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
## Client Preferences

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<th>HV</th>
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TAC Travel

Valuation = 1000 - travelPenalty + hotelBonus + funBonus

\[
\text{travelPenalty} = 100(|IAD - AD| + |IDD - DD|)
\]

\[
\text{hotelBonus} = \begin{cases} 
HV & \text{if } H = G \\
0 & \text{otherwise}
\end{cases}
\]

funBonus = entertainment values
TAC 2000

Allocation

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</table>

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.

$$\max \sum_{b} v_{b} x_{b} \quad \text{(1)}$$

subject to

$$\sum_{b} q_{bi} x_{b} \leq n_i \quad \forall i \quad \text{(2)}$$

$$x_{b} \in \{0, 1\} \quad \forall b \quad \text{(3)}$$

$$x_{b} \in \{0, 1\} \quad \forall b \quad \text{(4)}$$
Acquisition

Buyer Pricelines

- $\vec{p_i} = \langle 0, 0, 0, 0, 25, 40, 65, 100, \infty, \infty, \ldots \rangle$

- $\vec{p_i^c} = \langle -2, -1, 25, 40, 65, 100, \infty, \infty, \ldots \rangle$

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

subject to
\[
\sum_b q_{bi} x_b \leq y_i \quad \forall i
\]

\[
x_b \in \{0, 1\} \quad \forall b
\]

\[
y_i \in \mathbb{N} \quad \forall i
\]
Description of the image:

**Completion**

**Seller Pricelines**

- $\pi_i^* = \langle 20, 15, 10, 5, 0, 0, \ldots \rangle$
- $\pi_i^\infty = \langle 3, 1, -2, -4, -\infty, -\infty, \ldots \rangle$

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

subject to

\[
\sum_b q_{bi} x_b \leq y_i - z_i \quad \forall i 
\]  

\[
x_b \in \{0, 1\} \quad \forall b 
\]  

\[
y_i, z_i \in \mathbb{N} \quad \forall i 
\]
Reduction Technique

Completion Problem \((Q, P, \Pi)\)

\[\xrightarrow{\text{Optimal Solver}}\]

Completion Solution \((X^*, Y^*, Z^*)\)

\[h\]

Acquisition Solution \((X'_*, Y'_*)\)

Acquisition Problem \((Q', P')\)
Completion $\leq$ 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
$N \in \mathbb{N}^{\left|G\right|}$ is a multiset on $G$ with $N = \langle N_1, \ldots, N_{\left|G\right|} \rangle$
package $M$ is a submultiset of $N$: i.e., $M_g \leq N_g$ for all $g \in G$
$X \subseteq Q \subseteq \prod_{g \in G} N_g \times \mathbb{R}$ is a set of package-value pairs

\[
X_g = \sum_{\langle M, v \rangle \in X} M_g
\]  \hspace{1cm} (13)

\[
\text{Valuation}(X) = \sum_{\langle M, v \rangle \in X} v
\]  \hspace{1cm} (14)

\[
\text{Cost}(Y, P) = \sum_{g \in G} \sum_{n=1}^{Y_g} p_{gn}
\]  \hspace{1cm} (15)

\[
\text{Revenue}(Z, \Pi) = \sum_{g \in G} \sum_{n=1}^{Z_g} \pi_{gn}
\]  \hspace{1cm} (16)
Definitions

Objective Function:

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

Constraints: \( X_g \leq Y_g, \quad \forall g \)

Objective Function:

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

Constraints: \( X_g \leq Y_g - Z_g, \quad \forall g \)
Obvious Reduction

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

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

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

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

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:

\[ \text{Arbitrage}(P, \Pi) = \max_{Y, Z \subseteq N} (\text{Revenue}(Z, \Pi) - \text{Cost}(Y, P)) \]  \hspace{1cm} (19)

Constraints: \( Z_g \leq Y_g, \forall g \)

Lemma

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

\[ \forall P, \Pi \quad \text{Arbitrage}(P, \Pi) = \sum_{g \in G} \sum_{n=1}^{A_g} (\pi_{gn} - p_{gn}) \]  \hspace{1cm} (20)
Not-so-Obvious Reduction

\[(Q, P, \Pi) \longrightarrow (Q', P')\]

- \(q_{gn} = \max\{\pi_{gn}, p_{gn}\}\)
- \(\tilde{p}_g' = \text{sort}(\tilde{q}_g)\)

\[h(X', Y') = (X', Y, Z)\]

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

**Theorem**

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

$$\iota(x) = v(\{x\})$$  \hspace{1cm} (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

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

\textbf{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 $x \in X$,

$$\nu(x) = \max_{Y \subseteq X} v(Y) - \max_{Y \subseteq X \setminus \{x\}} v(Y)$$  \hspace{1cm} (22)

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

Complementary Goods

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

MV: Bid 499 on camera; Bid 499 on flash

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

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

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<th>Complements</th>
<th>Substitutes</th>
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<td>MV</td>
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**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 $v : 2^X \rightarrow \mathbb{R}$
given a pricing mechanism $p : X \rightarrow \mathbb{R}$
for all $x \in X$,

$$\mu(x) = \left( \max_{Y \subseteq X} v(Y) - p(Y \setminus \{x\}) \right) - \left( \max_{Y \subseteq X \setminus \{x\}} v(Y) - p(Y) \right)$$ \hspace{1cm} (23)

for all $Y \subseteq X$,

$$p(Y) = \sum_{y \in Y} p(y)$$ \hspace{1cm} (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
($2 - N < 1 \text{ since } N > 1$)
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

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

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

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

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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

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

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

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

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

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

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 $k$th 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 $i$?

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

\[
\max_{\vec{a}} \pi(\vec{a}, \vec{b}, \vec{p}, \vec{v}) \quad (26)
\]

subject to:

\[
\sum_i a_{ijk} \leq 1, \quad \forall j, k \quad (27)
\]

\[
a_{ijk} \in \{0, 1\}, \quad \forall i, j, k \quad (28)
\]
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 \( i \)?

\[
\max_{\vec{b}} \int \max_{\vec{\alpha}} \pi(\vec{\alpha}, \vec{b}, \vec{p}, \vec{v}) f(\vec{p}) d\vec{p}
\]

subject to:

\[
\sum_i a_{ijk} \leq 1, \quad \forall j, k \tag{30}
\]

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

\[
b_{jk} \in \mathbb{R}^+, \quad \forall j, k \tag{32}
\]
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

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TAC Travel Bidding Problem
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### TAC Travel Bidding Problem

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### TAC SCM Scheduling Problem
TAC Travel Offline Experimental Results

Stochastic vs. Deterministic Bidding in TAC Classic

Valuation - Cost + Revenue (on Average)

Number of Samples in Model

Time to Generate Policy (in seconds)

Stochastic vs. Deterministic Bidding in TAC Classic

SAARoxyBotRoxyBot Mean

0 5 10 15 20 25 30

0 5 10 15 20 25 30 35 40 45

0 5 10 15 20 25 30

SAA RoxyBot

52
## TAC Travel Experimental Results

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Trading Agent Architecture

REPEAT

1. Price Prediction
2. Optimization
   (a) Deterministic: Completion Problem + MU
   (b) Stochastic: Bidding Problem

FOREVER
Summary

Theory
Completion $\leq$ Acquisition $\Rightarrow$ Completion $\simeq$ Acquisition
RoxyBot’s heuristic is optimal, assuming perfect price prediction

Experiments
Stochastic $\gg$ Deterministic
Future Directions

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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!

Amy Greenwald
amy@brown.edu
http://www.cs.brown.edu/people/amy

http://www.sics.se/tac