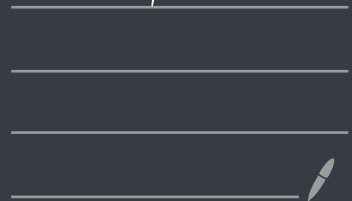


Geometry Helps to Compare PDs

(part 2)

11/16/2022



Plan:

hand
work

- Recall Wasserstein distance
- Combinatorial Methods to compute it (auction algos)
- Geometric Adaptations (kd trees)
- Experimental findings

Botleneck Distance (∞ -Wasserstein)

$$W_\infty(X, Y) = \inf_{\eta: X \rightarrow Y} \sup_{x \in X} \|x - \eta(x)\|_\infty$$

q -Wasserstein Distance

$$W_q(X, Y) = \left[\inf_{\eta: X \rightarrow Y} \sum_{x \in X} \|x - \eta(x)\|_\infty^q \right]^{1/q}$$

Fix $q \geq 1$ and compute q -Wasserstein cost in
bipartite weighted graph $G = (\underbrace{U \cup V}, E, \underbrace{w: E \rightarrow \mathbb{R}^+})$

Idea Auction Algorithm (Bertsekas, 1974)

$u \in U$ are "Bidders"

$v \in V$ are "Objects"

$w(e)$, $e \in E$, are benefits between Bidders + Objects

price $p_v = 0$ initially

value $(u, v) = (w(u, v) - p_v)$

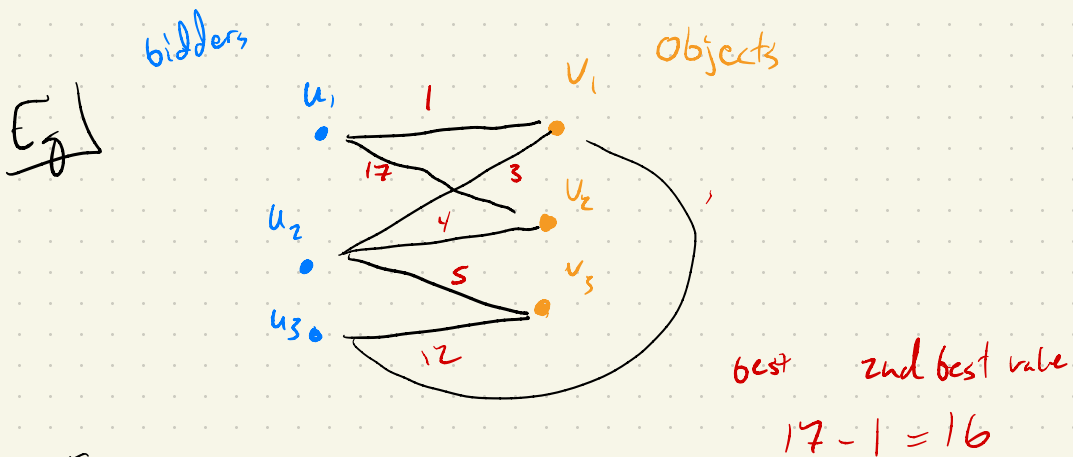
At each iteration, an unassigned bidder u

chooses object v with maximal value

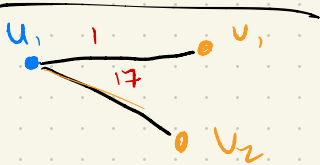
object v is assigned to u

Let $\Delta p_{u,v}$ be the difference between highest value at u and second highest.

Then $p_v = p_v + \Delta p_{u,v}$ for next iteration.



Iteration 1:



$$w(u_1, v_1) = 1$$

$$w(u_1, v_2) = 17$$

$$p_{v_1} = 0, p_{v_2} = 0$$

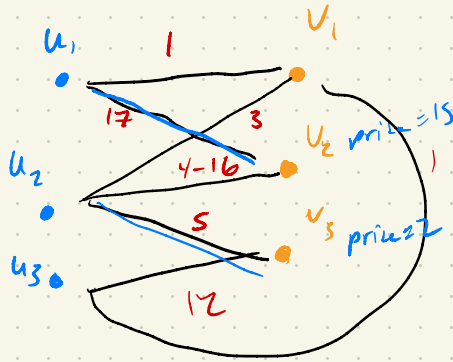
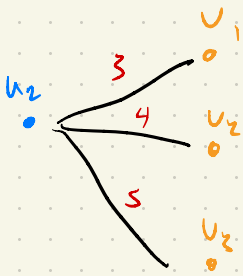
$$\text{value}(u_1, v_1) = 1$$

$$\text{value}(u_1, v_2) = 17$$

choose u_1, v_2

$$\underline{p(v_2)} = 0 + 16 = \underline{16} \text{ for next round.}$$

Iteration 2:



$$\text{value}(u_2, v_1) = 3 - 0 = 3$$

$$\text{value}(u_2, v_2) = 4 - 16 = -12$$

$$\text{value}(u_2, v_3) = 5 - 0 = 5$$

choose

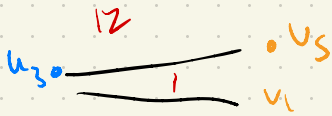
best 2nd best

$$p(v_3) = 5 - 3 = 2 + \epsilon$$

initial

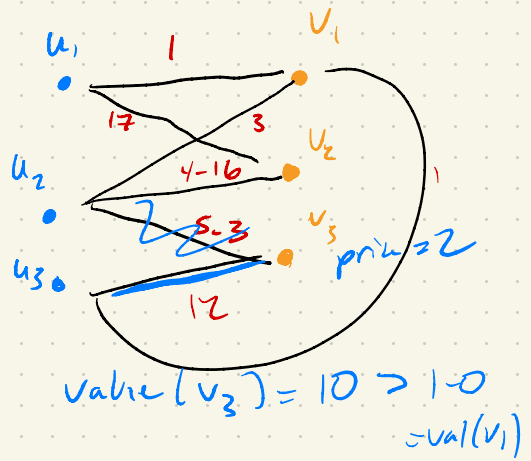
$$p(v_3) = 0 + 2 + \epsilon$$

Iteration 3:

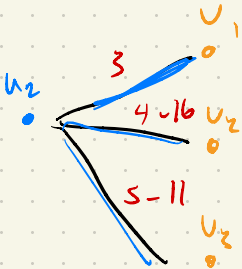


$p_{v_5} = 12 - 1 = 11 + \epsilon$ for next iteration,

u_2 is now out bid

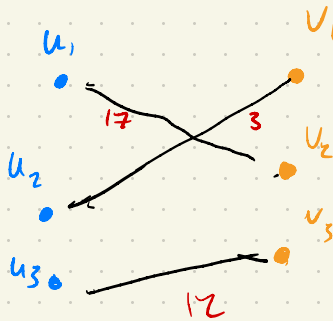


Iteration 4:



pair u_2, v_1

and we're done!



Remarks:

Another version: Jacobi Auction, every unassigned bidder makes a bid at each iteration. If several bidders want the same object, it goes to whoever has highest price increase.

This version is more expensive, on average (esp) many objects have same price for many bidders.



X auction also from 1974 is way 2 go!

Choosing ϵ : Note, the smaller the ϵ , the longer the time of convergence for the auction. But, the more precise a solution.

can compute q -Wasserstein distance with this procedure.

Fixing an approximation parameter $\delta \in (0, 1)$, let d denote the q th root of the value of an obtained matching in the algorithm.

Conclude algorithm if:

$$d^q \leq (1 + \delta)^q (d^q - n \varepsilon),$$

and return d .

We can turn these matchings into q -Wasserstein distance by taking q th roots + q th powers of L_∞ distances.

Conclude algorithm when matching is optimal, up to error term δ .

Formally,

ALGORITHM 1: AUCTION ALGORITHM

Input: Two persistence diagrams X, Y with $|X|, |Y| \leq n, q \geq 1, \delta > 0$ (maximal relative error)

Output: δ -approximate q -Wasserstein distance $W_q(X, Y)$

Initialize $d \leftarrow 0$ and $\varepsilon \leftarrow \frac{5}{4} \cdot (\text{max. edge length})$

while $d^q > (1 + \delta)^q (d^q - n\varepsilon)$ **do**

$\varepsilon \leftarrow \varepsilon/5$

Let M be an empty matching

while there exists some unassigned bidder i **do**

Find the best object j with value v_{ij} and the second best object k with value v_{ik} for i

Assign j to i in M and increase the price of j by $(v_{ij} - v_{ik}) + \varepsilon$

$d \leftarrow q$ -th root of the cost of the (perfect) matching M

return d

What is the crux?

Bidding: Comparing max value object + price increase is tricky!

Brute Force: Exhaustive search over all objects per bidder

Lazy heaps: Keep a heap for each bidder of object values

uses $O(n^2)$ space

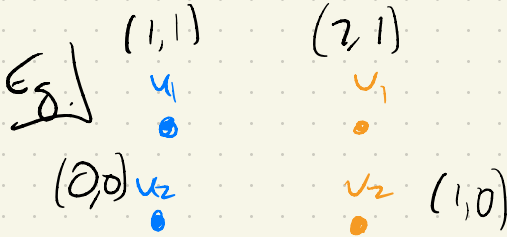
Geometry: Use a k -d tree with $O(n)$ space

Geometry:

Need to configure a k-d tree

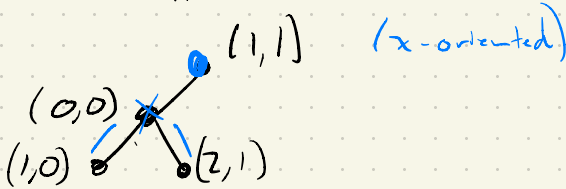
- Initially, when prices are zero,

find best two objects by proximity search.

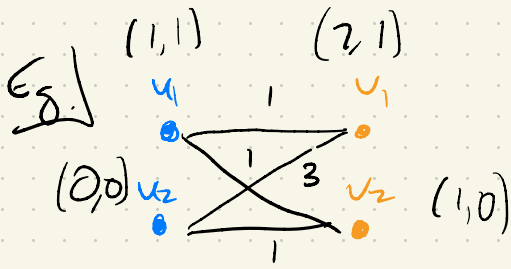


k-d tree

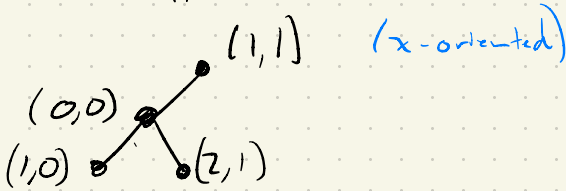
(when all prices are zero)



Need to take changing prices
into account

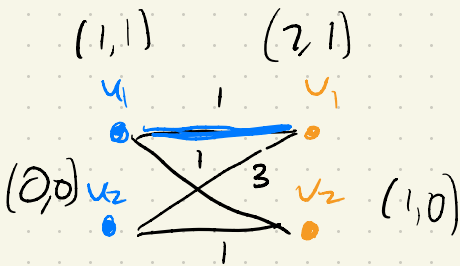


k-d tree



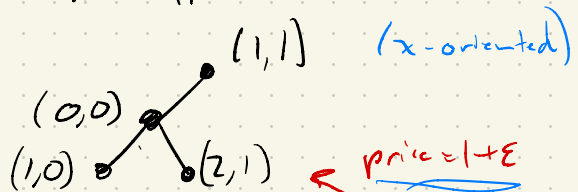
Store prices as weights in k-d tree!

Record minimum weight of any node in subtree of internal nodes.

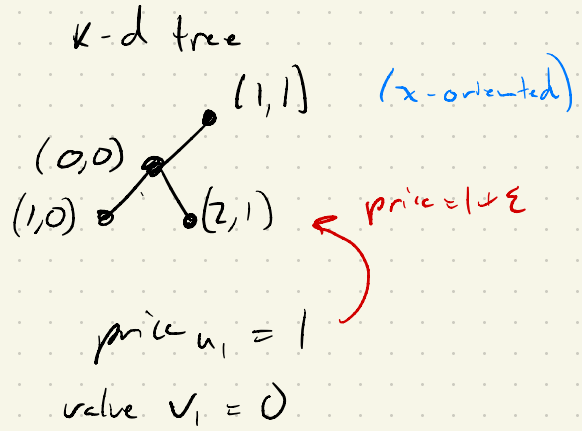
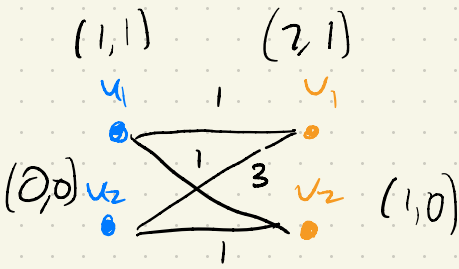


pair $(1,1), (2,1)$
 u_1 v_1

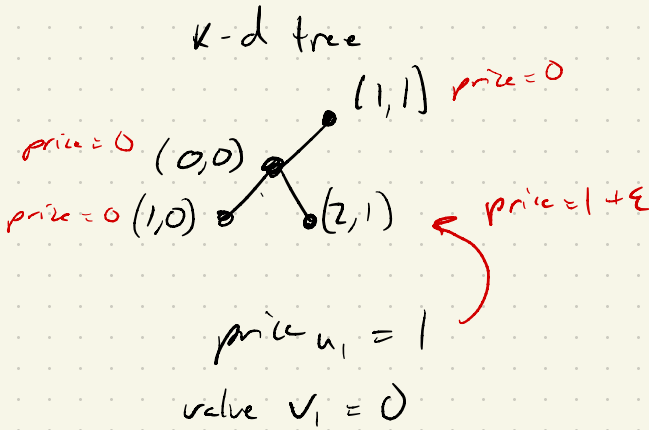
k-d tree



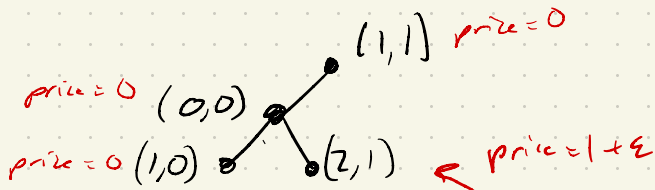
price $u_1 = 1$
 value $v_1 = 0$



Save minimum weight of any node
in subtree of internal nodes



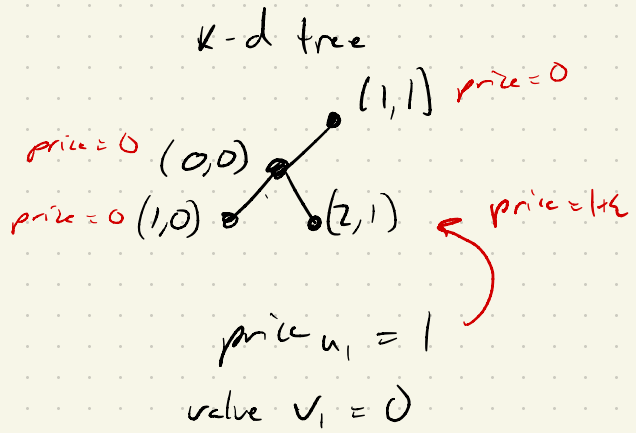
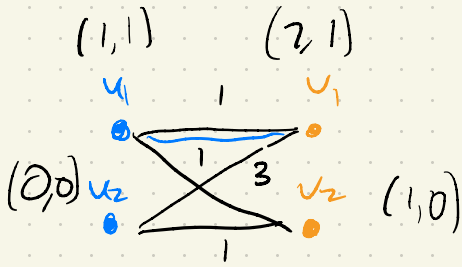
k-d tree



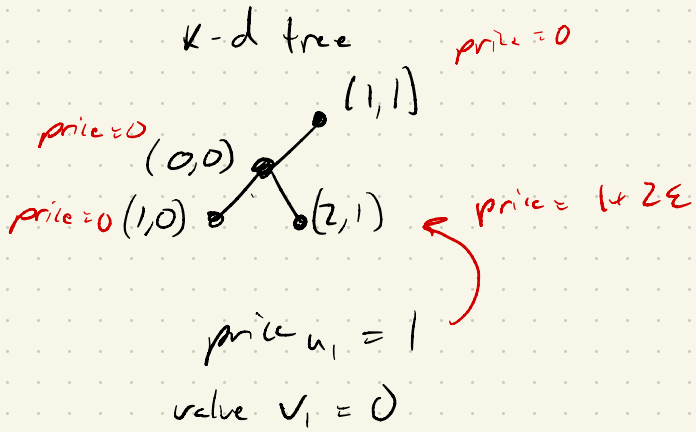
$$\text{price } u_i = 1$$

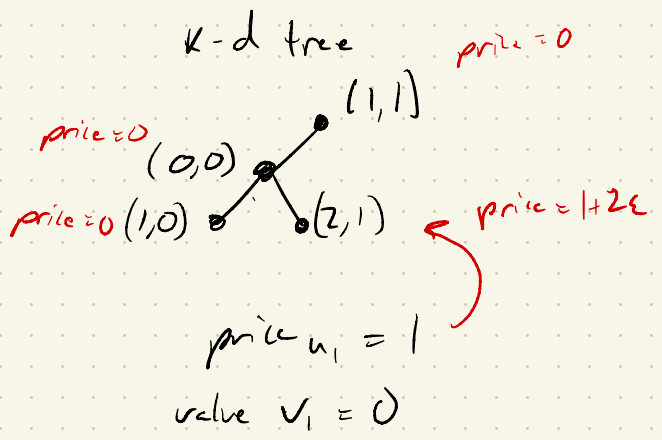
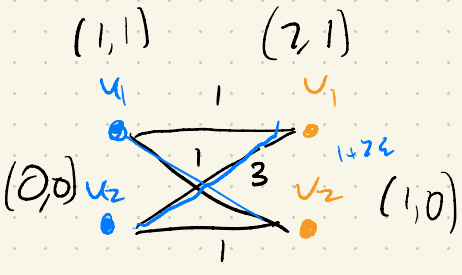
$$\text{value } v_i = 0$$

prune subtrees if q^{th} power of distance
from query point to the box containing
subtree plus minimum weight in subtree
exceeds second best candidate

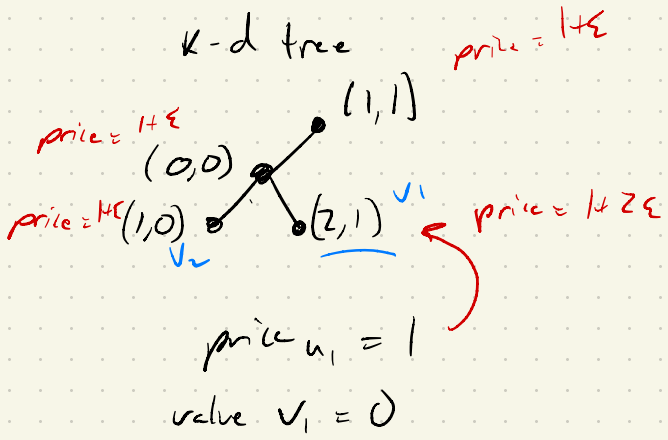


pair
 u_2, v_1
price v_1
 $= 1 + \epsilon + \epsilon$





pair
 u_1, v_2

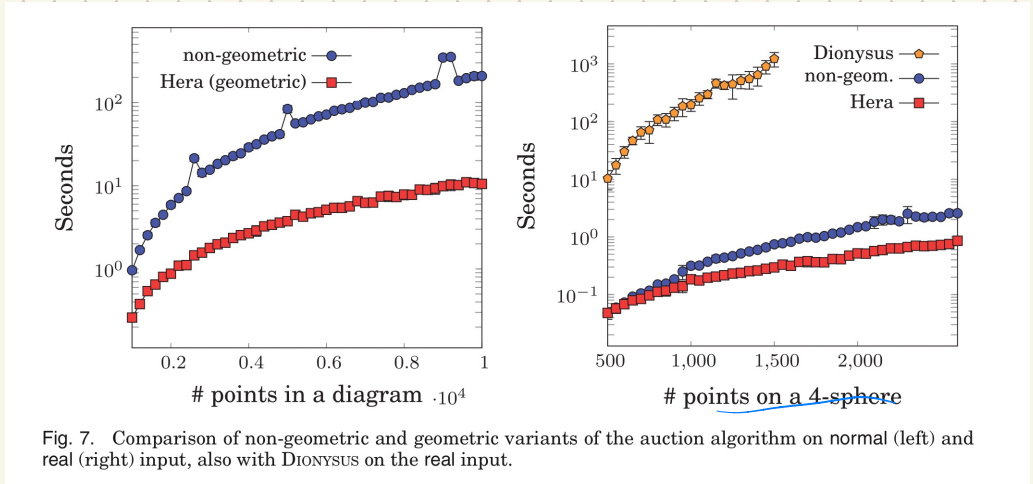
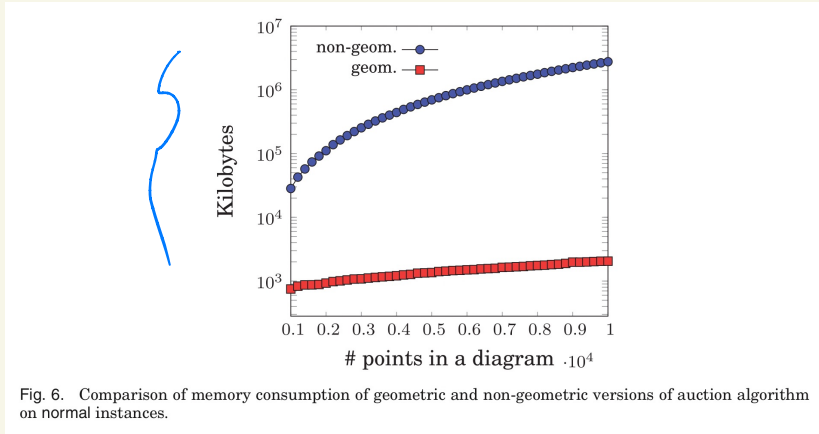


Persistence Diagrams Need Extra Care

↳ Diagonal bidders can only bid for one object

↳ Off-diagonal bidders can bid for every off-diagonal object but only one on-diagonal object (its projection)

Experimental Results:



More on repeated parts in paper...

Similar techniques implemented using kd trees.

Takeaways:

- In matching-related problems, kd trees are a great data structure to use if matching occurs in a metric space
- One can tweak kd trees to consider changing variables relevant for matching (prices for example)
- The best algorithms on paper might be awful to implement!