Bid Determination in Simultaneous Auctions
Lessons from TAC Travel

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`ebay` Auctions

Simultaneous Auctions

Combinatorial Valuations

- Complementary Goods
  - $v(A) + v(B) \leq v(A \cup B)$
  - camera, flash, and tripod
- Substitutable Goods
  - $v(A) + v(B) \geq v(A \cup B)$
  - Canon AE-1 and Canon A-1

Overview

I. TAC Travel

   (a) Simultaneous Auctions

   (b) Combinatorial Valuations

II. Bid Determination Problems

   (a) Allocation

   (b) Acquisition

   (c) Completion

III. Bidding Heuristics

   (a) Independent Valuations

   (b) Marginal Valuations

   (c) Marginal Utilities

IV. Trading Agent Architectures

   (a) Price Prediction & Optimization

   (b) Deterministic & Stochastic Variants

I. TAC Travel

An Example

- Simultaneous Auctions
- Combinatorial Valuations

TAC Travel

Complementary and Substitutable Goods

- **Flights**: Inbound and Outbound
- **Hotels**: Grand Hotel and Le FleaBag Inn
- **Entertainment**: Red Sox, Symphony, Theatre

TAC Travel

Simultaneous Auctions

- Flights: infinite supply, prices follow random walk, clear continuously, no resale permitted
- Hotels: ascending, multi-unit, 16th price auctions, random auction closes each minute, no resale permitted
- Entertainment: continuous double auctions, initial endowment, resale is permitted

TAC Travel

Feasible Packages

- arrival date prior to departure date
- same hotel on all intermediate nights
- at most one entertainment event per night
- at most one of each type of entertainment

TAC Travel

Client Preferences

Client	IAD	IDD	HV	R	S	T
1	1	3	99	134	118	65
2	1	4	131	170	47	49
3	1	2	147	13	55	49
4	3	4	145	130	60	85
5	1	4	82	136	68	87
6	2	4	53	94	51	105
7	1	3	54	156	126	71
8	1	5	113	119	187	143

TAC Travel

Valuation = 1000 - travelPenalty + hotelBonus + funBonus

$$
\begin{aligned}
\text{travelPenalty} &= 100(|\text{IAD} - \text{AD}| + |\text{IDD} - \text{DD}|) \\
\text{hotelBonus} &= \begin{cases} \text{HV} & \text{if H} = \text{G} \\ 0 & \text{otherwise} \end{cases} \\
\text{funBonus} &= \text{entertainment values}
\end{aligned}
$$

TAC 2000

Allocation

Client	AD	DD	H	Ticket	Valuation
1	1	3	G	S1, R2	1351
2	1	3	G	R1	1201
3	1	2	G	—	1147
4	3	4	G	R3	1275
5	1	3	F	R1, T2	1123
6	3	4	G	T3	1058
7	1	3	F	S1, R2	1282
8	1	5	G	T1, S3, R4	1562

Score = Valuation − Cost + Revenue

II. Bid Determination Problems

Definitions

- Allocation
- Acquisition
- Completion

Theorem

Completion $\preceq$ Acquisition $\Rightarrow$ Completion $\simeq$ Acquisition

Bid Determination Problems

Allocation

- given only the set of goods I already hold, how can I allocate those goods to packages so as to maximize my valuation?

Acquisition

- given ask prices in all open auctions, on what set of additional goods should I bid so as to maximize my valuation less procurement costs, subject to the constraint that I can only allocate goods that I buy?

Completion

- given ask and bid prices in all open auctions, on what set of additional goods should I place bids or asks so as to maximize my valuation less procurement costs plus sales revenues, subject to the constraint that I can only allocate or sell goods that I buy?

Winner Determination Problems

Combinatorial Auctions

- WDP $\cong$ Allocation
- WDR $\cong$ Acquisition

Combinatorial Exchanges

- WDP $\succeq$ Completion

Allocation

An agent owns n_i copies of good i

An agent has valuations of the form $\langle \vec{q_b}, v_b \rangle$, where

- $\vec{q_b}$ denotes a package and $q_{bi} \in \mathbb{N}$ is the quantity of good i in this package
- $v_b \in \mathbb{R}^+$ is the bidder's valuation of this package: the price at below which the bidder is willing to buy this package

$$\max_{\vec{x}} \sum_b v_b x_b \tag{1}$$

$$\text{subject to} \quad \sum_b q_{bi} x_b \leq n_i \qquad \forall i \tag{2}$$

$$x_b \in \{0, 1\} \qquad \forall b \tag{3}$$

$$\tag{4}$$

Acquisition

Buyer Pricelines

- $\vec{p}_{\hat{i}} = \langle 0, 0, 0, 0, 25, 40, 65, 100, \infty, \infty, \ldots \rangle$
- $\vec{p}_{\hat{\hat{i}}} = \langle -2, -1, 25, 40, 65, 100, \infty, \infty, \ldots \rangle$

$$\max_{\vec{x},\vec{y}} \sum_b v_b x_b - \sum_i \sum_{j=1}^{y_i} p_{ij} \tag{5}$$

$$\text{subject to} \quad \sum_b q_{bi} x_b \leq y_i \qquad \forall i \tag{6}$$

$$x_b \in \{0, 1\} \qquad \forall b \tag{7}$$

$$y_i \in \mathbb{N} \qquad \forall i \tag{8}$$

Completion

Seller Pricelines

- $\vec{\pi}_{\hat{i}} = \langle 20, 15, 10, 5, 0, 0, \ldots \rangle$
- $\vec{\pi}_{\hat{\hat{i}}} = \langle 3, 1, -2, -4, -\infty, -\infty, \ldots \rangle$

$$\max_{\vec{x},\vec{y},\vec{z}} \sum_b v_b x_b - \sum_i \left(\sum_{j=1}^{y_i} p_{ij} - \sum_{j=1}^{z_i} \pi_{ij} \right) \tag{9}$$

$$\text{subject to} \quad \sum_b q_{bi} x_b \leq y_i - z_i \quad \forall i \tag{10}$$

$$x_b \in \{0, 1\} \quad \forall b \tag{11}$$

$$y_i, z_i \in \mathbb{N} \quad \forall i \tag{12}$$

Reduction Technique

$$\begin{tikzcd}
\text{Completion Problem } (Q, P, \Pi) \arrow[r] \arrow[d, "\text{Optimal Solver}"] & \text{Acquisition Problem } (Q', P') \arrow[d, "\text{Optimal Solver}"] \\
\text{Completion Solution } (X_*, Y_*, Z_*) & \text{Acquisition Solution } (X'_*, Y'_*) \arrow[l, "h"']
\end{tikzcd}$$

Completion $\preceq$ Acquisition

Obvious Reduction

- fold seller pricelines into "bids" via singleton packages
- problem size increases

Not-so-Obvious Reduction

- fold seller pricelines into buyer pricelines
- problem size decreases

Sandholm, et al. 02: WDP in CE is harder than WDP and WDR in CA
Corollary: Completion is no harder than WDR in CA (i.e., Acquisition)

Notation

G is a set of types of good on the market
$N \in \mathbb{N}^{|G|}$ is a multiset on G with $N = \langle N_1, \ldots, N_{|G|} \rangle$
package M is a submultiset of N: i.e., $M_g \leq N_g$ for all $g \in G$
$X \subseteq Q \subseteq \prod_{g \in G} \mathbb{N}_g \times \mathbb{R}$ is a set of package-value pairs

$$X_g = \sum_{\langle M,v \rangle \in X} M_g \tag{13}$$

$$\text{Valuation}(X) = \sum_{\langle M,v \rangle \in X} v \tag{14}$$

$$\text{Cost}(Y, P) = \sum_{g \in G} \sum_{n=1}^{Y_g} p_{gn} \tag{15}$$

$$\text{Revenue}(Z, \Pi) = \sum_{g \in G} \sum_{n=1}^{Z_g} \pi_{gn} \tag{16}$$

Definitions

Objective Function:

$$\text{Acquisition}(Q, P) = \max_{X \subseteq Q, Y \subseteq N} (\text{Valuation}(X) - \text{Cost}(Y, P)) \tag{17}$$

Constraints: $X_g \leq Y_g, \ \forall g$

Objective Function:

$$\text{Completion}(Q, P, \Pi) = \max_{X \subseteq Q, Y, Z \subseteq N} (\text{Valuation}(X) - \text{Cost}(Y, P) + \text{Revenue}(Z, \Pi)) \tag{18}$$

Constraints: $X_g \leq Y_g - Z_g, \ \forall g$

Obvious Reduction

$(Q, P, \Pi) \longrightarrow (Q, P)$

- $\Pi' = \{\langle e_g, \pi_{gn}\rangle \mid \forall g \in G, 1 \le n \le N_g\}$
- $Q' = Q \cup \Pi'$ and $P' = P$

$h(X', Y') = (X, Y, Z)$

- $X = X' \cap Q$ and $Y = Y'$
- $Z_g = (X' \cap \Pi')_g$, for all $g \in G$

Theorem

- $f'(i(X, Y, Z), P') = f(X, Y, Z, P, \Pi), \ \forall X \subseteq Q, Y, Z \subseteq N$
- $f(h(X', Y'), P, \Pi) = f'(X', Y', P'), \ \forall X' \subseteq Q', Y' \subseteq N$

Arbitrage

Objective Function:

$$\text{Arbitrage}(P, \Pi) = \max_{Y,Z \subseteq N} (\text{Revenue}(Z, \Pi) - \text{Cost}(Y, P)) \tag{19}$$

Constraints: $Z_g \leq Y_g, \ \forall g$

Lemma

If $A \subseteq N$ is the multiset of arbitrage opportunities,
then

$$\forall P, \Pi \quad \text{Arbitrage}(P, \Pi) = \sum_{g \in G} \sum_{n=1}^{A_g} (\pi_{gn} - p_{gn}) \tag{20}$$

Not-so-Obvious Reduction

$(Q, P, \Pi) \longrightarrow (Q', P)$

- $q_{gn} = \max\{\pi_{gn}, p_{gn}\}$
- $\vec{p}'_g = \mathrm{sort}(\vec{q}_g)$

$h(X', Y') = (X', Y, Z)$

- for all $g \in G$
  - $gn \in Y$ iff $gn \in A \cup Y'$
  - $gn \in Z$ iff $gn \in A \setminus Y'$

Theorem

- $f'(i(X, Y, Z), P') + \mathrm{Arbitrage}(P, \Pi) \geq f(X, Y, Z, P, \Pi), \ \forall X \subseteq Q, Y, Z \subseteq N$
- $f(h(X', Y'), P, \Pi) = f'(X', Y', P') + \mathrm{Arbitrage}(P, \Pi), \ \forall X' \subseteq Q', Y' \subseteq N$

Bid Determination Problems

Definitions

- Allocation
- Acquisition
- Completion

Theorem

Completion $\preceq$ Acquisition $\Rightarrow$ Completion $\simeq$ Acquisition

III. Bidding Heuristics

Definitions

- Independent Valuations
- Marginal Valuations
- Marginal Utilities

Theorem

RoxyBot's heuristic is optimal, assuming perfect price prediction

Environments

Auctions

- simultaneous
  - sealed-bid
  - ascending
- second-price
  - payment rule: pay the clearing price
  - winner determination rule: win by bidding at least the clearing price

1st Bidding Heuristic

Independent Valuation (IV)
given a set of goods X
given a valuation function $v : 2^X \rightarrow \mathbb{R}$
for all $x \in X$,

$$\iota(x) = v(\{x\}) \tag{21}$$

- For each good x, bid (up to) its independent valuation $\iota(x)$

Heuristic IV

Complementary Goods

$v(\text{camera} + \text{flash}) = 500$
$v(\text{camera}) = v(\text{flash}) = 1$

IV: Bid 1 on camera; Bid 1 on flash

$p(\text{camera}) = 200$
$p(\text{flash}) = 100$

Agent loses both goods, but wishes it had won both
(since $500 > 300$)

Heuristic IV

Substitutable Goods

$v(\text{Canon}) = 300$
$v(\text{Olympus}) = 200$
$v(\text{Canon} + \text{Olympus}) = 400$

IV: Bid 300 on Canon; Bid 200 on Olympus

$p(\text{Canon}) = 275$
$p(\text{Olympus}) = 175$

Agent wins both goods, but wishes it had lost either
(since $400 < 450$)

2nd Bidding Heuristic

Marginal Valuation (MV)
given a set of goods X
given a valuation function $v : 2^X \to \mathbb{R}$
for all $x \in X$,

$$\nu(x) = \max_{Y \subseteq X} v(Y) - \max_{Y \subseteq X \setminus \{x\}} v(Y) \tag{22}$$

- For each good x, bid (up to) its marginal valuation $\nu(x)$

Heuristic MV

Complementary Goods

v(camera + flash) = 500
v(camera) = v(flash) = 1

MV: Bid 499 on camera; Bid 499 on flash

p(camera) = 500
p(flash) = 400

Agent wins one good, but wishes it had won neither
(since $1 < 400$)

Heuristic MV

Substitutable Goods

$v(\text{Canon}) = 300$
$v(\text{Olympus}) = 200$
$v(\text{Canon} + \text{Olympus}) = 400$

MV: Bid 200 on Canon; Bid 100 on Olympus

$p(\text{Canon}) = 275$
$p(\text{Olympus}) = 175$

Agent loses both goods, but wishes it had won either
(since $300 > 275$ and $200 > 175$)

Summary of Bidding Heuristics

	Complements	Substitutes
IV	Wins too few goods	Wins too many goods
MV	Wins too many goods	Wins too few goods

Exposure Problem for Complements: Agent bids more on an individual good than its independent valuation of that good [e.g., Milgrom 2000]

Exposure Problem for Substitutes: Agent bids more on a set of goods than its combinatorial valuation of that set of goods

3rd Bidding Heuristic

Marginal Utility (MU)

given a set of goods X
given a valuation function $v : 2^X \to \mathbb{R}$
given a pricing mechanism $p : X \to \mathbb{R}$
for all $x \in X$,

$$\mu(x) = \left(\max_{Y \subseteq X} v(Y) - p(Y \setminus \{x\})\right) - \left(\max_{Y \subseteq X \setminus \{x\}} v(Y) - p(Y)\right) \tag{23}$$

for all $Y \subseteq X$,

$$p(Y) = \sum_{y \in Y} p(y) \tag{24}$$

- For each good x, bid (up to) its marginal utility $\mu(x)$

Environments

Auctions

- simultaneous
  - sealed-bid: predict clearing prices
  - ascending: assume clearing prices = current prices
- second-price
  - payment rule: pay the clearing price
  - winner determination rule: win by bidding at least the clearing price

Environments

Auctions

- simultaneous
  - sealed-bid: predict clearing prices
  - ascending: predict clearing prices
- second-price
  - payment rule: pay the clearing price
  - winner determination rule: win by bidding at least the clearing price

Heuristic MU*

Substitutable Goods

$N > 1$ goods up for auction, simultaneously
value of one or more goods is 2
price of each good is 1

MU: Bid 1 on each good

Agent wins all the goods, but wishes it had won only one
($2 - N < 1$ since $N > 1$)

Heuristic MU*

Theorem

If $A^* \subseteq X$ is an optimal solution to the acquisition problem $\alpha(X, v, p)$, then $\mu(x) \geq p(x)$ if and only if $x \in A^*$.

Corollary

If $A^* \subseteq X$ is the unique solution to the acquisition problem $\alpha(X, v, p)$, then the following bidding heuristic is optimal: bid (up to) $q(x)$, where $q(x) \geq p(x)$, for all $x \in A^*$.
In particular, the bidding heuristic MU* is optimal.

4th Bidding Heuristic

RoxyBot 2000

1. predict clearing prices

2a. solve completion (as acquisition)

2b. bid marginal utilities on goods in completion

Theorem

RoxyBot's heuristic is optimal, assuming perfect price prediction

Examples Revisited

Complementary Goods

$v(\text{camera} + \text{flash}) = 500$
$v(\text{camera}) = v(\text{flash}) = 1$

$p(\text{camera}) = 200$
$p(\text{flash}) = 100$

Bid to win camera and flash

$p(\text{camera}) = 500$
$p(\text{flash}) = 400$

Bid to lose camera and flash

Examples Revisited

Substitutable Goods

$v(\text{Canon}) = 300$
$v(\text{Olympus}) = 200$
$v(\text{Canon} + \text{Olympus}) = 400$

$p(\text{Canon}) = 275$
$p(\text{Olympus}) = 175$

Bid to win Canon or Olympus

Summary of Bidding Heuristics

	Complements	Substitutes
IV	Wins too few goods	Wins too many goods
MV	Wins too many goods	Wins too few goods
MU*	Optimal Bidding	Win too many goods
Roxy*	Optimal Bidding	Optimal Bidding

Exposure Problem for Complements: Agent bids more on an individual good than its independent valuation of that good [e.g., Milgrom 2000]

Exposure Problem for Substitutes: Agent bids more on a set of goods than its combinatorial valuation of that set of goods

IV. Trading Agents

Architecture

1. Price Prediction
2. Optimization

Variants

- Deterministic
- Stochastic

Trading Agent Architecture: Deterministic

REPEAT

0. Update current prices and holdings for each auction.

1. Estimate prices, in the form of supply and demand curves, for each good.

2a. Determine supply and demand sets: i.e., # of each good to buy and sell.

2b. Bid marginal utilities strategically, given the auction designs.

FOREVER

Trading Agent Architecture: Stochastic

REPEAT

0. Update current prices and holdings for each auction.
1. Estimate distributions of auction prices.
2. Calculate optimal bids.

FOREVER

Example

$v(\text{camera} + \text{flash}) = 750$
$v(\text{camera}) = v(\text{flash}) = 0$

$p(\text{camera}) = 500$, with probability $\frac{1}{2}$
$p(\text{camera}) = 1000$, with probability $\frac{1}{2}$
$p(\text{flash}) = 50$, with probability 1

Policy A: $(500, 50)$ is optimal, with probability $\frac{1}{2}$
Policy B: $(0, 0)$ is optimal, with probability $\frac{1}{2}$

$\text{Value}(A) = \frac{1}{2}(200) + \frac{1}{2}(-50) = 75$
$\text{Value}(B) = 0$

Expected Value Method

$v(\text{camera} + \text{flash}) = 750$
$v(\text{camera}) = v(\text{flash}) = 0$

$p(\text{camera}) = 750$, with probability 1
$p(\text{flash}) = 50$, with probability 1

Policy B: $(0, 0)$ is optimal
Value$(B) = 0$

Value of Stochastic Information $= 75$

Stage 2: Allocation

v_i: value of package i

$b_{jk} \in \mathbb{R}_+$: bid on copy k of good j

$p_{jk} \in \mathbb{R}_+$: price of the kth copy of good j

$n_{ij} \in \mathbb{N}$: number of copies of good j in package i

binary decision variables $a_{ijk} \in \{0, 1\}$: is copy k of good j is allocated to i?

$$\pi(\vec{a}, \vec{b}, \vec{p}, \vec{v}) = \sum_i v_i \left(\prod_{j \in i} \mathbf{1} \left[n_{ij} \leq \sum_k a_{ijk} \mathbf{1}[p_{jk} \leq b_{jk}] \right] \right) - \sum_{jk} p_{jk} (\mathbf{1}[p_{jk} \leq b_{jk}]) \tag{25}$$

$$\max_{\vec{a}} \pi(\vec{a}, \vec{b}, \vec{p}, \vec{v}) \tag{26}$$

$$\text{subject to:} \qquad \sum_i a_{ijk} \leq 1, \quad \forall j, k \tag{27}$$

$$a_{ijk} \in \{0, 1\}, \quad \forall i, j, k \tag{28}$$

Stage 1: Bidding

$f(\vec{p})$: joint probability distribution over prices $\vec{p}$

continuous decision variables $b_{jk} \in \mathbb{R}_+$: bid for copy k of good j

binary decision variables $a_{ijk} \in \{0, 1\}$: is copy k of good j is allocated to i?

$$\max_{\vec{b}} \int_{\vec{p}} \max_{\vec{a}} \pi(\vec{a}, \vec{b}, \vec{p}, \vec{v}) f(\vec{p}) d\vec{p} \tag{29}$$

$$\text{subject to:} \qquad \sum_i a_{ijk} \leq 1, \quad \forall j, k \tag{30}$$

$$a_{ijk} \in \{0, 1\}, \quad \forall i, j, k \tag{31}$$

$$b_{jk} \in \mathbb{R}_+, \quad \forall j, k \tag{32}$$

TAC Travel Offline Experimental Setup

Price Prediction

- Competitive Equilibrium Prices
  - Walverine: Tatonnement [Cheng, et al. 04]
  - Simultaneous Ascending Auction [Milgrom 00]

Optimization

- Sample Average Approximation [Kleywegt, et al. 01]
  - E: evaluations; S: scenarios; P: policies
- Expected Value Method
  - Marginal Utility Bidding [UAI 04]
  - RoxyBot 2000: Completion + MU [EC 01]
- ATTac 2001: Average Marginal Utility Bidding [Stone, et al. 01]

TAC Travel Offline Experimental Results

Time	Reward	E	S	P
1.47	3318	64	1	1
1.48	3456	128	1	1
1.48	3502	2	1	1
1.49	3548	16	1	1
2.45	3550	32	4	1
2.45	3577	2	4	1
3.38	3695	2	1	2
3.89	3705	4	1	2
4.12	3912	128	8	1
4.16	3947	32	8	1
8.43	3967	2	16	1
10.55	4014	8	8	2
16.75	4043	32	8	2
17.95	4045	64	32	1
18.09	4064	1	32	1
18.12	4065	32	32	1
33.50	4077	32	8	4
38.52	4099	16	32	2
41.26	4132	32	64	1
82.20	4134	1	64	2
84.81	4136	32	32	4
85.99	4141	16	64	2
88.81	4142	32	64	2
115.27	4146	128	64	2

TAC Travel Bidding Problem

TAC Travel Offline Experimental Results

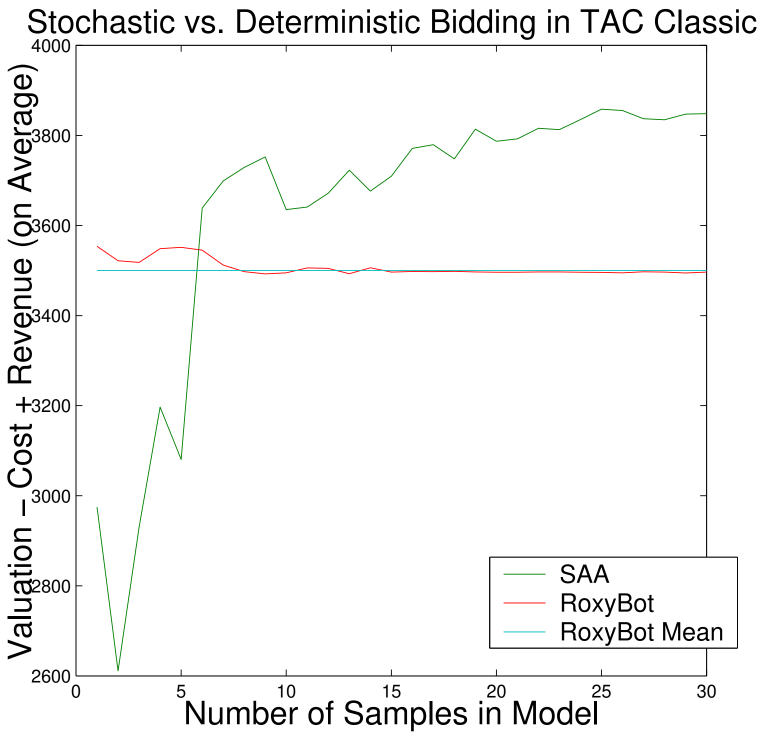
Time	Reward	E	S	P
1.47	3318	64	1	1
1.48	3456	128	1	1
1.48	3502	2	1	1
1.49	3548	16	1	1
2.45	3550	32	4	1
2.45	3577	2	4	1
3.38	3695	2	1	2
3.89	3705	4	1	2
4.12	3912	128	8	1
4.16	3947	32	8	1
8.43	3967	2	16	1
10.55	4014	8	8	2
16.75	4043	32	8	2
17.95	4045	64	32	1
18.09	4064	1	32	1
18.12	4065	32	32	1
33.50	4077	32	8	4
38.52	4099	16	32	2
41.26	4132	32	64	1
82.20	4134	1	64	2
84.81	4136	32	32	4
85.99	4141	16	64	2
88.81	4142	32	64	2
115.27	4146	128	64	2

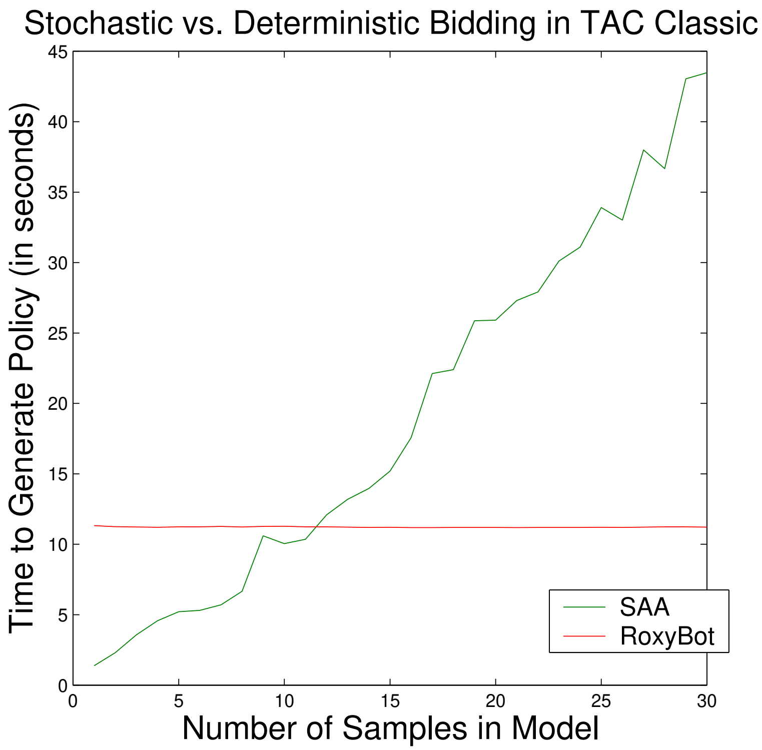
TAC Travel Bidding Problem

Time	Lower	Upper	E	S	P
0.03	468310	754507	10	1	1
0.04	517559	688963	10	2	1
0.07	535059	657833	10	3	1
0.11	548218	647722	10	4	1
0.29	550930	639010	10	5	1
0.38	554046	637546	100	5	1
0.40	559796	630666	10	6	1
0.56	561418	628053	100	6	1
1.31	562798	624235	100	7	1
1.36	567807	661136	100	3	8
1.58	575676	647877	100	4	7
2.84	577965	646174	100	4	13
3.06	579369	638006	100	5	9
4.13	581433	636296	100	5	13
5.47	582306	629457	100	6	9
5.65	582504	635982	100	5	17
7.30	583621	637376	100	5	21
8.50	583998	630956	100	6	13
9.44	584043	646170	100	4	43
10.00	584287	636188	100	5	29
10.92	585094	645841	100	4	49
12.63	585543	636626	100	5	37

TAC SCM Scheduling Problem

TAC Travel Offline Experimental Results





TAC Travel Experimental Results

Teams	Means		z-test	Wilcoxon	Games
Average MU < MU	964	1908	.999	.999	25
MU < RoxyBot 2000	1508	1612	.793	.803	75
RoxyBot 2000 < RoxyBot 2002	1837	2031	.977	.996	50
Average MU < RoxyBot 2000	1334	2034	.999	.999	25
MU < RoxyBot 2002	1705	1987	.976	.993	50
Average MU < RoxyBot 2002	915	1920	.999	.999	25

Trading Agent Architecture

REPEAT

1. Price Prediction

2. Optimization

   (a) Deterministic: Completion Problem + MU

   (b) Stochastic: Bidding Problem

FOREVER

Summary

Theory

Completion $\preceq$ Acquisition $\Rightarrow$ Completion $\simeq$ Acquisition

RoxyBot's heuristic is optimal, assuming perfect price prediction

Experiments

Stochastic $\gg$ Deterministic

Future Directions

Optimal	Simultaneous	Sequential
Deterministic	Roxy	MU
Stochastic	SP	DP

Heuristics	Simultaneous	Sequential
Deterministic	Roxy	MU
Stochastic	SAA	Average MU

Given this set of bidders, what is the preferred auction design?

- from the point of view of the auctioneer
- from the point of view of the bidders

Thank You!

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