

## **Advanced Data Structures**

Lecture 11: BSP Trees and Recap

Florian Kurpicz

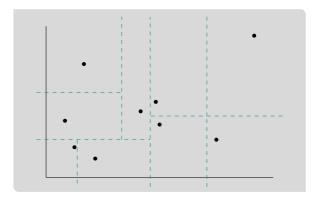




# Recap: 2-Dimensional Rectangular Range Searching

## **Important**

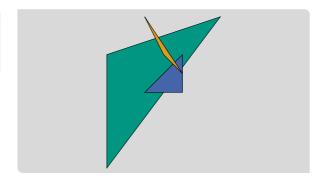
- assume now two points have the same x- or y-coordinate
- generalize 1-dimensional idea
- 1-dimensional
  - split number of points in half at each node
  - points consist of one value
- 2-dimensional
  - points consist of two values
  - split number of points in half w.r.t. one value
  - switch between values depending on depth



## **Motivation**



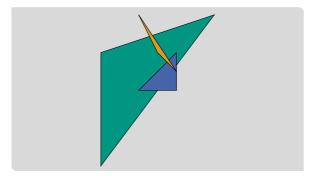
- hidden surface removal
- which pixel is visible
- important for rendering



## z-Buffer Algorithm



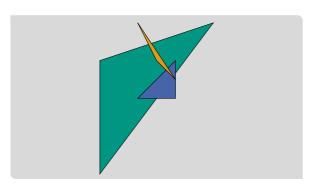
- transform scene such that viewing direction is positive z-direction
- consider objects in scene in arbitrary order
- maintain two buffers
  - frame buffer () currently shown pixel
  - z-buffer ① z-coordinate of object shown
- compare z-coordinate of z-buffer and object



## z-Buffer Algorithm

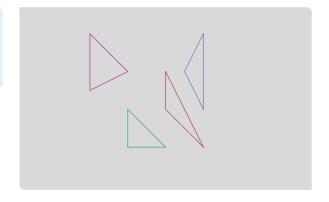


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- consider objects in scene in arbitrary order
- maintain two buffers
  - frame buffer () currently shown pixel
  - z-buffer ① z-coordinate of object shown
- compare z-coordinate of z-buffer and object
- first sort object in depth-order
- depth-order may not always exist <a></a>
- how to efficiently sort objects?



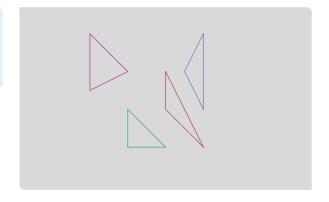


- partition space using hyperplanes
- binary partition of similar to kd-tree
- hyperplanes create half-spaces and cut objects into fragments





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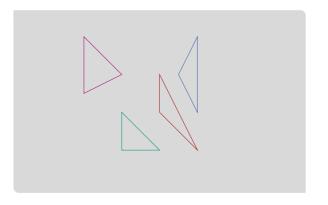




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$$h^+ = \{(x_1, \ldots, x_d) \colon a_1 x_1 + \cdots + a_d x_d > 0\}$$

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$$h^- = \{(x_1, \ldots, x_d) : a_1x_1 + \cdots + a_dx_d < 0\}$$

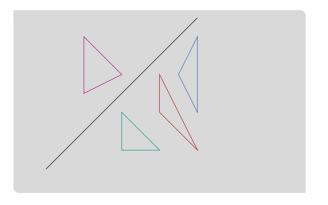




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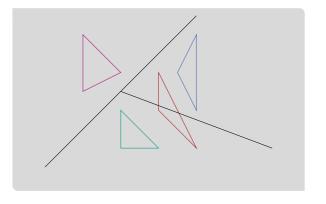




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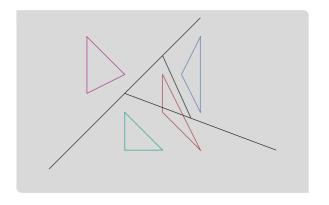




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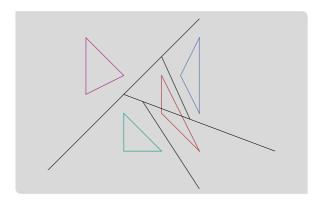




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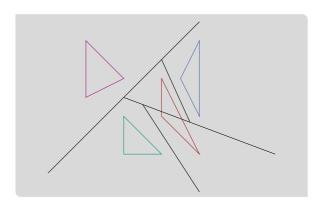


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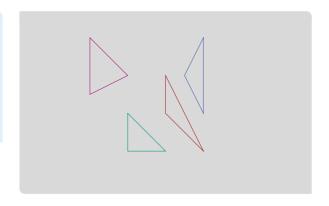
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$$h^- = \{(x_1, \ldots, x_d) : a_1x_1 + \cdots + a_dx_d < 0\}$$

- each split creates two nodes in a tree
- if number of objects in space is one: leaf
- otherwise: inner node



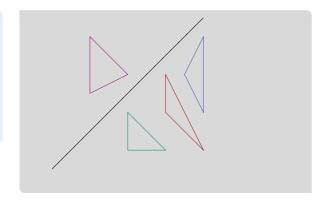


- for leaf: store object/fragment
- for inner node v: store hyperplane  $h_v$  and the objects contained in  $h_v$
- left child represents objects in upper half-space h<sup>+</sup>
- right child represents objects in lower half-space h<sup>-</sup>



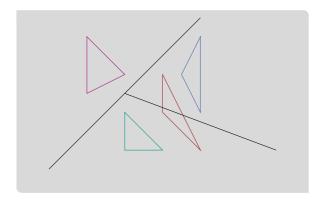


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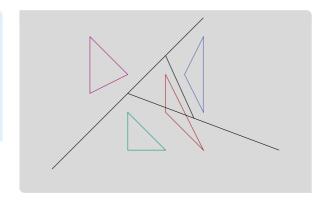


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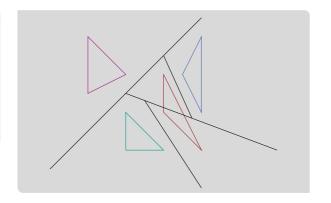


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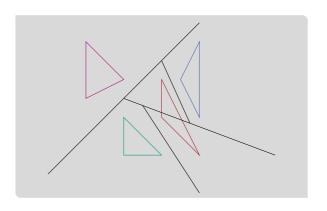


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- space of BSP tree is number of objects stored at all nodes
- what about fragments?
- too many fragments can make the tree big



## **Auto-Partitioning**

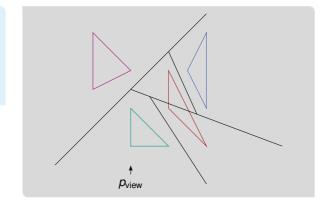


- sorting points for kd-trees worked well
- BSP-tree is used to sort objects in dept-order
- auto-partitioning uses splitters through objects
  - 2-dimensional: line through line segments
  - 3-dimensional: half-plane through polygons

## Painter's Algorithm

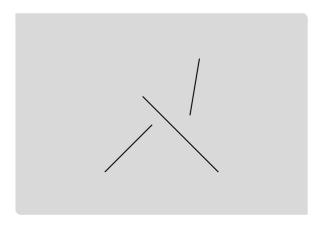


- consider view point p<sub>view</sub>
- traverse through tree and always recurse on half-space that does not contain p<sub>view</sub> first
- then scan-convert object contained in node
- then recurse on half-space that contains p<sub>view</sub>



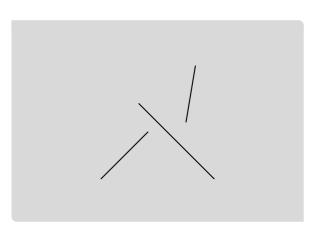


- use auto-partitioning
- construction similar to construction of kd-tree
- store all necessary information
  - hyperplane
  - objects in hyperplane
- how to determine next hyperplane?
- creating fragments increases size of BSP tree



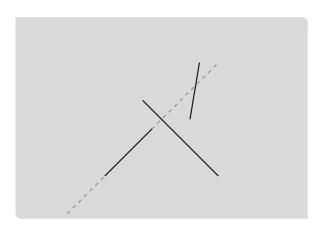


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- let s be object and  $\ell(s)$  line through object
- order matters



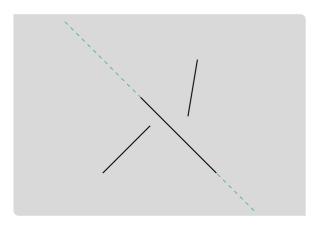


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The expected number of fragments generated when iterating through the line segments using a random permutation is  $O(n \log n)$ 



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### Proof (Sketch

```
distance of lines dist_{s_i}(s_j) = \begin{cases} \# \text{ segments inters. } \ell(s_i) \\ \text{between } s_i \text{ and } s_j \\ \infty \end{cases} \qquad \ell(s_i) \text{ inters. } s_j
```

example on the board <a>П</a>





### Lemma: Number Line Fragments

example on the board <a>=</a>

The expected number of fragments generated when iterating through the line segments using a random permutation is  $O(n \log n)$ 

### Proof (Sketch)

## Proof (Sketch, cnt.)

- let  $dist_{s_i}(s_j) = k$  and  $s_{j_1}, \ldots, s_{j_k}$  be segments between  $s_i$  and  $s_j$
- what is the probability that  $\ell(s_i)$  cuts  $s_i$ ?
- this happens if no  $s_{i_x}$  is processed before  $s_i$
- since order is random

$$\mathbb{P}[\ell(s_i) \text{ cuts } s_j] \leq \frac{1}{\textit{dist}_{s_i}(s_i) + 2}$$





#### Proof (Sketch, cnt.)

expected number of cuts

$$\mathbb{E}[ exttt{# cuts generated by } s_i] \leq \sum_{j \neq i} rac{1}{ exttt{dist}_{s_i}(s_j) + 2} \leq 2 \sum_{k=0}^{n-2} rac{1}{k+2} \leq 2 \ln n$$

all lines generate at most 2n ln n fragments

11/13





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#### Lemma: BSP Construction

A BSP tree of size  $O(n \log n)$  can be computed in expected time  $O(n^2 \log n)$ 



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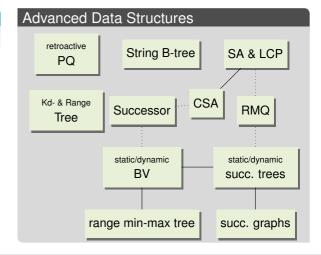
- computing permutation in linear time
- construction is linear in number of fragments to be considered
- number of fragments in subtree is bounded by n
- number of recursions is n log n





#### This Lecture

BSP trees



#### **Conclusion and Outlook**

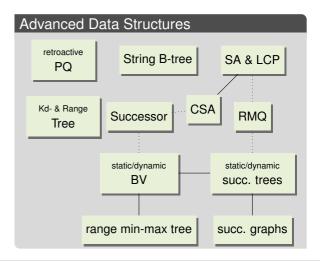


#### This Lecture

BSP trees

#### **Next Lecture**

your presentations





bit vectors



- bit vectors
- succint trees

13/13



- bit vectors
- succint trees
- dynamic bit vectors and trees



- bit vectors
- succint trees
- dynamic bit vectors and trees
- predecessor and RMQ queries



- bit vectors
- succint trees
- dynamic bit vectors and trees
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- suffix array and string B-tree



- bit vectors
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- dynamic bit vectors and trees
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- binary space partitions