Learning strong-substitutes demand correspondences

Edwin Lock joint work with Paul W. Goldberg and Francisco Marmolejo Department of Computer Science, University of Oxford 7 April, 2020

Introduction

Auctions - demand correspondences

Consider an auction setting with goods $\{1, \ldots, n\}$, where goods are available in multiple items.

Bidders need to communicate their demand to the auctioneer, in some fashion.

Bidders have a **demand correspondence** mapping price vectors $p \in \mathbb{R}^n$ to bundles demanded at those prices.

$$D(\mathbf{p}) := \{ \text{bundles demanded at } \mathbf{p} \}$$

Quasi-linear demand correspondences

Classic definition

The valuation function v assigns a value to each bundle $x \in \mathbb{Z}^n$.

The demand correspondence is defined as

$$D_{v}(\textbf{p}) := \operatorname*{arg\,max}_{\textbf{x} \in \mathbb{Z}^{n}} (v(\textbf{x}) - \textbf{p}.\textbf{x}).$$

(We assume quasi-linear utilities v(x) - p.x.)

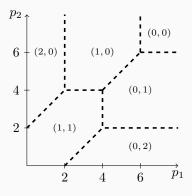
Geometric approach (uses tropical geometry)

Theorem (Baldwin and Klemperer, 2019)

For every integral valuation, the demand correspondence $D_{\nu}(p)$ partitions price-space into an weighted integral polyhedral complex.

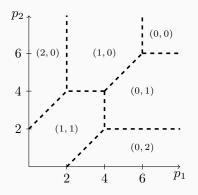
Strong-substitutes demand

Example demand with two goods



Strong-substitutes demand

Example demand with two goods



Theorem (Baldwin and Klemperer, 2019)

A demand correspondence is **strong substitutes** iff its facets are normal to e^i or $e^i - e^j$ for some $i, j \in \{1, ..., n\}$.

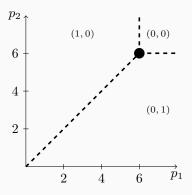
Representing a demand correspondence

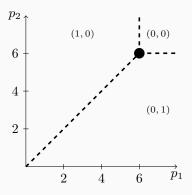
How to represent demand?

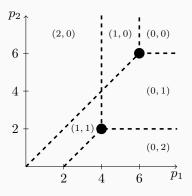
- Valuation
- Facets
- Vertices

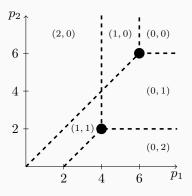
The Product-Mix Auction [Klemperer 2009] introduces a **dot-bid** language.

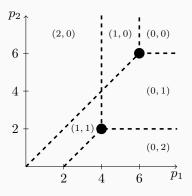
Finite set of special (weighted) points in price space that define demand correspondence.



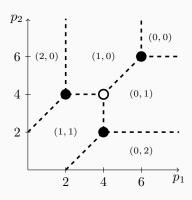




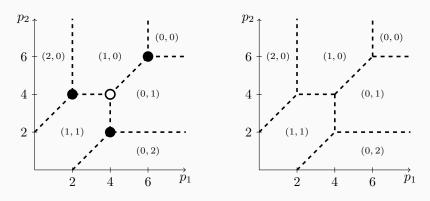




Dot bid example



Dot bid example



Theorem (Baldwin and Klemperer, in preparation)

Every strong-substitutes demand correspondence can be expressed uniquely as a list of positive and negative dot bids.

The converse does not hold!

Learning dot-bid lists

Suppose a bidder wishes to participate in the product-mix auction.

- In high dimensions (=many goods), it is not clear how to construct the list of dot bids ad hoc.
- A bidder may not have full information about their valuation or demand correspondence (in geometric or algebraic terms).

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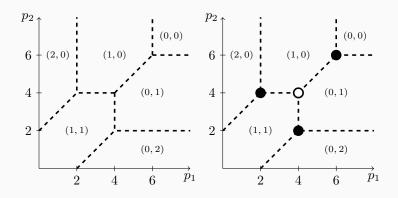
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Challenge: Provide an algorithm that outputs the list of dot bids corresponding to a bidder's strong-substitutes demand.

We assume a **demand oracle** $\delta(p)$, which returns a bundle demanded at prices p.



Output: three positive bids at (2,4),(4,2) and (6,6), one negative bid at (4,4).

Our results

Challenge: Provide an algorithm that determines the list of dot bids corresponding to a bidder's strong-substitutes demand using access only to $\delta(\cdot)$.

Measure query complexity, in terms of size of output: number of goods n, number of bids B, and $\log M$, where $M = \max_b \|b\|_{\infty}$.

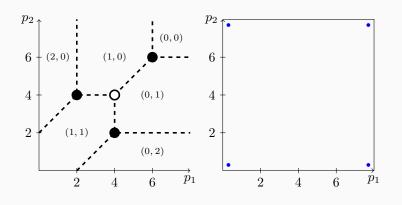
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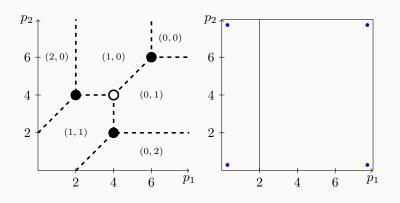
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Main results

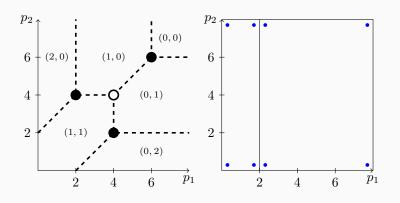
- A linear-time algorithm for learning bid lists in the case that all bids are positive (not discussed today).
- An exponential algorithm for the general case where bids can be positive and negative.
- A super-polynomial lower bound on the query complexity in the general case.



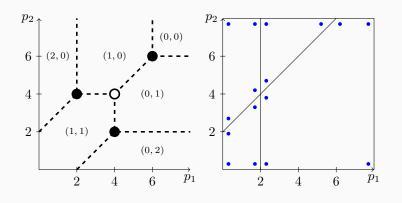
Stage 1: Learn all hyperplanes that contain a facet.



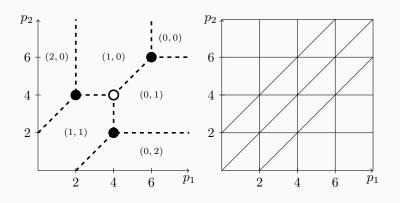
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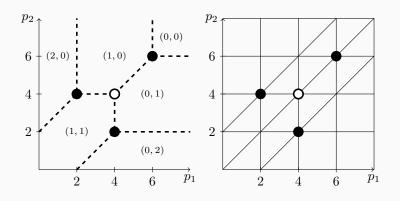
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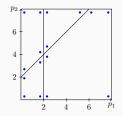
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Stage 2: Check all intersections of n hyperplanes for the presence of a bid.

Query complexity



The hyperplane-finding algorithm has worst-case query complexity

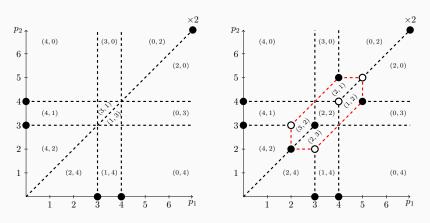
$$\underbrace{\binom{\binom{n}{2}}{n}2^n n!}_{\text{cost of intersection queries}} + \underbrace{O\left(\binom{n}{2}\log M\right)}_{\text{cost of binary searching}}.$$

For n constant, this is

$$O(B^n + B\log(M))$$
.

Island gadget lower bound

We introduce an island gadget.



The island gadget requires 2^{n+1} bids in n dimensions.

Island gadget lower bound

An **adversary** plays a game in which he places the gadget at one of $(M/4)^n$ candidate locations.

As a gadget only changes demand locally, a **player** must query inside the gadget to detect its presence.

Using this idea, it can be shown that

$$\Omega\left(\left(\frac{B-2^{n+1}}{8n^2}\right)^n\right)$$

queries are required to learn the location of the gadget.

For *n* constant, this is

$$\Omega(B^n)$$
.

Outlook

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Our algorithms are interesting beyond their immediate application to the product-mix auction.

- Dot bids are a natural way to represent demand correspondences.
- The size of the bid list may be a good measure of the complexity of a demand correspondence.

Thank you!

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Questions or comments? Please feel free to email me at edwinlock@gmail.com.