

STOCHASTIC LOCAL SEARCH  
FOUNDATIONS AND APPLICATIONS

## Combinatorial Auctions

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# Introduction

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Auctions are attractive as mechanisms for ...

- E-commerce (business transactions, sales)
- resource allocation  
(radio frequencies, pollution rights, scheduling)
- coordinating agents in multi-agent systems

↪ *AI community shows an increasing interest in auctions*

## **Standard, single item auctions:**

- winner determination is easy
- can't express complementarities of goods

*Example:*

Auctioning flight tickets: people want specific combination of travel dates.

Bidder A wants to fly from Austin to London over the weekend, thus has to bid for Fri (or Sat) and Sun flights.

$\rightsquigarrow$  *bidding for bundles (= combinations of items)*

## Bidding for bundles ...

- minimises buyer's risk of getting incomplete combinations
- allows to express preferences more directly

Bids for combinations of items can overlap

↪ winner determination is hard!

# Combinatorial Auctions

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## Given:

- set of goods  $G = \{g_1, \dots, g_n\}$  to be auctioned
- set of bids  $B = \{(c_i, v_i) \mid c_i \subseteq G, v_i \in \mathbb{R}^+\}$

## Definition:

An *assignment* is a function  $A : G \mapsto B$  mapping goods to bids.

A bid  $b_i = (c_i, v_i)$  is *satisfied by*  $A$  if  $\forall g \in c_i : A(g) = b_i$ .

### **Winner determination problem for CAs:**

Find an assignment  $A$  which maximises the total revenue, i.e.,  
 $\sum\{v_i | b_i = (c_i, v_i) \in B \wedge b_i \text{ satisfied by } A\}$ .

**Bad news:** This problem (decision version) is NP-complete.

**Even worse:** It is not even polynomially approximable within  
 $k \leq n^{1-\epsilon}$ .

## Schematic Bids

Standard CAs can't express *substitutabilities* (or indifference) between goods.

*Example (flight tickets):*

I want to make the weekend trip to London, but don't care whether I depart on Fri or Sat, and I am indifferent between returning on Sun or Mon.

↷ can be expressed in standard CAs, but creates lots of bids



## Richer, logical languages for bids:

- CNF bids: allow bids for bundles of disjunctions, e.g.  $(\text{Fri} \vee \text{Sat}) \wedge (\text{Sun} \vee \text{Mon})$
- $k$ -of bids: allow bids for bundles of subset selections, e.g.  $2\text{-of}\{\text{Fri}, \text{Sat}, \text{Sun}, \text{Mon}\} \wedge 2\text{-of}\{\text{Mon}, \text{Tue}, \text{Thu}\}$

Considered here for the first time — no algorithms available!

# SLS Algorithms for CAs

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## Stochastic local search is ...

- popular and very successful for many combinatorial problems (TSP, CSP, SAT, scheduling, planning, ...)
- typically easy to implement
- often easy to parallelise
- often the method of choice for hard, large problems

## CASLS family of SLS algorithms for CA:

- *search space*: space of feasible, partial assignments
- *solution set*: assignments with optimal / given revenue
- *neighbourhood relation*: assignments reachable by reassigning set of goods such that one formerly unsat bid becomes satisfied
- *search initialisation function*: start with empty assignment
- *search step function*: picks a neighbour according to stochastic heuristic  $h$

## Casanova algorithm:

- member of the CASLS family using a heuristic which is closely related to one of the most successful SLS algorithms for SAT, Novelty<sup>+</sup> (Hoos 1999; McAllester, Selman, Kautz 1997).
- several parameters which can be optimised, including two noise parameters controlling the degree of randomness in  $h$ .
- conceptually very simple (compared to systematic algorithms)
- easy to implement

# Empirical Results

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Tested Casanova against CASS, the better of the two known systematic algorithms for CAs.

Used a range of synthetic problem sets with various properties.

For each problem instance, measured

- mean solution quality (revenue) for fixed run-time
- mean run-time for finding optimal solutions

Compare these over the test-sets.

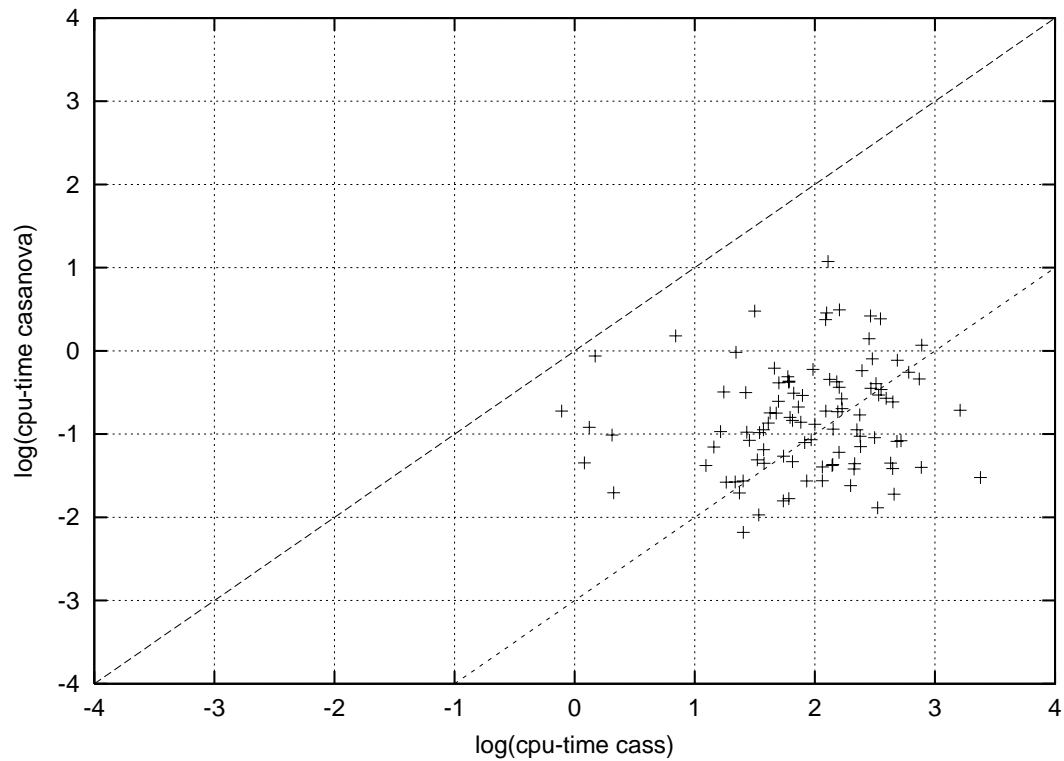
## Regular bids: Revenue for CASS vs. Casanova (fixed run-time)

test-set	# inst	cutoff	CASS			Casanova		
			median	Q <sub>90</sub>	Q <sub>10</sub> /Q <sub>90</sub>	median	Q <sub>90</sub>	Q <sub>10</sub> /Q <sub>90</sub>
UNI-3-100-1000	100	10s	130396	133838	1.0489	<b>134216</b>	136203	1.0314
UNI-3-200-2000	100	10s	252084	257643	1.0438	<b>264814</b>	267573	1.0212
UNI-3-100-5000	100	30s	142947	144015	1.0172	<b>143886</b>	144666	1.0104
UNI-3-200-10000	100	60s	281413	284033	1.0189	<b>286164</b>	287632	1.0102
BIN-0.01-500-5000	10	60s	583279	594931	1.0367	<b>616708</b>	623624	1.0351
DEC-0.75-500-5000	10	60s	668458	678830	1.0380	<b>675198</b>	279919	1.0090
EXP-5-100-1000	10	30s	<b>135027</b>	135658	1.0298	132705	134412	1.0295
EXP-5-500-5000	10	60s	647629	650302	1.0240	<b>655329</b>	659238	1.0199

## Regular bids: Search cost for CASS vs. Casanova (finding optimal solutions)

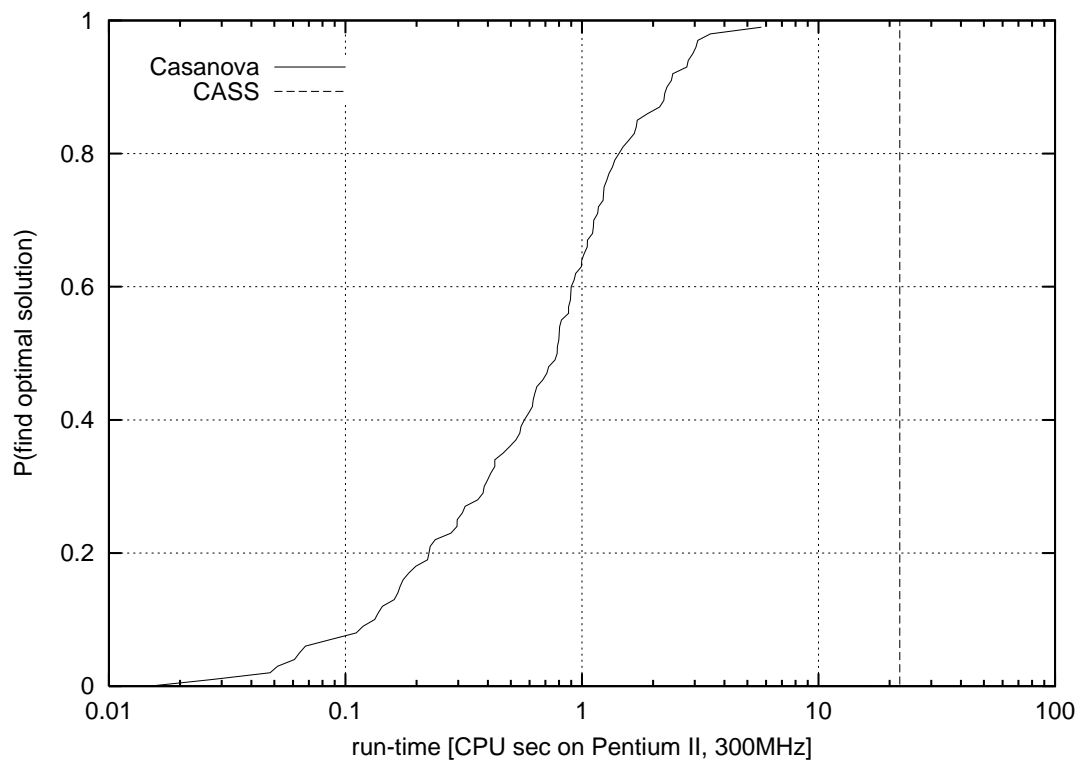
test-set	# inst	CASS			Casanova		
		median	Q <sub>90</sub>	Q <sub>10</sub> /Q <sub>90</sub>	median	Q <sub>90</sub>	Q <sub>10</sub> /Q <sub>90</sub>
UNI-3-50-50	100	0.058	0.125	9.09	<b>0.0092</b>	0.029	7.61
UNI-3-75-75	100	2.211	6.222	10.91	<b>0.030</b>	0.197	24.99
UNI-3-100-100	100	96.41	446.50	27.17	<b>0.136</b>	0.964	36.24
UNI-3-50-100	100	0.487	1.40	15.20	<b>0.091</b>	0.543	21.29
UNI-3-75-150	100	125.76	409.95	17.24	<b>1.078</b>	3.974	25.59
UNI-3-20-2000	100	33.99	140.55	462.86	<b>1.725</b>	5.160	6.911
UNI-10-200-200	100	147.99	308.92	15.72	<b>1.677</b>	6.051	10.54
BIN-0.2-20-500	100	<b>0.051</b>	0.066	1.48	7.980	31.447	11.08
DEC-0.75-200-200	10	252.82	1061.04	44.62	<b>6.236</b>	632.35	800.747
EXP-5-20-500	100	<b>0.0282</b>	0.0315	1.21	0.852	8.689	749.01

Correlation of search cost (finding optimal solution), test-set  
UNI-3-100-100 (100 goods, 100 bids).

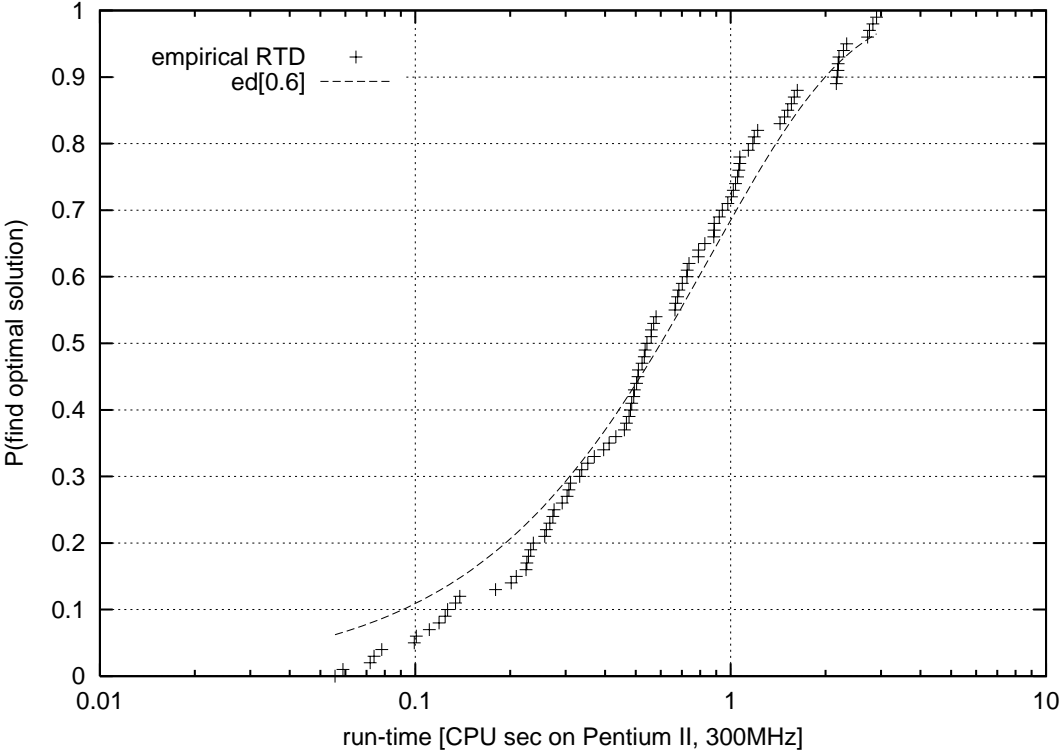




# Run-time distributions for finding optimal solution for a UNI-3-100-100 (100 goods, 100 bids) instance



Run-time distributions for finding optimal solution for a  
DEC-0.75-200-200 (200 goods, 200 bids) instance



## CNF and $k$ -of bids: Revenue for CASS vs. Casanova (fixed run-time)

test-set	# inst	cutoff	CASS			Casanova		
			median	$Q_{90}$	$Q_{10}/Q_{90}$	median	$Q_{90}$	$Q_{10}/Q_{90}$
CUNI-3-50-50	100	10s	55015	58479	1.1458	<b>63360</b>	65745	1.0900
CUNI-3-100-100	100	60s	104868	108687	1.1017	<b>127011</b>	130440	1.0613
CUNI-3-50-250	100	60s	52245	56943	1.1975	<b>70158</b>	70551	1.0176
CPOIS-2-50-50	100	10s	53204	56397	1.1542	<b>60398</b>	63115	1.1049
CPOIS-2-100-100	100	60s	99238	105275	1.1334	<b>117889</b>	122673	1.0691
CPOIS-2-50-250	100	60s	53066	56094	1.1272	<b>69608</b>	70755	1.0317
CPOIS-2-100-500	100	60s	101568	105941	1.1043	<b>135973</b>	138266	1.0323
KUNI-2-4-2-100-100	10	60s	48812	50608	1.1988	<b>59938</b>	63194	1.0940

**CNF and  $k$ -of bids: Search cost for CASS vs. Casanova  
(finding optimal solutions)**

test-set	# inst	CASS			Casanova		
		median	$Q_{90}$	$Q_{10}/Q_{90}$	median	$Q_{90}$	$Q_{10}/Q_{90}$
CUNI-3-20-20	100	791.11	2904.89	180.58	<b>0.050</b>	0.138	5.24
CPOIS-2-20-20	100	1.855	9.355	41.15	<b>0.240</b>	1.048	17.74
KUNI-2-4-2-20-20	100	24.364	48.690	72.40	<b>0.474</b>	4.678	24.40

## Summary of results:

- Casanova outperforms CASS on large problems with fixed cutoff times
- Although incomplete, Casanova finds optimal solutions to small instances, often much faster than CASS
- Casanova's performance improves relative to CASS's with growing problem size
- Casanova can be easily parallelised with optimal speedup

*↪ for solving large problem instances (> 100 goods, > 1000 bids), SLS algorithms like Casanova significantly better than current systematic search procedures*