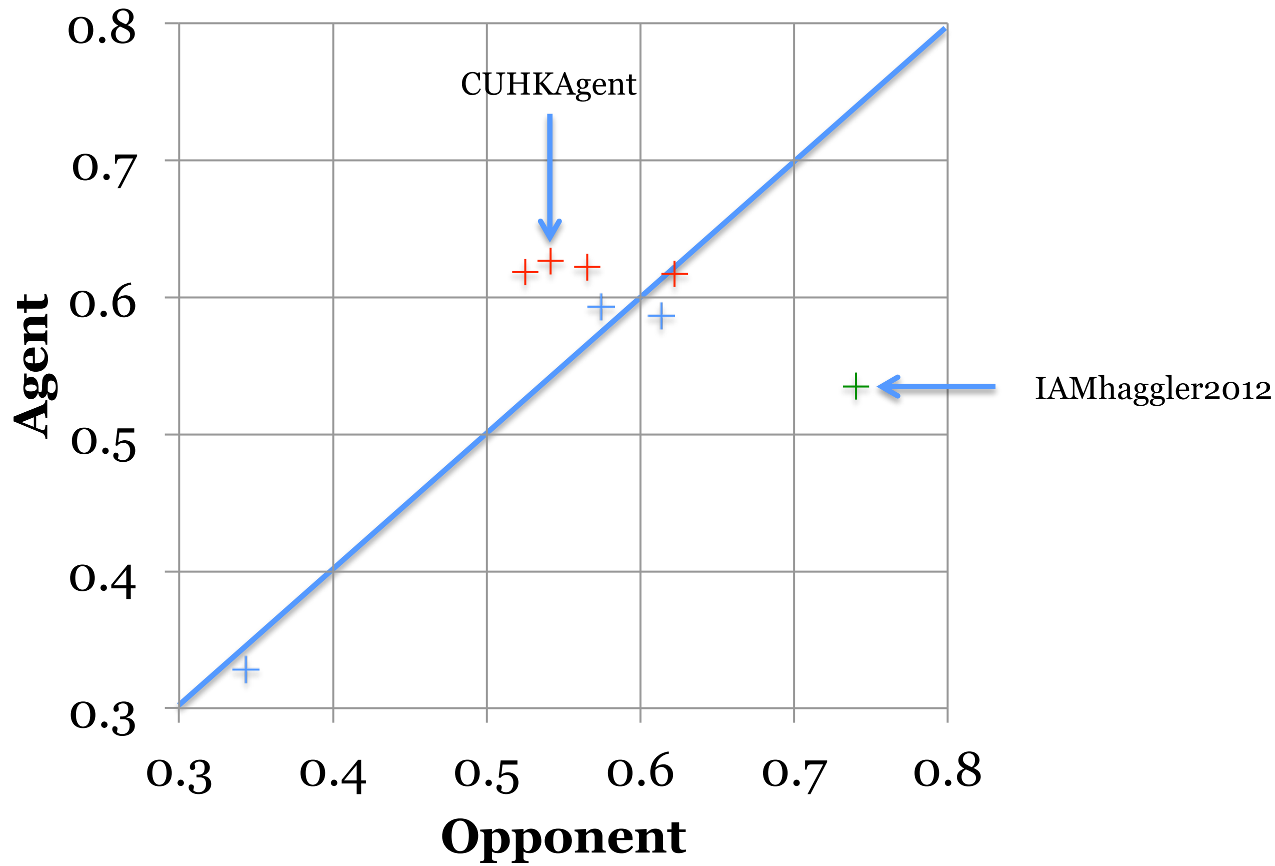


Most Social Agent

- Agent which maximises the sum of its own utility and its opponent's.

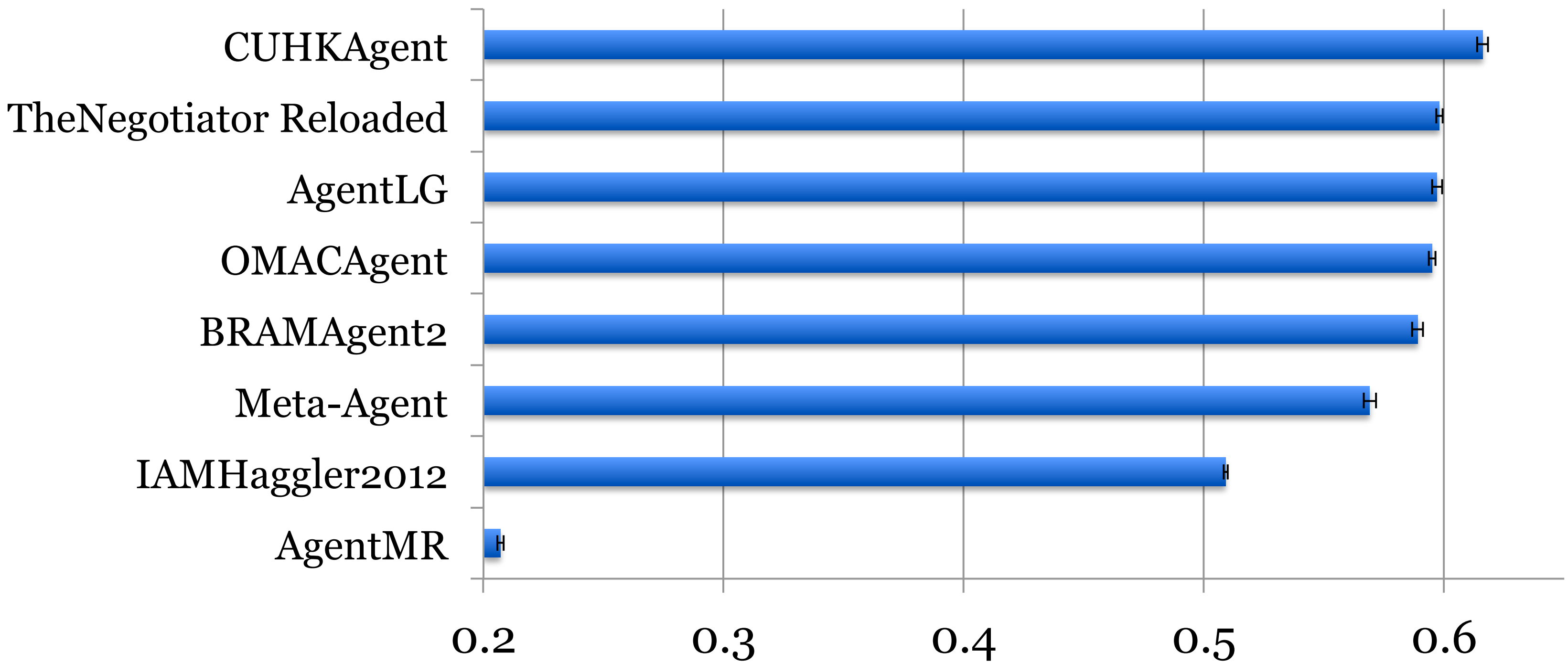


Agent vs Opponent



Compared to ANAC2011

- Considering only domains with zero reservation value.



Compared to ANAC2011

- Considering only domains with zero reservation value.