A Heuristic Bidding Strategy for Multiple Heterogeneous Auctions

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Problem:

- number of auction sites increases
- consumers want to track and bid multiple auctions
- consumers want to get the best deal
- need to adopt varying strategies for different auctions
- consumers need a **bidding agent** to help them

Simple Bidding Proxies Limitations:

- sites like eBay and Yahoo!Auction provide bidding proxies
- will bid in a stated auction up to some predefined limit
- fixed to operate at a single auction
- fixed to operate with a particular auction protocol
- bidding decisions are left to the human users

Goals / Expectations:

- participate in multiple heterogeneous auctions
- make purchases autonomously
- never bids above the private value
- consistent with consumer's preferences

(eg. earliest time, lowest price)

Previous Work:

A genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are categorized as global search heuristics. Genetic algorithms are particular class of evolutionary algorithms (also know as evolutionary computation) that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, or crossover (also called recombination).

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- strategies are heavily influenced by the nature of environment
- search for strategy using genetic algorithm

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Design Environment:

- auctions : English, Dutch, Vickrey
- known start time of all auctions
- known end time of English and Vickrey
- deadlines to purchase : t_{max}
- private value : p_r
- types of intentions : bargain, desperate, combination
- buy no more than one instance

Intelligent Bidding Strategy:

a collection of strategies for a single agent

while t < t_{max} **&&** item_is_not_acquired **do**

build active action list *L(t)*

calculate current maximum bid based on **<u>bidding constraints</u>**

select from *L(t)* the potential auctions to bid in

select target auction that maximizes agent's expected utility

bid the target action, but less than p_r

end

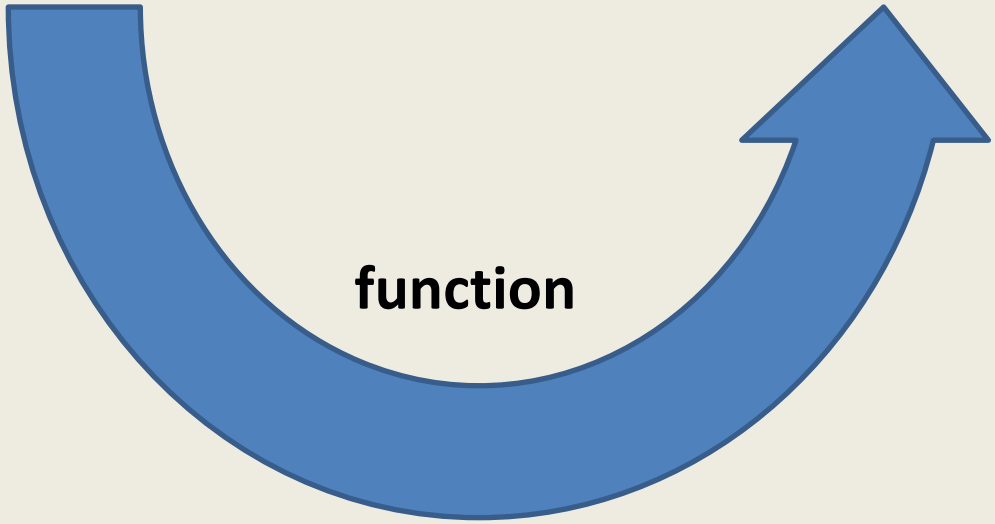
Bidding constraints:

- remaining time left
- remaining auctions left
- desire for bargain
- level of desperateness

we put weight on each constrain

ex. (0.25, 0.25, 0.25, 0.25) all constraints are equal
ex. (0.5, 0, 0.5, 0) agent considers only remaining time and desire for bargain

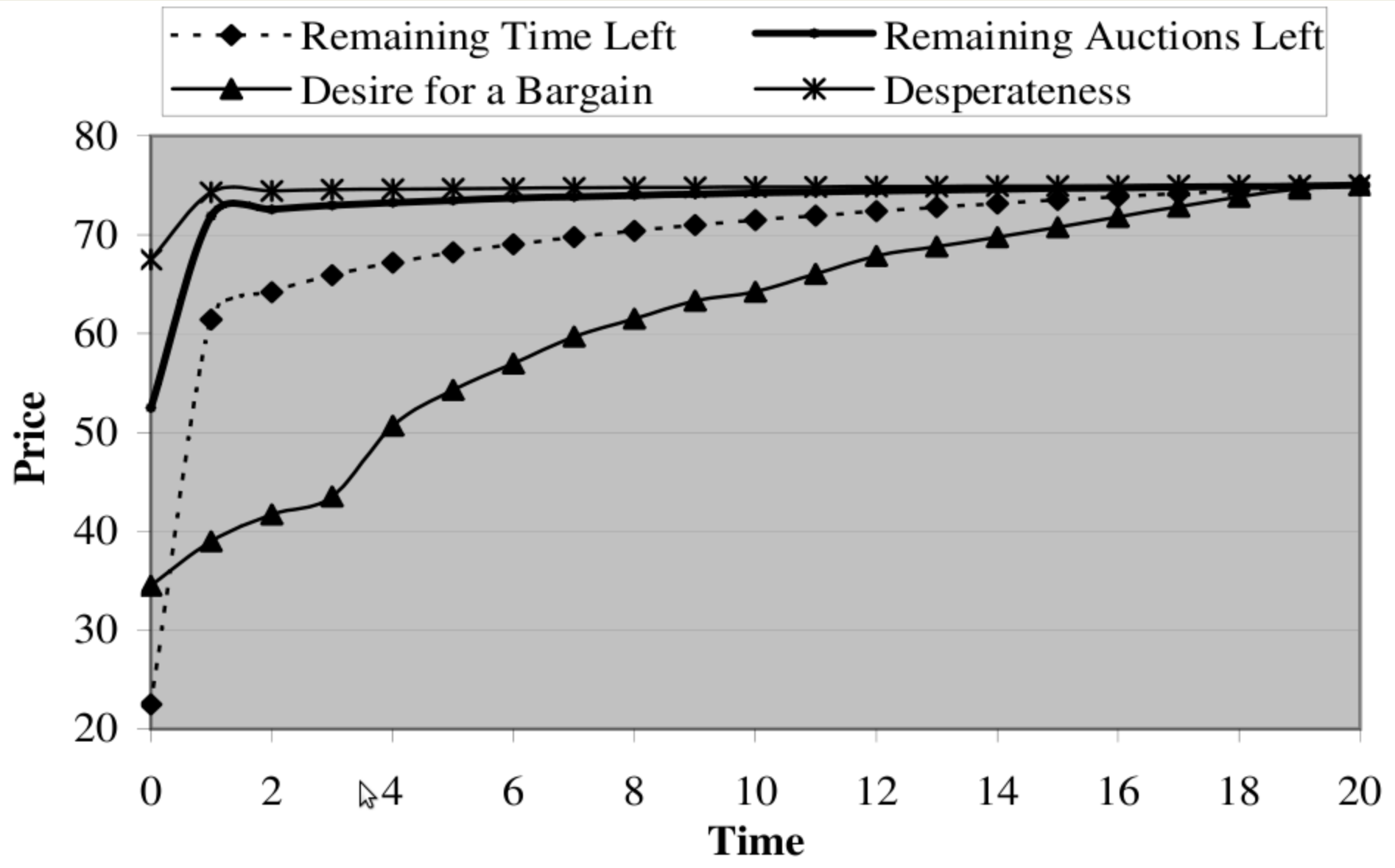
Bidding constraints Bidding value

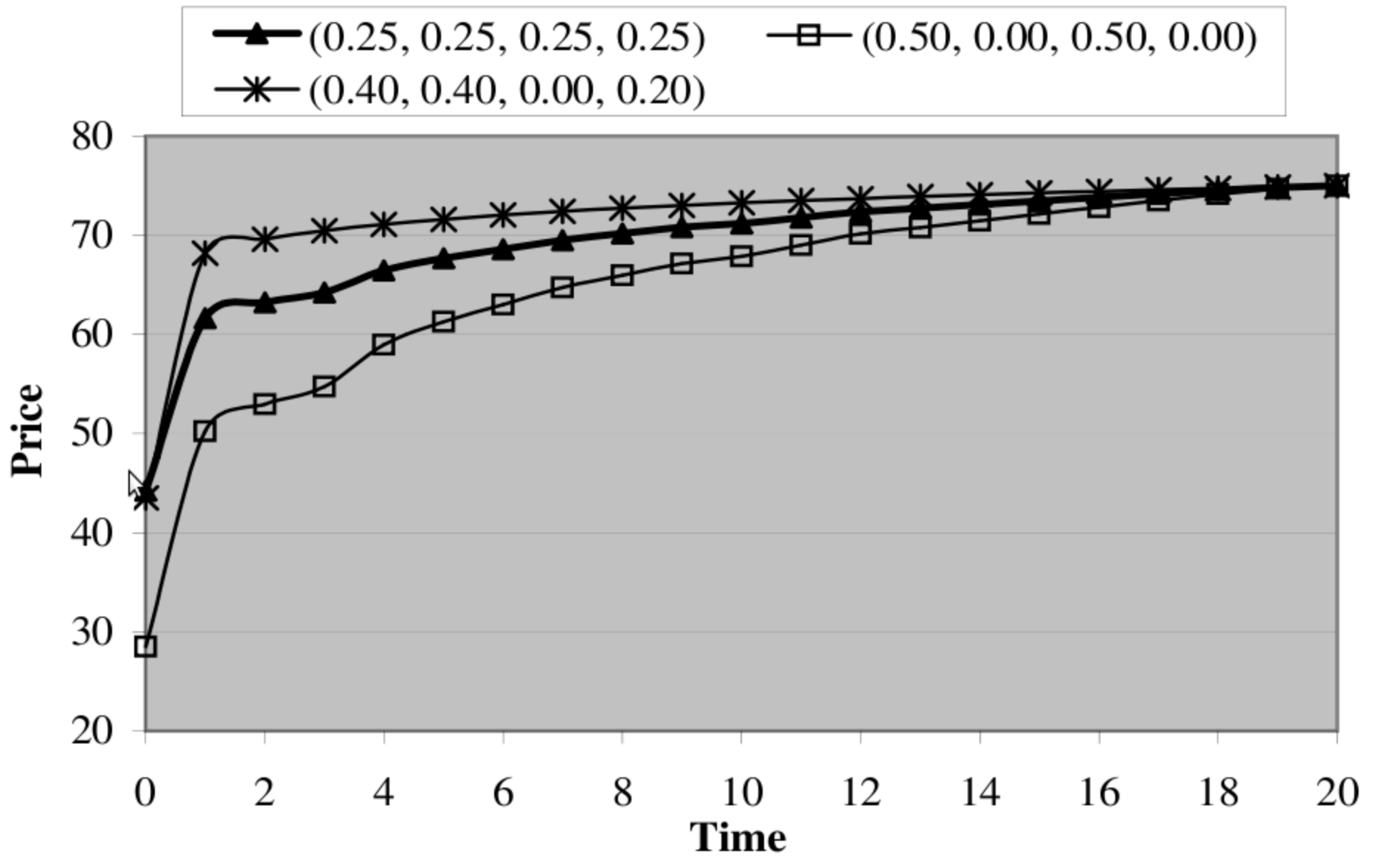


Function with two parameters

k - range [0..1] starting bidding value ($k * p_r$)

β - range [0.005..1000] rate of concession to p_r


Remaining Time Left
Remaining Auctions Left
Desire for a Bargain
Desperateness
80
70
60
50
40
30
20
Price
0
2
4
6
8
10
12
14
16
18
20
Time


(0.25, 0.25, 0.25, 0.25)
(0.50, 0.00, 0.50, 0.00)
(0.40, 0.40, 0.00, 0.20)
Price
80
70
60
50
40
30
20
0
2
4
6
8
10
12
14
16
18
20
Time

Early experiments results:

- p_r is the most effective factor
- successful strategies require precise definition of the environment's characteristics
- the key defining characteristics of environment is the number of auctions that are active before t_{max}

Evolving Strategies:

- performance relates to strategy
- strategy is based on k, β, and weights on bidding constraints
- so number of strategies is infinite!
- use GAs to search for strategy
- do the search assuming that agent knows which strategies are effective in which environment , and can assess the environment accurately

Categories of Environments:

1. agent private value

   RP1 → Low RP2 → Medium RP3 → High

2. agent behavior

   FE1 → Desperate FE2 → Bargain FE3 → Balance

3. bidding Time and number of Auctions

   x T y A x → Short; Medium; Long y → Less; Many

Ex: RP1 FE2 STMA

RP1	FE1	STLA	RP2	FE1	STLA	RP3	FE1	STLA
		STMA			STMA			STMA
		MTLA			MTLA			MTLA
		MTMA			MTMA			MTMA
		LTLA			LTLA			LTLA
		LTMA			LTMA			LTMA
	FE2	STLA		FE2	STLA		FE2	STLA
		STMA			STMA			STMA
		MTLA			MTLA			MTLA
		MTMA			MTMA			MTMA
		LTLA			LTLA			LTLA
		LTMA			LTMA			LTMA
	FE3	STLA		FE3	STLA		FE3	STLA
		STMA			STMA			STMA
		MTLA			MTLA			MTLA
		MTMA			MTMA			MTMA
		LTLA			LTLA			LTLA
		LTMA			LTMA			LTMA

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Experimental Evaluation:

1. to show that intelligent bidding strategy perform effectively in wide range of bidding contexts
2. to understand what will happen when there are multiple such agents in the environment

Experimental Evaluation Model:

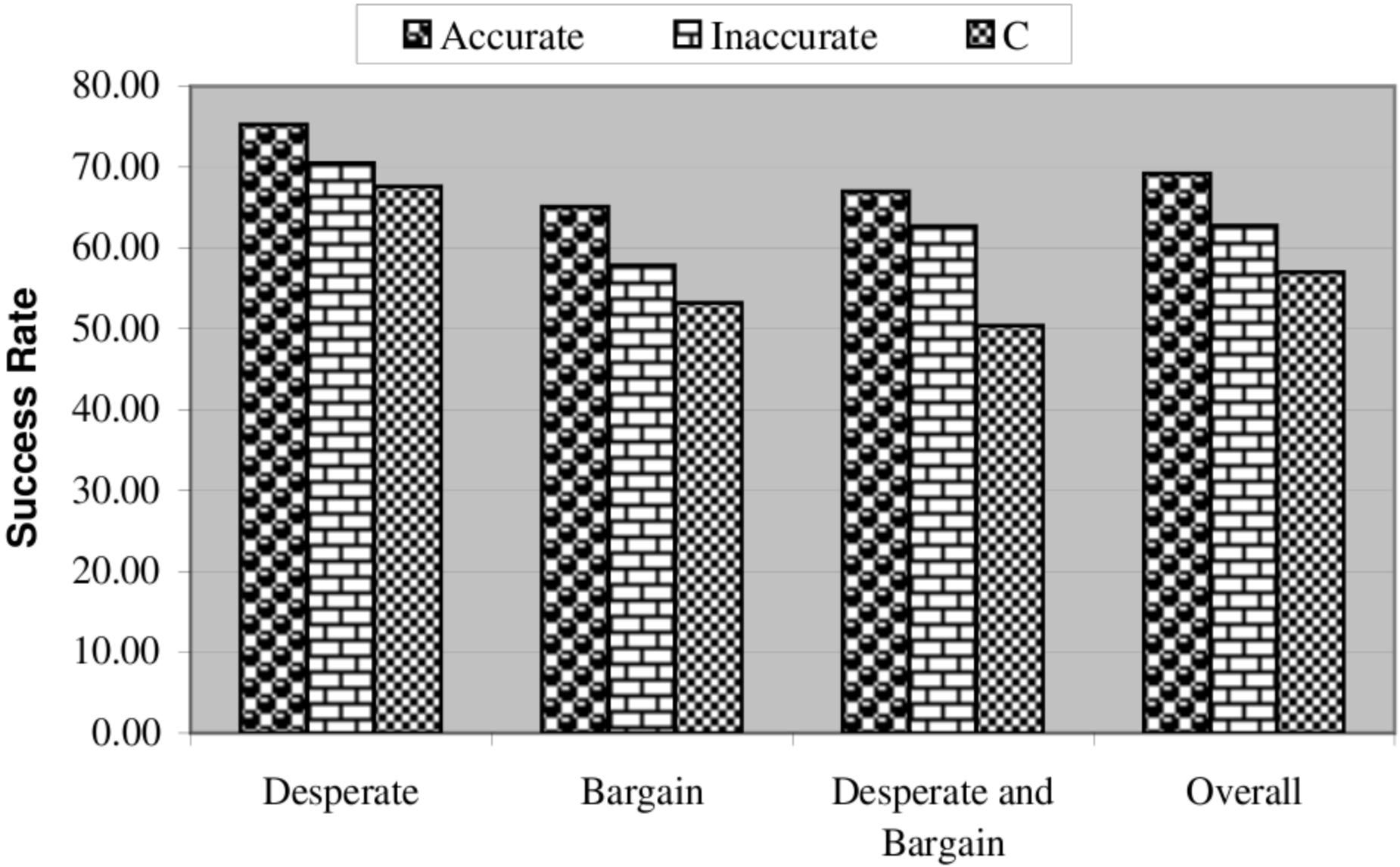
1. Accurate Agent – correctly determine environment
2. Inaccurate Agent – incorrectly determines environment

Actual Environment	Inaccurate Prediction
Short	Medium
Medium	Short
Long	Medium

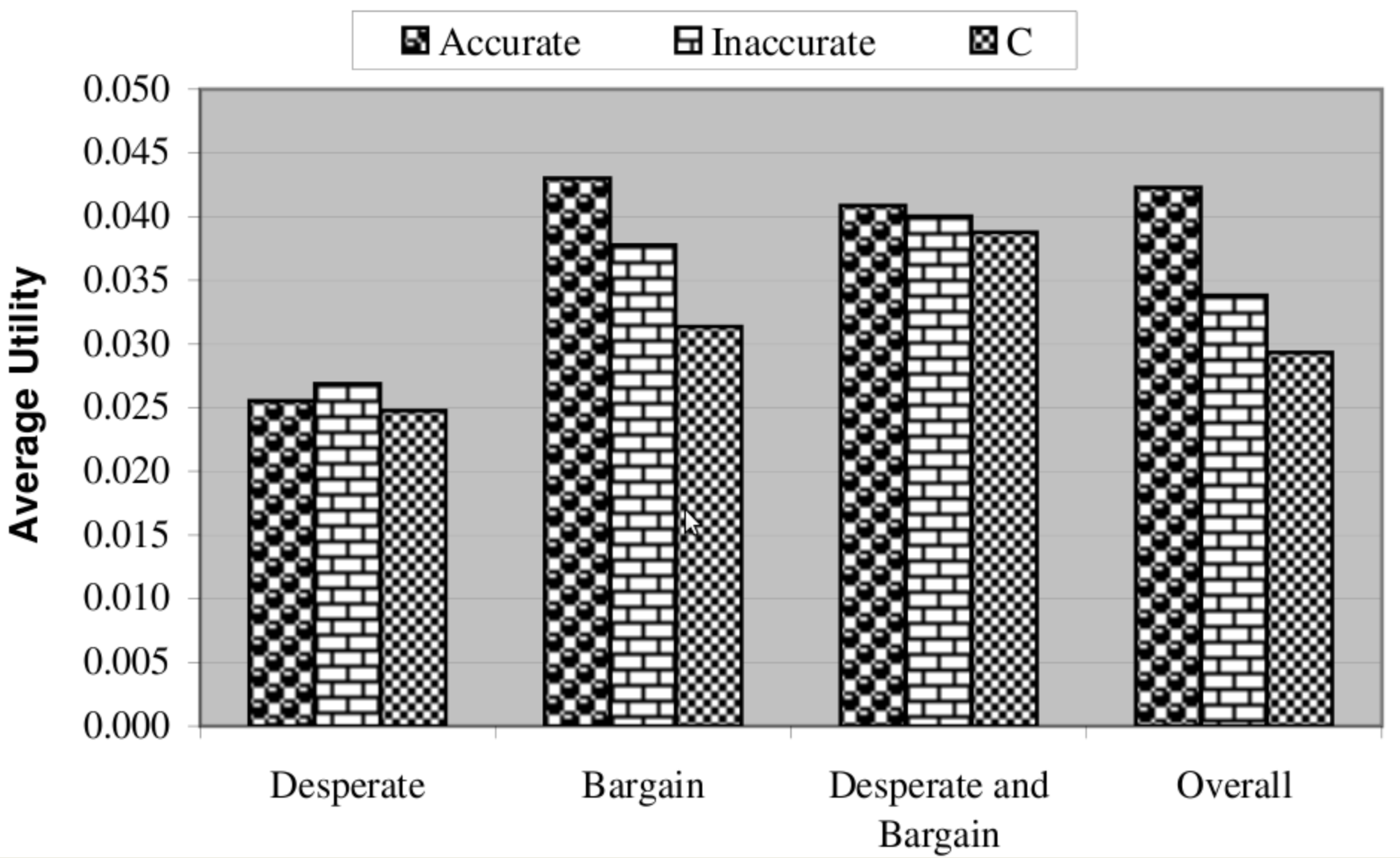
3. Agent C – fixed strategy

- bargain: RP2 FE2 MTMA
- desperate: RP2 FE1 MTMA
- both: RP2 FE3 MTMA

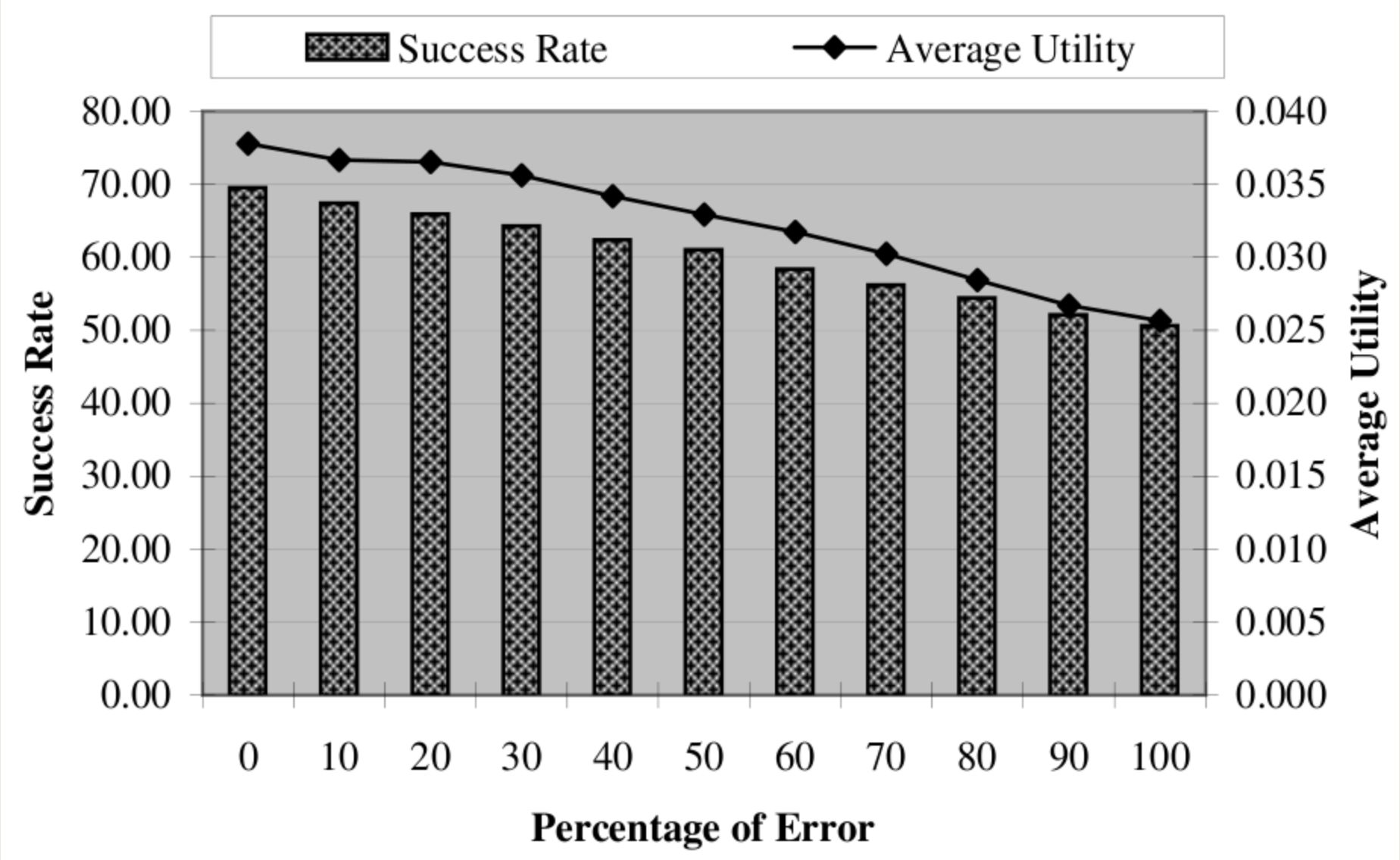
Success Rate Comparison



Average Utility Comparison



Agent's Performance with Varying Environment Prediction Accuracy



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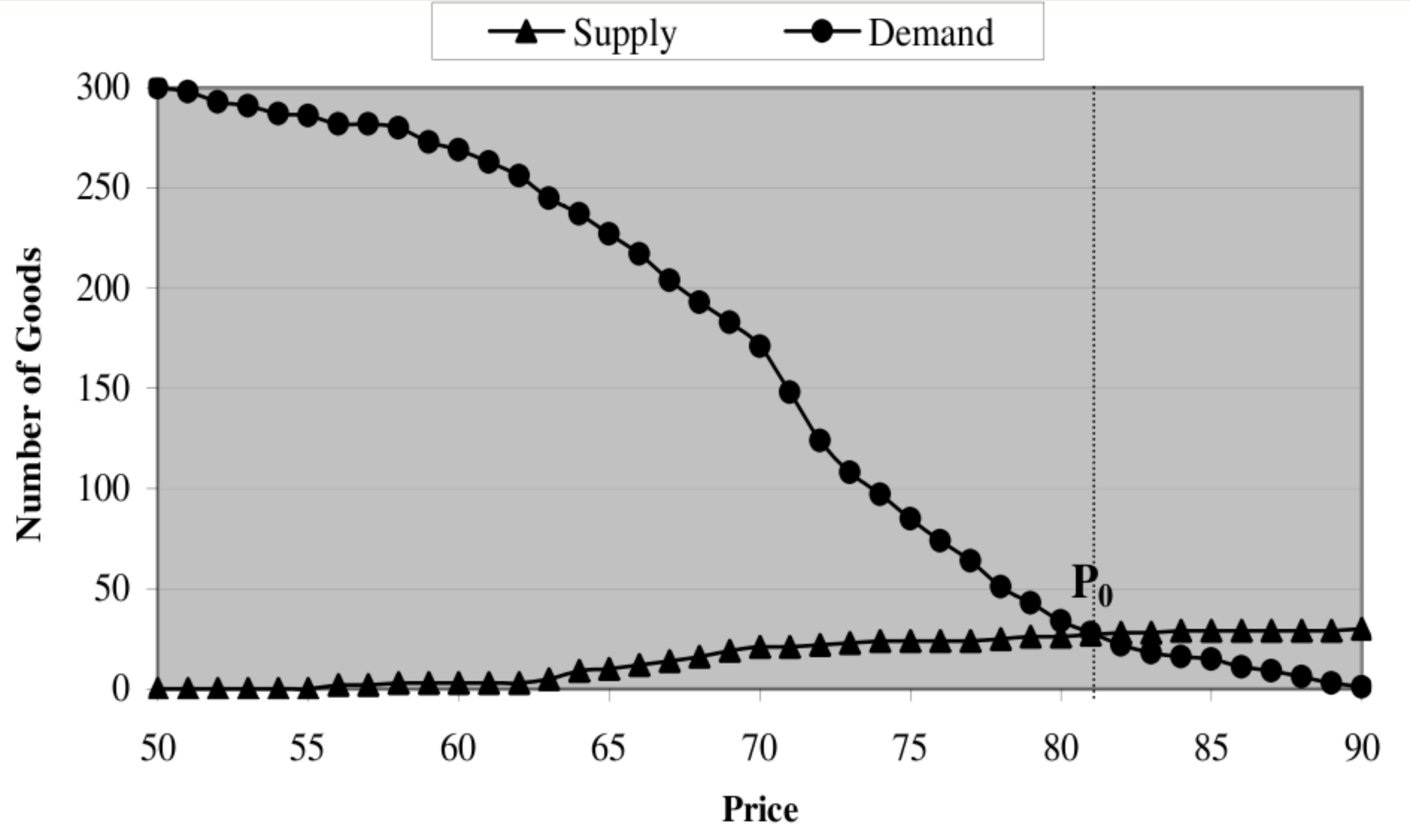
Market Model:

1. Dummy Bidder
   - have intention and poses behavior
   - maintain information about target, private value starting bid, and increment
   - values generated randomly from standard probability distribution
2. Intelligent Agent
   - have individual an environmental parameters
   - values generated as in dummy bidders
3. Set equilibrium: price at 81 and quantity at 25

Supply and Demand Curve for the Market



Effectiveness of the Market:

Allocative efficiency is defined as the total actual profit earned by all the sellers divided by the maximum total profit that could have been earned in an ideal market (expressed as percentage)

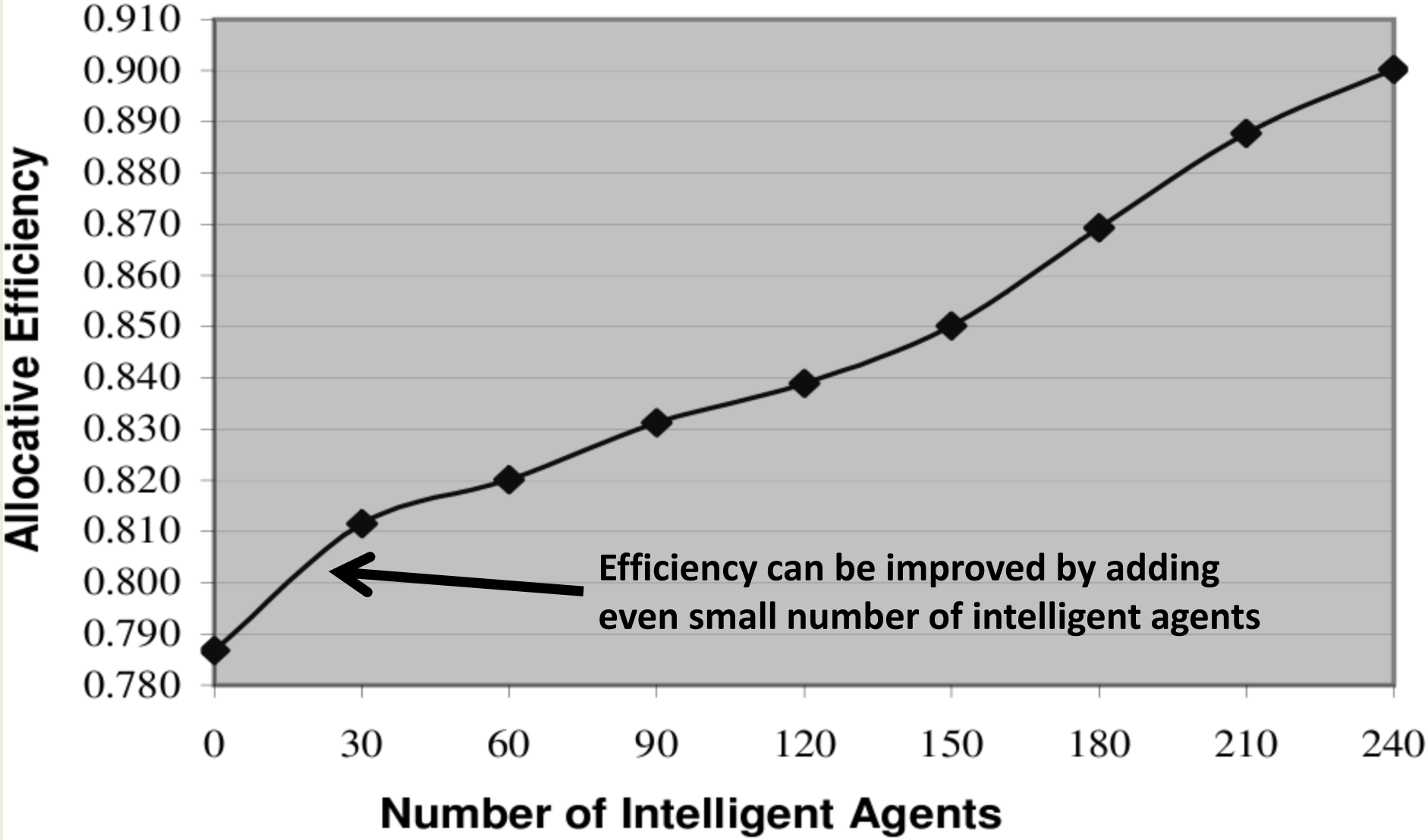
Smith's Alpha coefficient measures how close the actual trade prices are to the equilibrium, $\alpha = 100 * \sigma_0 / P_0$, where σ_0 is the standard deviation of trade prices around P_0.

The Bidder's Average Utility

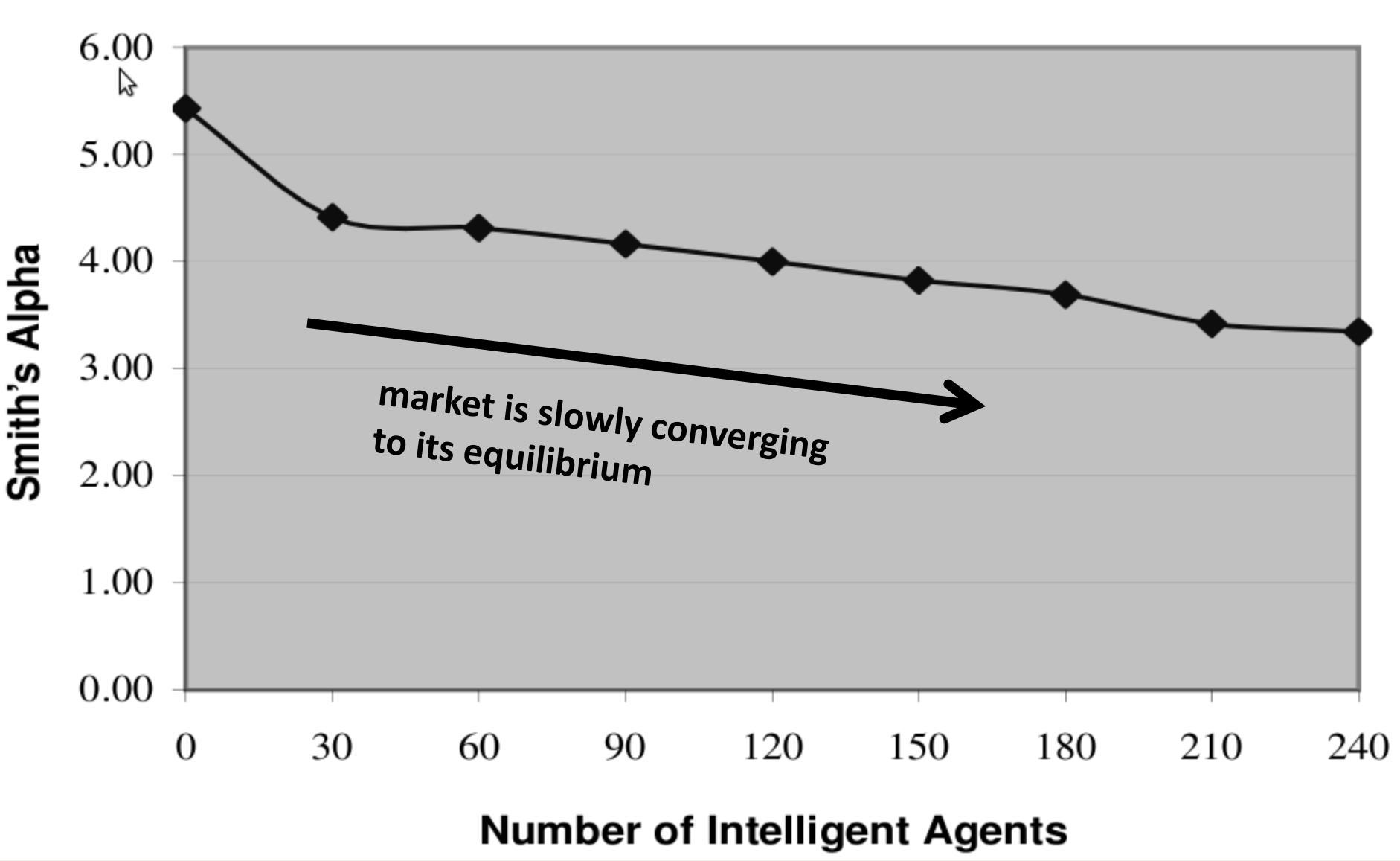
Number of Intelligent Agents	Intelligent Agents		Dummy Bidders	
	Average Utility	Average Number of Auctions Won	Average Utility	Average Number of Auctions Won
0			0.003419	26.85
30	0.007401	5.00	0.002807	20.70
60	0.006836	9.90	0.002593	16.60
90	0.006180	12.20	0.002509	14.65
120	0.004716	13.00	0.002490	11.80
150	0.004584	15.65	0.002254	9.45
180	0.004507	18.50	0.002090	6.50
210	0.004343	19.30	0.001846	4.70
240	0.003819	20.10	0.001410	2.55

- total 300 agents
- start with 0 intelligent agents and then increase by 30

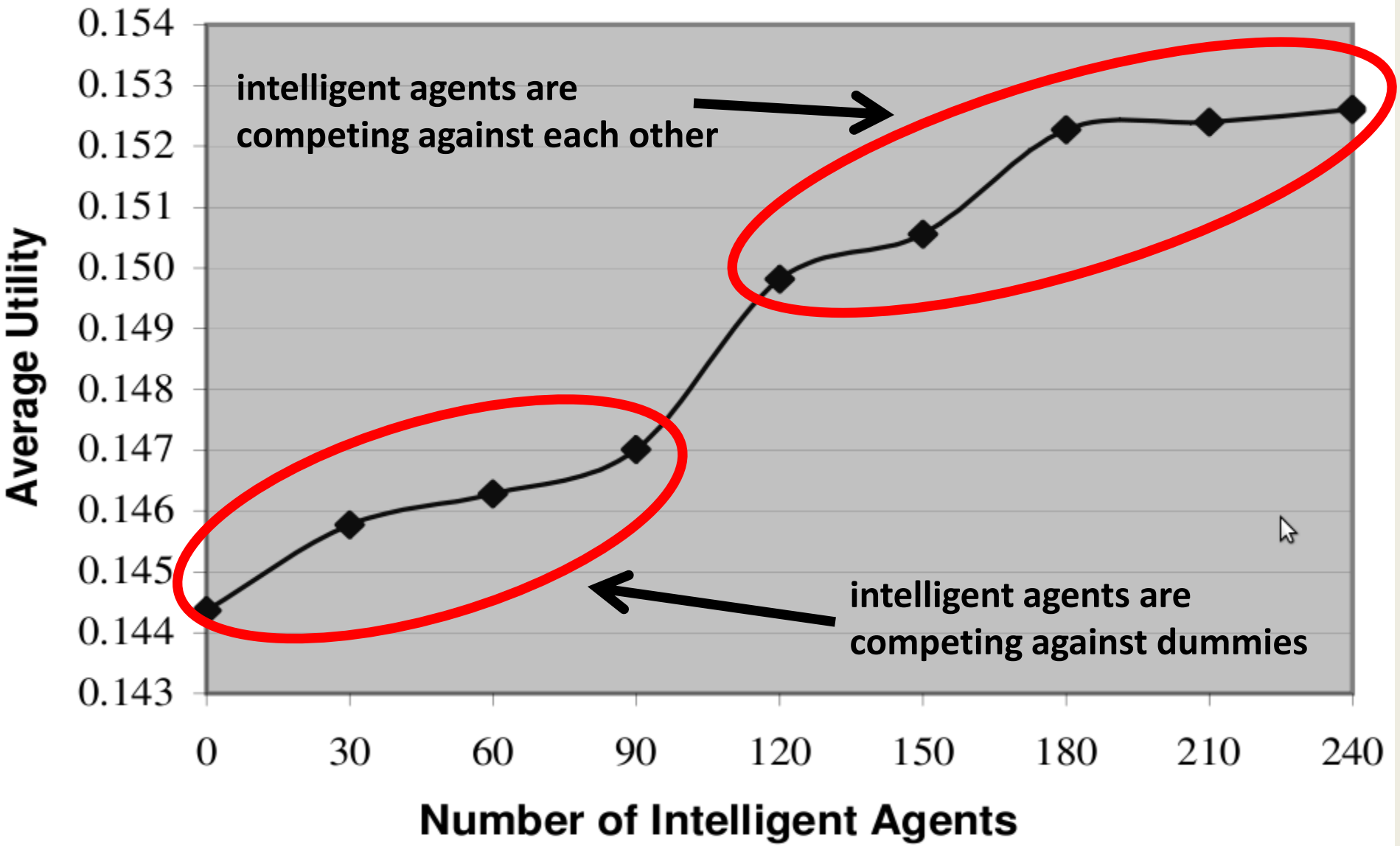
Number of Intelligent Agents vs. Allocative Efficiency



Number of Intelligent Agents vs. Smith's Alpha



Number of Intelligent Agents vs. Average Utility



Experiment Summary:

- intelligent bidding strategy can perform effectively in a wide range of environments
- achieves high success rate and average utility
- achieves high utility between many intelligent agents

Conclusion:

"… as the number of on intelligent agents increases, the market efficiency increases which, in turn, leads to an increase in profit to the sellers."

Future Work:

Determine methods such that agent can quickly and accurately determine the type of trading environment

Questions?

Thank You,

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