Automated Bargaining

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http://www.cfea-labs.net
Centre for Computational Finance and Economic Agents (CCFEA)

♦ Interdisciplinary centre
♦ Director: Sheri Markose (Economics)
♦ Deputy: Edward Tsang (Computer Science)
♦ Lecturer: Olaf Menkins (CCFEA)
♦ City Associates chair: Nick Constantinou HSBC
♦ 11 PhD students, 26 Doctoral+Master students
♦ Selected Projects:
  – Forecasting, bargaining, payments, herding
Automatic Bargaining Overview

- Maximize profit
- Satisfy constraints
  - purchase
  - sell
  - schedule

Who do I know?

Utility

Cost

Supply price defines my cost

Motivation in e-commerce: talk to many

How to bargain?
Aim: to agree on price, delivery time, etc.
Constraint: deadlines, capacity, etc.
Who to serve? Who to talk to next?
Bargaining work at CCFEA

- Realistic Problems
  - eg supply chain

- Simple Bargaining
- TAC / SSCM
- Bargaining Games
  - Evol. Comp.
  - Rubinstein Theory
- IPD

- Complex
- Approx?
- Exact?
- Evolve?
- Design?
- No information
- Perfect information
- Mathematical Solutions
  - (neat)
  - Procedures (scruffy)
The Automatic Bargaining Research Team at Essex

Abhinay Muthoo
Economics
Game Theory

Sheri Markose
Economics/CCFEA
Red Queen Effect

Maria Fasli
Computing
Agent Tech.

Edward Tsang
Computing/CCFEA
Constraints, Business models

Nanlin Jin
Computing
Extending Rubinstein Model
Evolving strategies

Tim Gosling
Computing/BT
Distributed scheduling
Evolving middlemen

Biliana Alexandrova-Kabadjova
CCFEA/BoMexico
Electronic money
Payment System

Wudong Liu
BT
Distributed Management
2005-
Bargaining Theory

Abhinay Muthoo
http://www.essex.ac.uk/economics/people/staff/muthoo.shtm
Bargaining in Game Theory

♦ Rubinstein Model:
  In reality:
  Offer at time \( t = f(r_A, r_B, t) \)
  Is it necessary?
  Is it rational? *(What is rational?)*

♦ A’s payoff \( x_A \) drops as time goes by
  A’s Payoff = \( x_A \exp(-r_A t\Delta) \)

♦ Important Assumptions:
  – Both players rational
  – Both players know *everything*

♦ Equilibrium solution for A:
  \( \mu_A = \frac{1 - \delta_B}{1 - \delta_A \delta_B} \)
  where \( \delta_i = \exp(-r_i \Delta) \)

Optimal offer: \( x_A = \mu_A \) at \( t=0 \)

Notice: No time \( t \) here
Iterative Prisoner’s Dilemma

Axelrod’s experiments

Tit-for-tat
Prisoner’s Dilemma

<table>
<thead>
<tr>
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<th>Player A</th>
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</table>

- What’s the optimal decision for A (or B)?
- What if this game is repeated?
Iterated Prisoner’s Dilemma (IPD)

- Axelrod organized two tournaments in 1980
  - Round one: 14 entries
  - Round two: 62 entries from 6 countries
- Tit-for-Tat was the winner in both runs
  - Start by cooperation
  - Then follow whatever the opponent did last round
- GRIM is an alternative local optimum
  - Like Tit-for-Tat, except being unforgiving
Evolutionary Bargaining Strategies

Nanlin Jin

http://cswww.essex.ac.uk/CSP/bargain
Evolutionary Bargaining Strategies

♦ Prisoners’ Dilemma
  – Co-evolution
  – GA vs PBIL

♦ Bubinstein’s Model
  – Offer at time \( t = f(r_A, r_B, t) \)
  – \( x_A^*, x_B^* \) emerged as best results
  – Other solutions emerged occasionally

♦ Current work
  – Asymmetric information
  – Outside options
Evolutionary Rubinstein Bargaining, Overview

- Game theorists solved Rubinstein bargaining problem
  - Subgame Perfect Equilibrium (SPE)
- Slight alterations to problem lead to different solutions
  - Outside option
  - Asymmetric information
  - Different time intervals
- Evolutionary computation
  - Succeeded in solving a wide range of problems
  - EC has found SPE in Rubinstein’s problem
  - Can EC find solutions close to unknown SPE?
- Co-evolution is an *alternative approximation* method to find game theoretical solutions
  - Less time for approximate SPEs
  - Less modifications for new problems
Rubinstein Solution vs Experimental Results

<table>
<thead>
<tr>
<th>((\delta_A, \delta_B))</th>
<th>Rubinstein Solution (x_A')</th>
<th>Experimental (x_A)</th>
<th>(\mu)</th>
<th>(\sigma)</th>
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<td>0.0917</td>
<td>0.1474</td>
<td>0.1023</td>
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</tbody>
</table>

\(x_A\): agreement made by the best strategies in the final \(300^{th}\) generation

Population size 100; Crossover rates 0 to 0.1; Mutation rates 0.01 to 0.5; Tournament size 3
Issues Addressed, EC for Bargaining

- **Representation**
  - Should $t$ be in the language?

- **One or two population?**

- **How to evaluate fitness**
  - Fixed or relative fitness?

- **How to contain search space?**

- **Discourage irrational strategies:**
  - Ask for $x_A > 1$?
  - Ask for more over time?
  - Ask for more when $\delta_A$ is low?
Two populations, co-evolution

- We want to deal with asymmetric games
  - E.g. two players may have different information
- One population for training each player’s strategies
- Co-evolution, using relative fitness
  - Alternative: use absolute fitness

Evolve over time
Representation of Strategies

♦ A tree represents a mathematical function \( g \)
♦ Terminal set: \( \{1, \delta_A, \delta_B\} \)
♦ Functional set: \( \{+, -, \times, \div\} \)
♦ Given \( g \), player with discount rate \( r \) plays at time \( t \)
  \( g \times (1 - r)^t \)
♦ Language can be enriched:
  – Could have included \( e \) or time \( t \) to terminal set
  – Could have included power \( ^\) to function set
♦ Richer language \( \rightarrow \) larger search space \( \rightarrow \) harder search problem
Incentive Method: Constrained Fitness Function

♦ No magic in evolutionary computation
  – Larger search space $\rightarrow$ less chance to succeed
♦ Constraints are heuristics to focus a search
  – Focus on space where promising solutions may lie
♦ Incentives for the following properties in the function returned:
  – The function returns a value in $(0, 1)$
  – Everything else being equal, lower $\delta_A \rightarrow$ smaller share
  – Everything else being equal, lower $\delta_B \rightarrow$ larger share

Note: this is the key to our search effectiveness
Models with known equilibriums

Complete Information
♦ Rubinstein 82 model:
  – Alternative offering, both A and B know $\delta_A$ & $\delta_B$
♦ Evolved solutions approximates theoretical
♦ Working on a model with outside option

Incomplete Information
♦ Rubinstein 85 model:
  – B knows $\delta_A$ & $\delta_B$
  – A knows $\delta_A$ and $\delta_B^{\text{weak}}$ & $\delta_B^{\text{strong}}$ with probability $\Omega_{\text{weak}}$
♦ Evolved solutions approximates theoretical
Models with unknown equilibriums

♦ Modified Rubinstein 85 models
♦ Incomplete knowledge
  – B knows $\delta_B$ but not $\delta_A$; A knows $\delta_A$ but not $\delta_B$
♦ Asymmetric knowledge
  – B knows $\delta_A$ & $\delta_B$; A knows $\delta_A$ but not $\delta_B$
♦ Asymmetric, limited knowledge
  – B knows $\delta_A$ & $\delta_B$
  – A knows $\delta_A$ and a normal distribution of $\delta_B$
♦ Working on limited knowledge, outside option and new bargaining procedures
Evolutionary Bargaining, Conclusions

♦ Demonstrated GP’s flexibility
  – Models with known and unknown solutions
  – Outside option
  – Incomplete, asymmetric and limited information
  – Trying on models with new bargaining procedures

♦ Co-evolution is an alternative approximation method to find game theoretical solutions
  – Relatively quick for approximate solutions
  – Relatively easy to modify for new models

♦ Genetic Programming with incentive / constraints
  – Constraints used to focus the search in promising spaces
Simple Supply Chain Management Models

Tim Gosling

http://cswww.essex.ac.uk/CSP/bargain
BTexact Studentship
Motivation

♦ Humans are very good at:
  – Situation analysis and negotiations

♦ Humans are not so good at:
  – Handling large volumes of info & transactions
  – Having several conversations at once

♦ Motivated by large electronic supply chains

♦ Computer based strategy called for

♦ Success is not simply affected by bargaining skills, but also the number of agents it can talk to and the volumes it can handle
The SSCM Mission

- Provides a simple supply chain trading model
- Defines three types of participants:
  - Customers
  - Supplier
  - Middlemen (who we are mainly interested in)
- Middlemen strategy parameterised
- EC is used for evolving strategies
- The method is hoped to be general & practical
Scenarios Studied

- Customers requirements specific & non-negotiable
  - Satisfiability
- Dedicated customers for each middleman
- Customers initiate trade
- Suppliers have limited supply of resources
- One supplier per product
- Suppliers passive: wait for requests from middlemen
- Middlemen task is to:
  - Evaluate requirements, reject those it can’t fulfil
  - Attempt to fulfil remaining requirements

S2: Customer requirements are negotiable
S3: Multiple suppliers per product
Population-based Incremental Learning (PBIL) in Simple Supply Chain Management (SSCM)

Market Simulation

Supplier → Trader → Customer
Supplier → Customer
Supplier → Customer

Change market behaviour

Agent Configurations
- Who to talk to next
- How to bargain
- ...

PBIL Strategy Information

<table>
<thead>
<tr>
<th>Gene1</th>
<th>Gene2</th>
<th>Gene3</th>
<th>Gene4</th>
</tr>
</thead>
<tbody>
<tr>
<td>A=0.2</td>
<td>A=0.0</td>
<td>A=0.0</td>
<td>A=1.0</td>
</tr>
<tr>
<td>B=0.6</td>
<td>B=0.2</td>
<td>B=0.8</td>
<td>B=0.0</td>
</tr>
<tr>
<td>C=0.2</td>
<td>C=0.8</td>
<td>C=0.2</td>
<td>C=0.0</td>
</tr>
</tbody>
</table>

Update frequencies

Define Agents
Observations, Simple Supply Chain

♦ On-going research

♦ Convergence of Probability Models:
  – Some parameters converged, some do not

♦ Analysis of Probability Models
  – Probability models shown visually
  – Need to analyse results scientifically

♦ When to stop?
  – Monitoring convergence
Population-based Incremental Learning (PBIL)

Model M:
\[
\begin{align*}
x &= v_1 (0.5) 0.6 \\
x &= v_2 (0.5) 0.4 \\
y &= v_3 (0.5) 0.4 \\
y &= v_4 (0.5) 0.6 
\end{align*}
\]

Sample from M solution X, eg \(<x,v_1><y,v_4>\)

Modify the probabilities

♦ Statistical approach
♦ Related to ant-colonies, GA
Trading Agents Competition for E-Commerce

Maria Fasli

http://cswww.essex.ac.uk/staff/mfasli
Trading Agents Competition (TAC)

♦ Classic Game *(Thalis)*
  - Simultaneous auctions with substitutable and interrelated goods
  - Dynamic bid configuration depending on historical data, current state and projected state
  - Application of Strategic Demand Reduction
  - Domain-specific heuristics
  - 3rd and 4th positions in TAC 2003 and 2004 respectively
TAC Work at Essex

- Supply Chain Management Game (*Socrates*)
  - An agent acts as a reverse auctioneer with the suppliers in multi-attribute auctions with substitutable and interrelated goods. Suppliers use a reputation mechanism and their delivery may be partial or complete.
  - Dynamic scheduling for production and delivery
  - Ordering strategy and factory utilisation are interdependent and crucial
  - ICEC-03: 7\textsuperscript{th} position
Bargaining as Constraint Satisfaction

Simple Bargaining Game
Edward Tsang

http://cswww.essex.ac.uk/CSP/edward
Local Constraint Optimisation

- Every agent is self-centred
- Agents constrain each other
- The simplest form of local constraint satisfaction / optimisation above
  - All deeper research depends on strategy in this problem
Information Available, Tournament 3.1

- No information on others’ constraints
  - No information about the range of costs and utilities were available
- Bid history available within each game
  e.g. [+45, -80, +40, -90]
- No information on previous games
  i.e. no knowledge on identity of opponent
Tournaments

♦ Tournament 3.1 (2002)
  – No information about opponents

♦ Tournament 3.2 (2003)
  – Ranges of cost/utilities/SBD/BBD known

♦ Tournament 6.0 (2003)
  – Chain bargaining

♦ Tournament 5.1 (2004)
  – No SBD/BBD, each round costs £k to the player
Simple Chain-Bargaining Game

Chain completes iff all adjacent players agree on deals

End-seller $\Rightarrow M_1 \Rightarrow \ldots \Rightarrow M_n \Rightarrow$ End-buyer

Cost
Days to Sell (DTS)

Utility
Days to Buy (DTB)

♦ More information $\Rightarrow$ more mathematical solutions
♦ Less information $\Rightarrow$ procedural (messy) strategies
Meet the Sellers

- The Jacob-Seller (dgiaco_s)
  - Drop price linearly, make obvious drop in penultimate move
- The Keen-Seller-2 (keen_s2)
  - Half price each turn, keen to accept deals
- The Stubbings-Seller (pmstub_s)
  - Reduce price at increasing rate, try to recognize deadlines
- The Stacey-Seller (rpstac_s)
  - Complex rules for various situations, hard-bargaining
- The Smart-Seller-4 (smart_s4)
  - Estimate buyer’s bottom line based on bid-history
Jacob-Seller (dgjaco_s)

- Accepts bids that are above the cost by a predefined margin,
- Or when it judgest (based on the bids history) that the buyer has reached its limit.
- Start offer: cost plus a predefined premium
- General rule: This offer is reduced linearly until 4th final day. It then offers cost plus a target profit (parameter to the program) for one move. The penultimate move makes an obvious drop in price to tempt the buyer. A minimum profit is demanded in the final offer.
Keen-Seller-2 (keen_s2)

- Relatively simple
- Keen to make deals as soon as the bid is above its cost, but...
- When time is available, attempt to get a better deal by delaying commitment by one round.
- Start by a very high offer
- General strategy: reduce price by half towards cost in each round.
Stubbings-Seller (pmstub_s)

- Special cases carefully checked and responded to
  - such as the buyer has bid below the cost of pmstub_s,
- General rule: offer MC×* (r²-d²)¹/²/r
  - where MC (minimum price) is 60% above cost,
  - 1+r is the given number of days to sell
  - d is the number of days gone.
    i.e. reduce offer price at an increasing rate
- Attempt to judge whether buyer has reached deadline
  - Check if (1+(b₁ - b₂ ))/(1+(b₂ – b₃ )) is below 10%,
  - where b₁, b₂ and b₃ are the last, last but one and two bids
Stacey-Seller (rpstac_s)

- Complex seller: 18 rules for various situations
- Drive hard bargains by various sensible means.
- When the bid is above cost, the bid is accepted if
  (i) the last two bids are 50% above cost;
  (ii) the last three bids are 25% above cost; or
  (iii) the last four bids are 15% above cost.
- Final 2 days’ strategies fine tuned with 7 rules
  - depending on its predetermined margin thresholds
  - and the buyer’s latest offer.
- General rule: reduce offer by 7.5% of the cost per
  round, as long as the offer is above cost.
Smart-Seller-4 (smart_s4)

♦ A Target is worked out
  – principally based on an estimation of the pattern of the buyer’s previous bids.

♦ Up to three bids are used to project the buyer’s next bid.

♦ Haggle until it runs out of time, or
  – it believes the buyer has reached its bottom line
  – and the bid is above its cost.
Meet the Buyers

♦ Keen-Buyer (keen_b)
  - Simple buyer that accepts any offer below its utility

♦ Progressive-Buyer-2 (progress_b2)
  - Linearly increase bid towards utility

♦ Tryhorn-Buyer (mjtryh_b)
  - Complex rules to predict target and drive hard bargain

♦ Sourtzinos-Tsang-Buyer (psourt_b)
  - Increase bids reflecting utility^2 ÷ seller’s offer

♦ Stacey-Buyer (rpstac_b)
  - Complex rules for various situations, hard-bargaining
Keen-Buyer (keen\_b)

- Simple buyer
- Keen to make deals
- Accept any offer that is below its utility
- Start: bid a low price
- General strategy: increase price by half towards the utility in each round
Progressive-Buyer-2 (progress_b2)

- Increasing the bid linearly towards utility
- This gives the seller a chance to chart its progress and predict its bottom line
- Philosophy: give the seller a chance to cooperate should the seller wants to
- When the offer is below the utility, it is accepted if:
  (a) there are less than 3 days left; or
  (b) the latest offer is within 95 and 100% of the previous offer (this is seen to be a sign of the seller reaching its limit).
Tryhorn-Buyer (mjtryh_b)

- Built upon two important modules:
  (a) a predictor that estimates the bottom line of the seller and
  (b) a purchase-adviser that decides whether an offer is acceptable.

- Attempt to compute seller’s arithmetic progress

- Complex rules were used to compute the next bid

- In general, drive a hard bargain by not raising its bids very much until late in the negotiation

- An offer is acceptable if it is the buyer’s last day to buy

- Whether an offer is acceptable depends on
  (a) the offer/utility ratio (the lower the better) and
  (b) the length of the negotiation (the longer the negotiation, the keener it is to accept the offer).
Sourtzinos-Tsang-Buyer (psourt_b)

- Use a combination of bidding rules
- Bid 1000\textsuperscript{th} of the seller’s first offer
- Then bid 100\textsuperscript{th} of seller’s second offer
  - As long as the bids are below its utility.
- General rule: bid $\frac{\text{Utility}^2}{\text{Last\_offer}}$
  - i.e. the fraction of the utility that reflects the ratio between the utility and the seller’s last offer
Stacey-Buyer (rpstac_b)

♦ Complex buyer: 20 rules to handle various situations
♦ Drive hard bargains by various sensible means
  – Even when offer is below its utility, delay acceptance
  – Refuse to raise its bid if seller has not lowered its price for three rounds
♦ Final 2 days’ strategies fine tuned with 6 rules
  – Depending on its predetermined margin thresholds (35%) and seller’s latest offer
♦ General rule: increase offer by 7.5% per round, as long as bid is below utility
Experiment 1: No Middleman

♦ Every seller plays every buyer
♦ 1,000 randomly generated problems per pair
♦ Days to sell & Days to buy: 3..20
♦ Cost range: 101..300
♦ Utility range:
  – Low profit: 301..500
  – Medium profit: 1001..1300
  – High profit: 5101..5300
Individual seller/buyer Performance

- Buyers generally do better
- Aggressive sellers/buyers generally do better
Experiment 2: Mixed Middlemen

- 1,000 randomly generated chains
  - With 1, 5 and 10 middlemen per chain
  - Each middleman = (random seller, random buyer)
- Days to sell & Days to buy: 3..20 (as before)
- Cost range: 101..300
- Utility range: low & high profit
- Utility range and # of games varied over chain length
Chains with Mixed Middlemen

Normalized Profit in chains with mixed middlemen

- Consistent in all length
- Progress_b so-so on its own

Best for length 1

(progress_b2, pmstub_s)

Random chains of length 1
Random chains of length 5
Random chains of length 10

(progress_b2, pmstub_s) is the best choice for length 1 and is consistent in all lengths.

Progress_b is so-so on its own.
Lessons from Mixed Middlemen Chains

♦ Recognizing others’ constraints is key to completion
♦ Middlemen that allow others to estimate their bottom-line performed reasonably well
  – E.g. (progress_b2, pmstub_s) & (keen_b, pmstub_s)
♦ Presence of hard-bargainers maintain high prices in the chain
  – With high prices, chains cannot complete even when constraints are recognized
  – When a chain failed to complete, everyone suffers
  – So the hard-bargainers performed reasonably well
♦ Long chains are less likely to complete
Experiment 3: Uniform Chains

- Chains with the same middleman repeated:
  (Seller, (B,S), (B,S), …, (B,S), Buyer)
- Useful to assess evolutionary stable middlemen
- 5 sellers x 5 buyers $\Rightarrow$ 25 possible middlemen
- Chains with 1, 5 and 10 middlemen
- Same set of problems for each of the 25 chains
Chains with Uniform Middlemen

Normalized Profit for Uniform Chains

Keen_b did very well

Rpstac_b good as buyer
But bad in middlemen
Lessons from Uniform Chains

♦ Consistent performers:
  – (keen_b, keen_s2), (keen_b, pmstub_s), (keen_b, rpstac_s), (keen_b, smart_s4), (psourt_b, pmstub_s)

♦ All but one involves easy-going players, keen_b or keen_s2

♦ Hard-bargainers rpstac_b and rpstac_s scored badly; they compromised too late
  – For any chain to complete, one buyer and one seller must initiate compromises
What are good components?

Average Normalized Profit by individuals

- Average over individual, uniform chains
- Average over individual, random chains
- Average over individual, all games
Summary: Lessons Learned

♦ No evolutionary stable strategy in our sample
♦ It pays to drive hard bargains in mixed chains
  – When a chain breaks down, everyone suffers
♦ Recognizing others’ constraints is important
  – Revealing one’s bottom line may not be too bad
♦ Performance depends on profit margin, chain length and chain formation
  – Adaptation is the only chance to succeed
Survival of the Fittest in Chain Bargaining

Fitter strategies make more copies
Will the population converge?
If so, converged to what?
Average copies of players, Simple Bargaining Game

- dgjaco_s
- keen_s2
- pmstub_s
- rpstac_s
- smart_s4
- mjtryh_b
- progress_b2
- psourt_b
- rpstac_b
- keen_b

94年11月21日星期一

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Average copies of players, High Profit

Profit vs. Rounds

- **dgjaco_s**
- **keen_s2**
- **pmstub_s**
- **rpstac_s**
- **smart_s4**
- **mjtryh_b**
- **progress_b2**
- **psourt_b**
- **rpstac_b**
- **keen_b**
Observations, evolutionary bargaining

- Even the weakest player species survive in some settings; the weakest players died in others
- Consistent results
- Any correlation between
  - copies of player x in time t
  - to copies of player y in time t+1?

Nothing significant observed
Discussions on Bargaining

http://cswww.essex.ac.uk/CSP/bargain
What is Rationality?

♦ Are we all logical?
♦ What if *Computation* is involved?
♦ Does *Consequential Closure* hold?
  – If we know P is true and P $\rightarrow$ Q, then we know Q is true
  – We know all the rules in Chess, but not the optimal moves due to *combinatorial explosion*
♦ “Rationality” depends on computation power!
  – Think faster $\rightarrow$ “more rational”
Combinatorial Explosion

- Put 1 penny in square 1
- 2 pennies in square 2
- 4 pennies in square 3, etc.
- Even the world’s richest man can’t afford it
  - $10^{19}$ p = £100,000,000 Billion
Stochastic Search, Motivation

♦ Schedule 30 jobs to 10 machines:
  – Search space: \( 10^{30} \) leaf nodes

♦ Generously allow:
  – Explore one in every \( 10^{10} \) leaf nodes!
  – Examine \( 10^{10} \) nodes per second!

♦ Problem may take \textbf{300 years} to solve!!!
  – May be lucky to find first solution
  – But finding optimality takes time
  – *Complete methods limited by combinatorial explosion*
Game Theory Hall of Frame

1994 Nobel Prize
John Harsanyi
John Nash
Reinhard Selten

2005 Nobel Prize
Robert Aumann
Thomas Schelling
1994 Nobel Economic Prize Winners

John Harsanyi (Berkeley)
Incomplete information

John Forbes Nash (Princeton)
Non-cooperative games

Reinhard Selten (Bonn)
Bounded rationality (after Herbert Simon)
Experimental economics
1978 Nobel Economic Prize Winner

- Artificial intelligence
- “For his pioneering research into the decision-making process within economic organizations"
- “The social sciences, I thought, needed the same kind of rigor and the same mathematical underpinnings that had made the "hard" sciences so brilliantly successful.”
- Bounded Rationality
  - *A Behavioral model of Rational Choice* 1957

Herbert Simon (CMU)

Artificial intelligence

2005 Nobel Economic Prizes Winners

- Robert J. Aumann, and Thomas C. Schelling won 2005’s Noel memorial prize in economic sciences
- For having enhanced our understanding of conflict and cooperation through game-theory analysis

Source: http://www.msnbc.msn.com/id/9649575/  Updated: 2:49 p.m. ET Oct. 10, 2005
Robert J. Aumann
Winner of 2005 Nobel Economic Prize

♦ Born 1930
♦ Hebrew Univ of Jerusalem & US National Academy of Sciences
♦ “Producer of Game Theory” (Schelling)
♦ Repeated games
♦ Defined “Correlated Equilibrium”
  – Uncertainty not random
  – But depend on info on opponent
♦ Common knowledge
Thomas C. Schelling
Winner of 2005 Nobel Economic Prize

♦ Born 1921
♦ University of Maryland
♦ “User of Game Theory” (Schelling)
♦ Book “The Strategy of Conflict” 1960
  – Bargaining theory and strategic behavior
♦ “Book Arms and Influence” 1966
  – foreign affairs, national security, nuclear strategy, ...
♦ Paper “Dynamic models of segregation” 1971
  – Small preference to one’s neighbour → segregation