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# Implicit Computation Geometry

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# Overview

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1. Introduction: Motivation for implicit computation
2. Skylines and convex hulls

# Motivation

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- Traditional focus in algorithm design: Running Time
- Here: Second core issue: Memory utilization.
- Historically: Space-Efficiency considered due to high memory prices.
- Nowadays: Space-Efficiency considered due to:
  - Larger datasets.
    - \* High-resolution surveillance data
    - \* Temporal and spatio-temporal data
  - Smaller computing devices.
    - \* Location based services for mobile communication networks
    - \* Data analysis and propagation in sensor networks
  - Limited (read/write)-memory



Sensor Networks



Car Navigation

## In-Place Algorithms

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### Definition 1.1

An algorithm  $A$  is called *in-place* iff during its execution  $A$  occupies  $\mathcal{O}(1)$  words, i.e.  $\mathcal{O}(\log_2 n)$  bits, in addition to the space required by the input.

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### Example:

- Heapsort is an in-place algorithm (uses in-place data structure).
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## Motivation: Dealing with Large Datasets

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### Algorithmic concepts for different scenarios:

- Small, fast working memory. Data resides on slow disks.
  - Cache-oblivious and I/O-efficient Algorithms: Minimize data (block) movement.
- Data is streamed and not constantly available.
  - Streaming algorithms: (Approximation of) data aggregates.
- (Almost) no memory to use additional to the given input.
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  - Because of: Memory-, disk-, network latencies, less garbage to collect, larger basecases ...
  - In-place model “in between” I/O- and Streaming-Model ...
  - May provide insights in computational complexity of problems.
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## Previous Results

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### In-Place Sorting and Related Problems:

- Heapsort [Floyd, 1964].
- Linear-time [merging/partitioning](#) [Mannila & Ukkonen, 1984; Geffert et al., 2000; Katajainen & Pasanen, 1999]. . .
- Linear-time [k-selection](#) [Carlsson & Sundström, 1995; Geffert & Kollar, 2001; Bose et al., 2006].

### In-Place, Cache-Oblivious(!) Dictionary:

- $\mathcal{O}(\log n)$  update/queries [Franceschini & Grossi, 2003].

## In-Place Computational Geometry:

- Closest Pair etc. [Bose et al., 2006].
- Line-Segment Intersection [Bose et al., 2006; Vahrenhold, 2005].
- Convex Hull and Maxima problems etc. [Brönnimann et al., 2004b; Brönnimann & M.Chan, 2004; Blunck & Vahrenhold, 2006].

# Sapce-efficient Computational Geometry Results

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## “Use-Polylog-Extra-Space-And-Time” Geometry Results:

- $3d$ -convex hull and related [Brönnimann et al., 2004c].
- Multidimensional search sctructures [Brönnimann et al., 2004a].
- Klee’s Measure Problem [Chen & M.Chan, 2005].

In this lecture . . .

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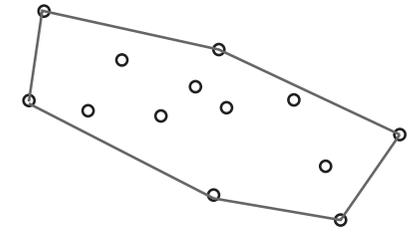
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**In-place techniques and algorithms for:**

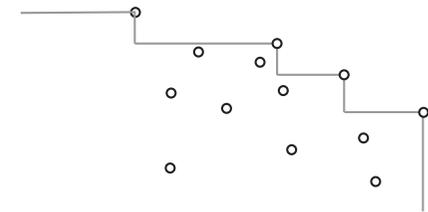
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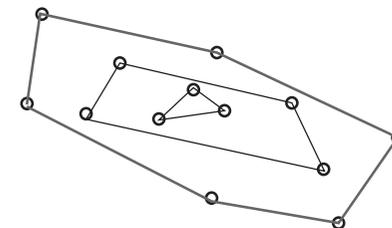
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- Convex hulls and sets of maxima ('skylines')



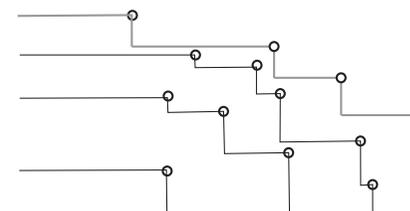
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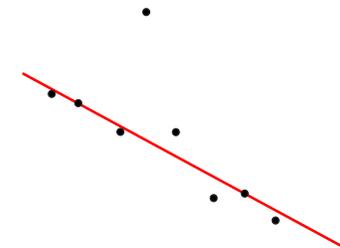
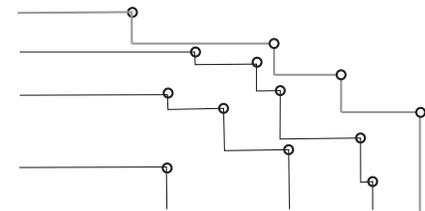
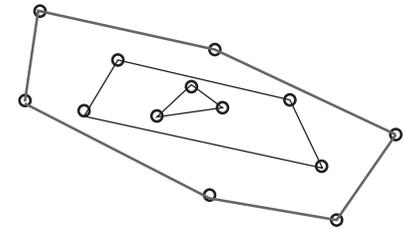


## In this lecture . . .

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### In-place techniques and algorithms for:

- Convex hulls and sets of maxima ('skylines')
- Layers of convex hulls and maxima
- Regression Analysis: Estimating linear correlations



# Overview

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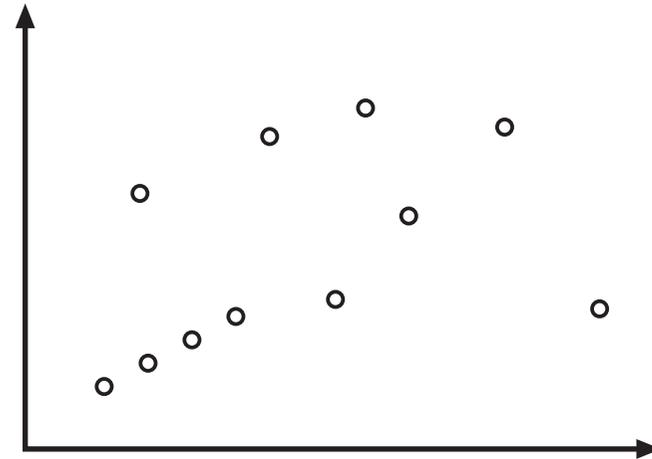
1. Introduction: Motivation for implicit computation
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# Computing the Skyline

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- Given: Set  $\mathcal{P}$  of  $n$  points in the plane.
- $p \in \mathcal{P}$  is maximal  $\Leftrightarrow$   
 $\forall q \in \mathcal{P} : p.x \geq q.x \vee p.y \geq q.y$







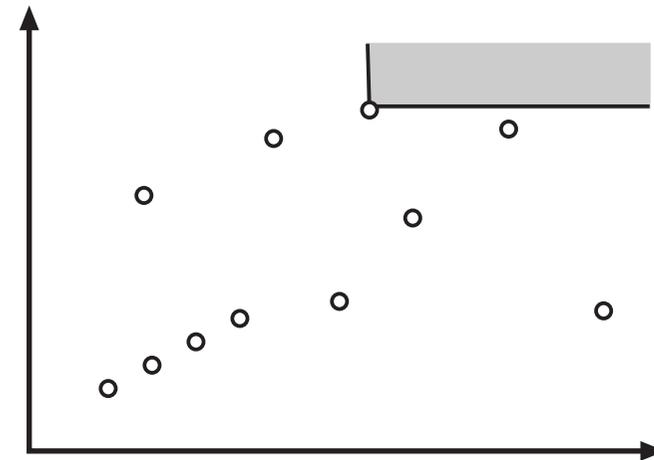


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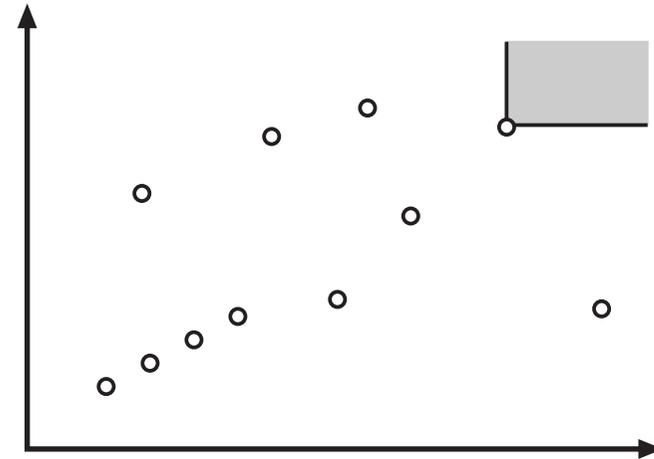


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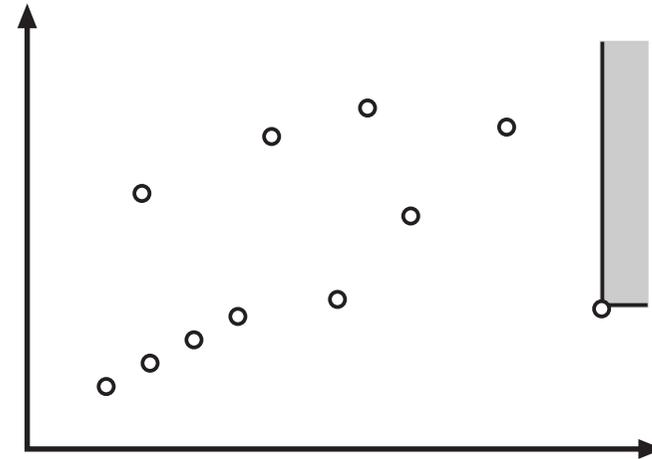


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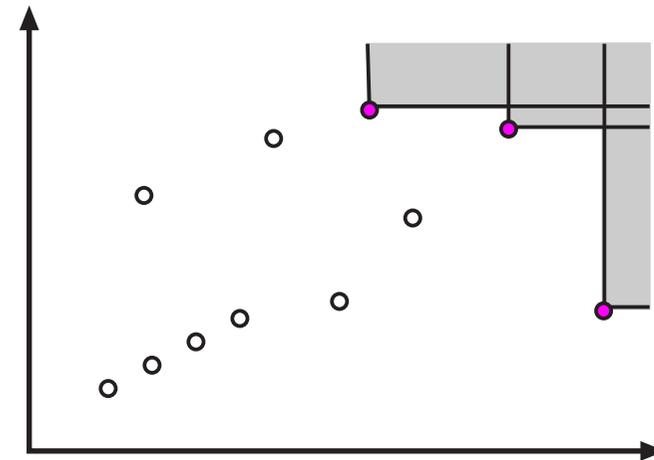


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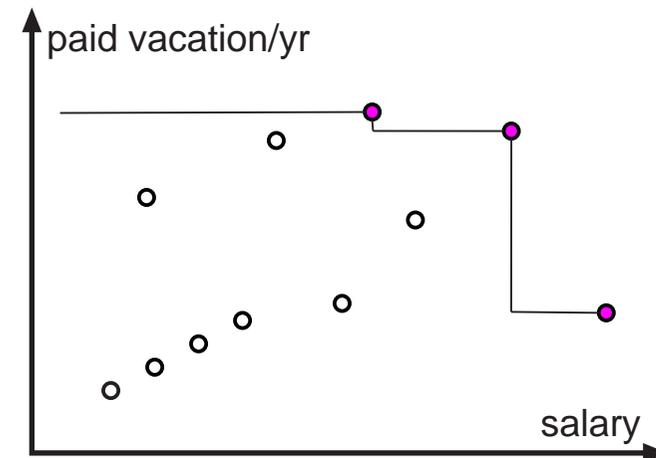


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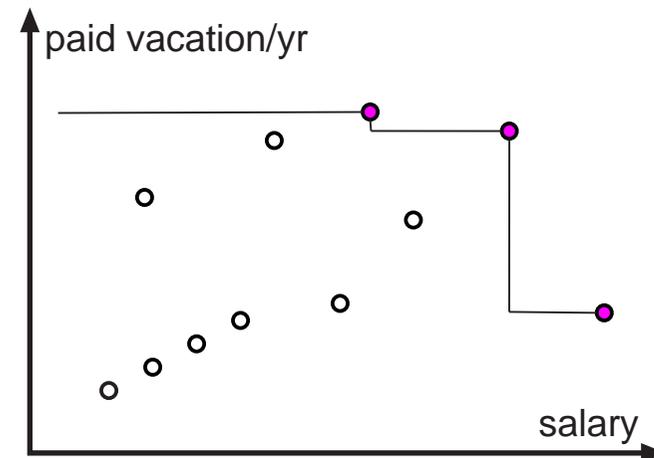
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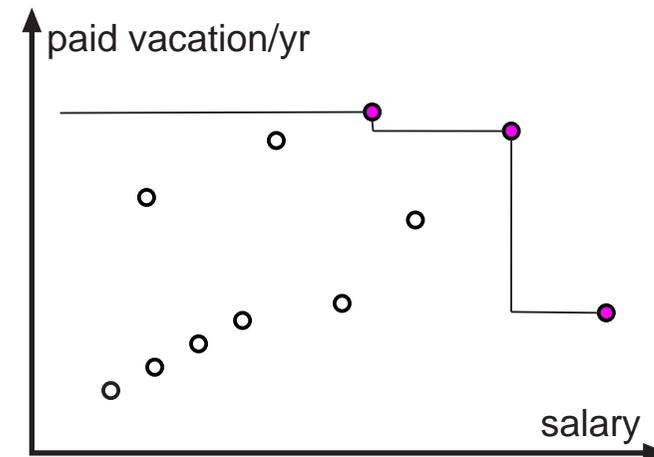
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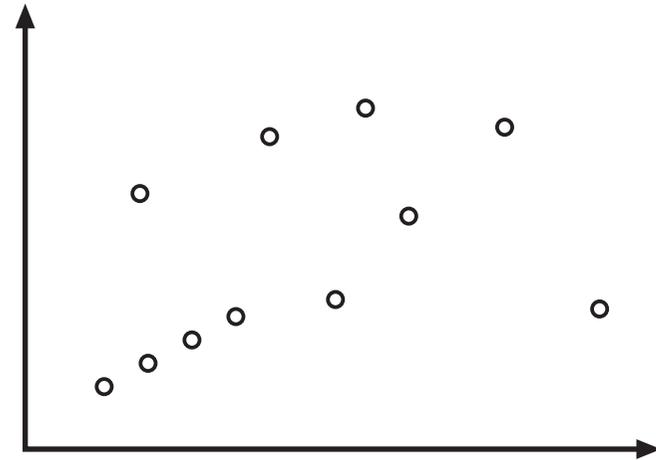
- Definition generalizes to:
  - Arbitrary dimensions  $d$ .
  - ‘Maxima’ w.r.t.  $d$  arbitrary chosen coordinate axes.



## Computing all skylines in-place

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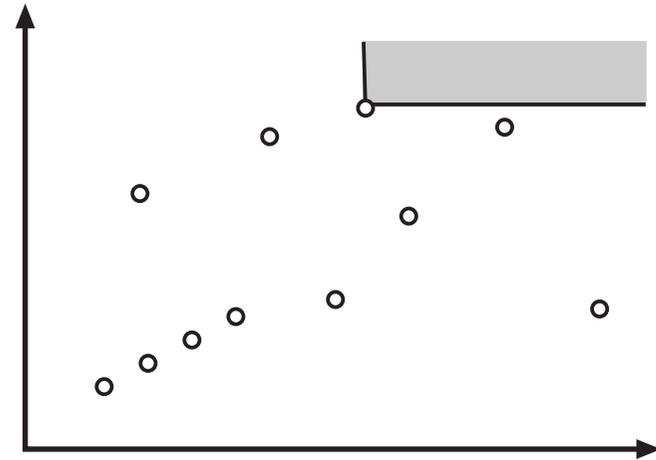
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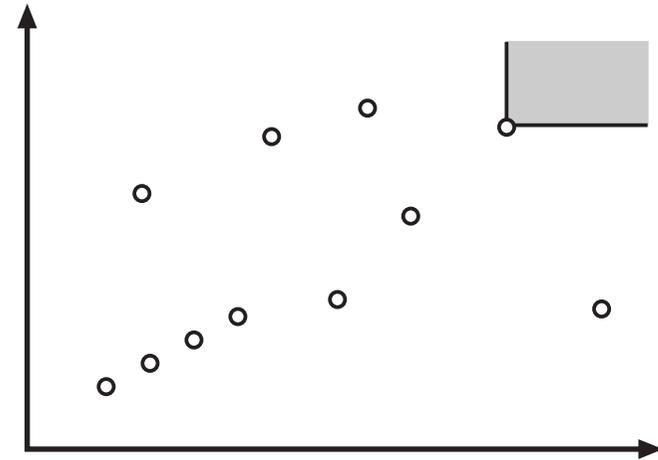
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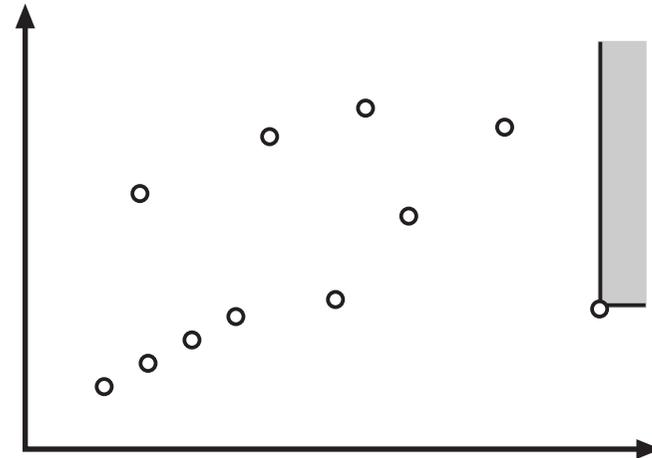
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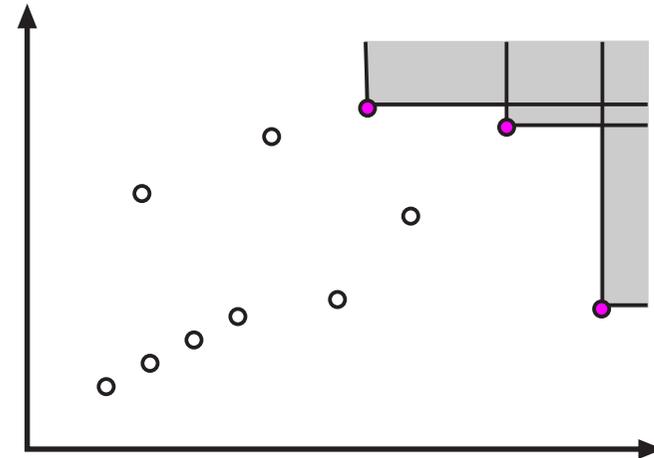


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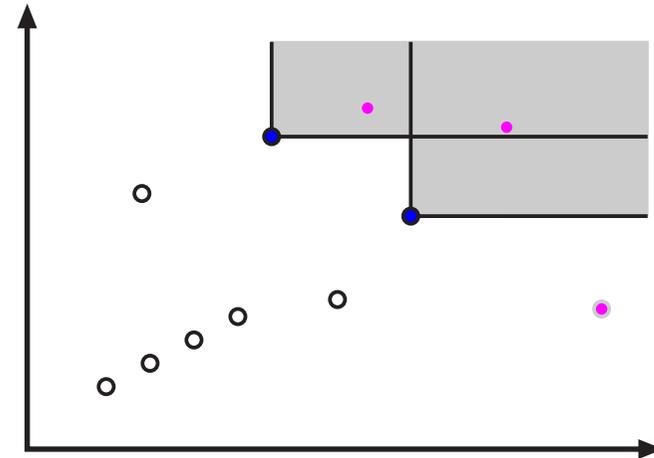


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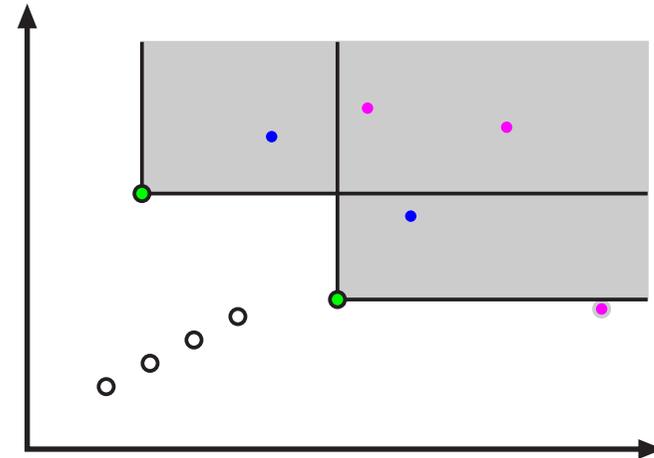


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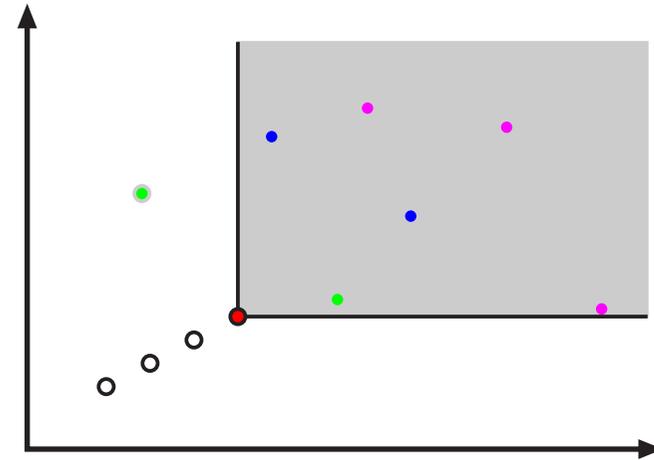


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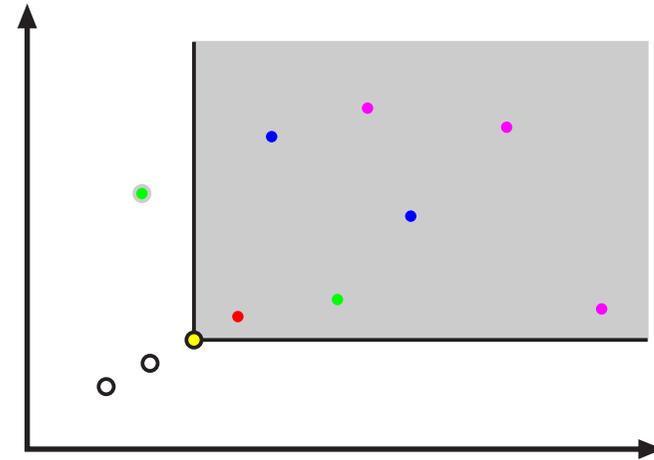


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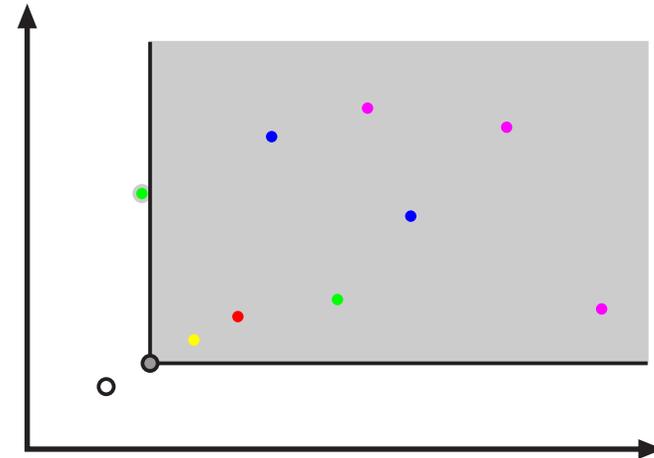


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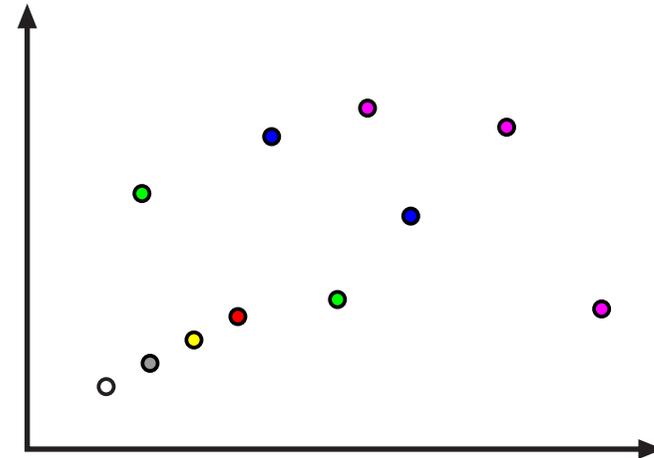


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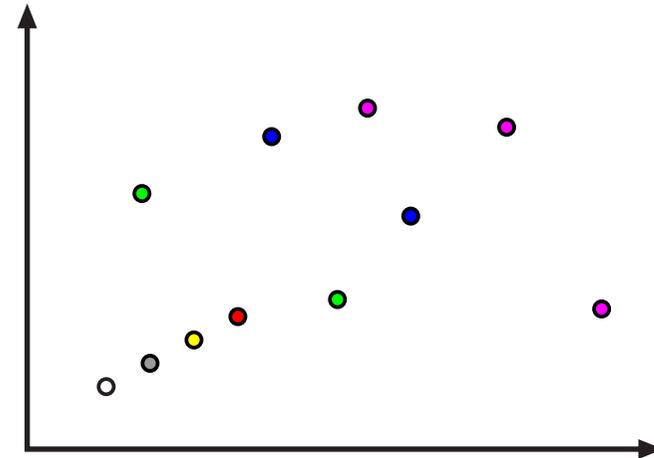
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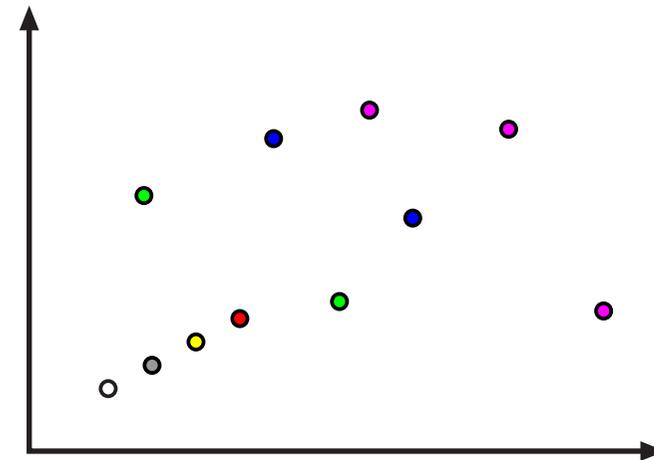
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### In-place setting:

- Group points by layer.
- In each layer: points sorted (by  $x$ ).



## Computing the Skyline: Selecting Maximal Points in 2D

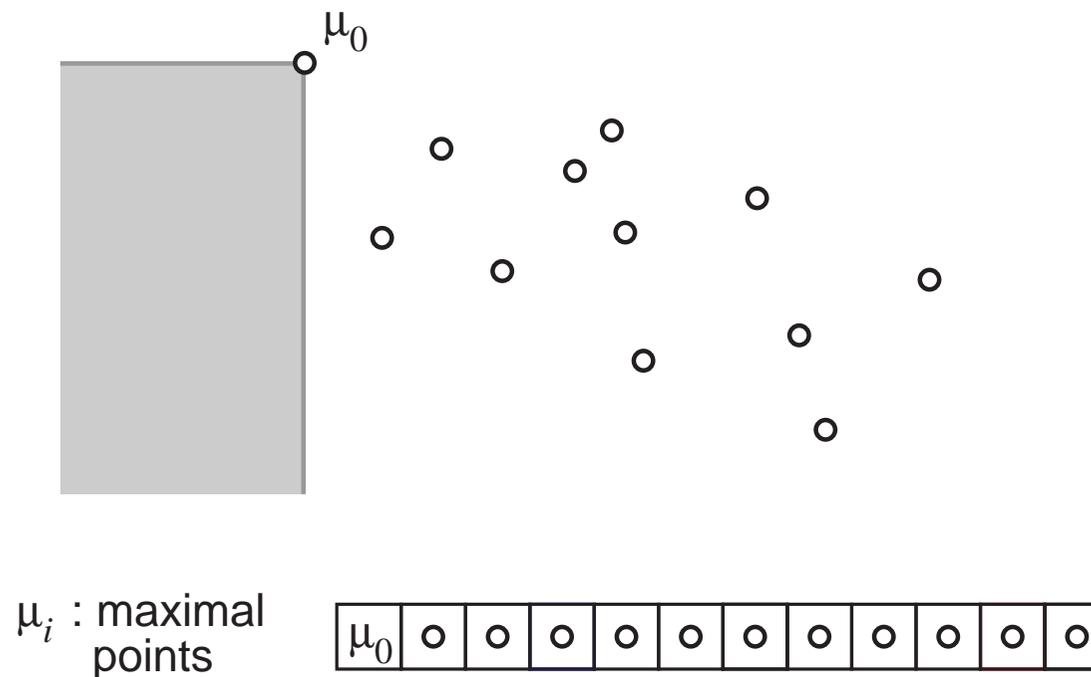
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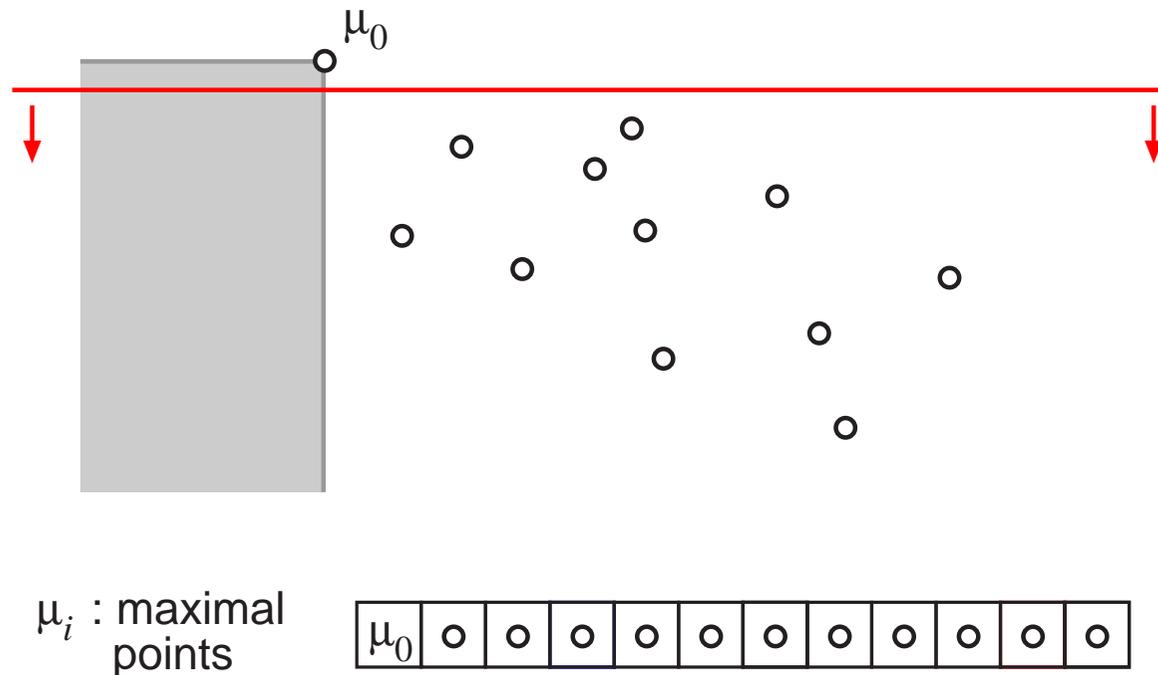
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  - **Invariant**: Next point  $p$ : is maximum  $\Rightarrow p$  right of tail.



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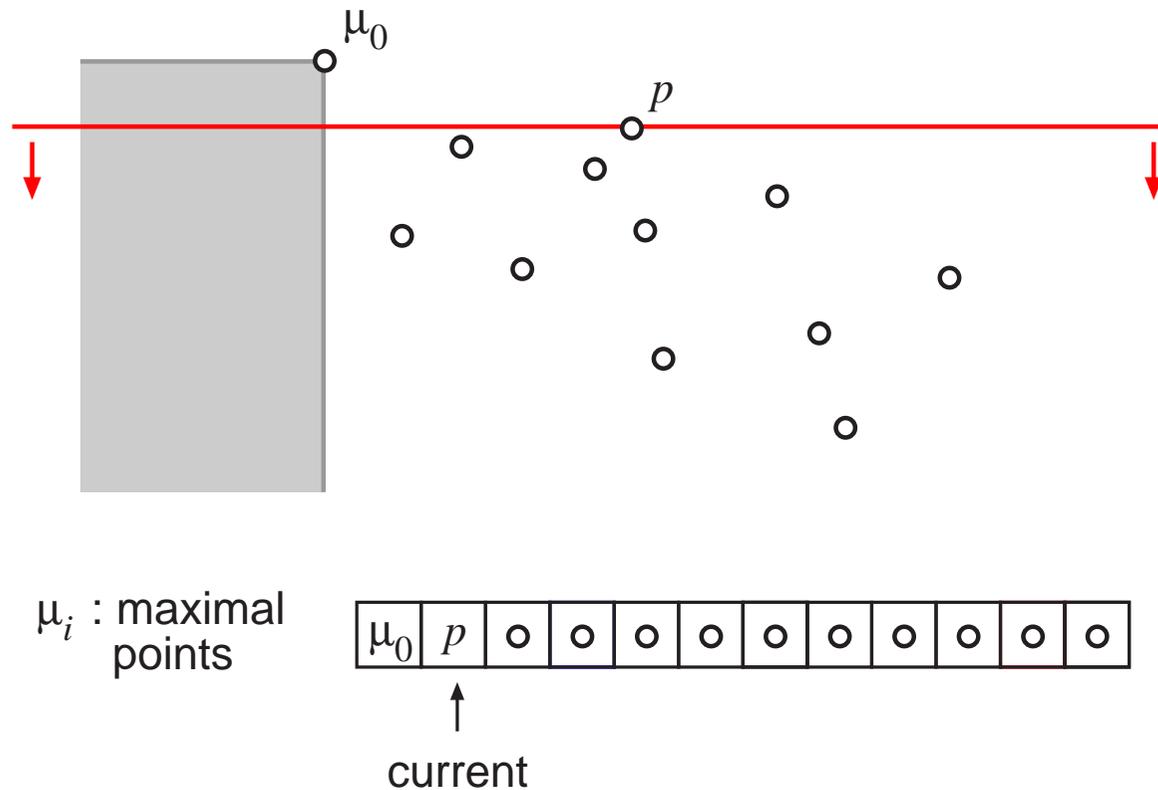
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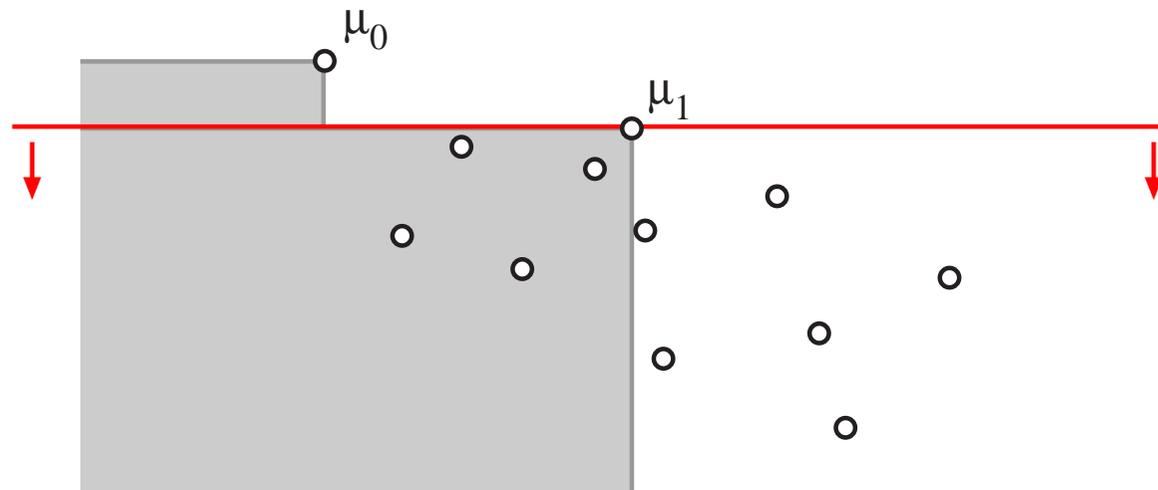
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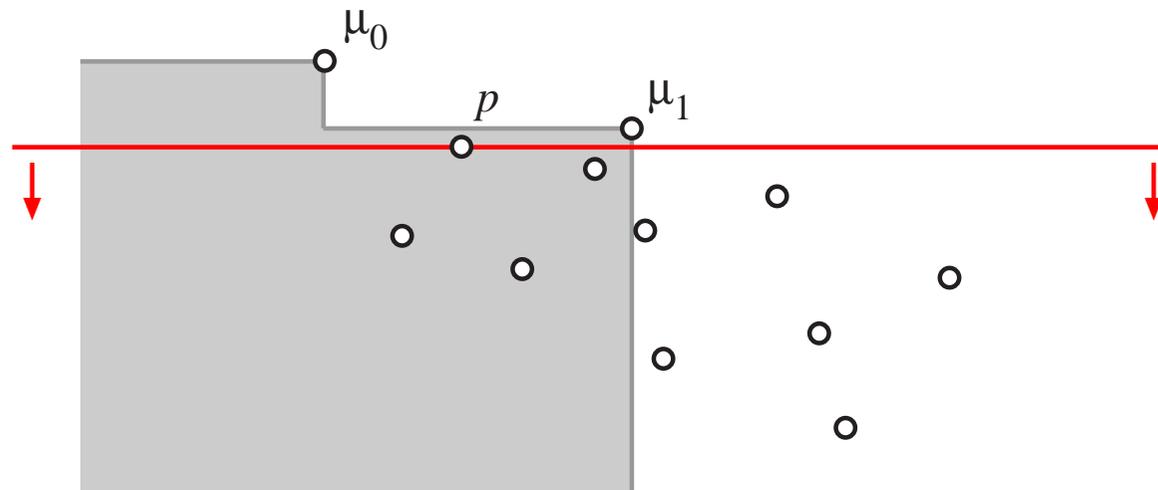


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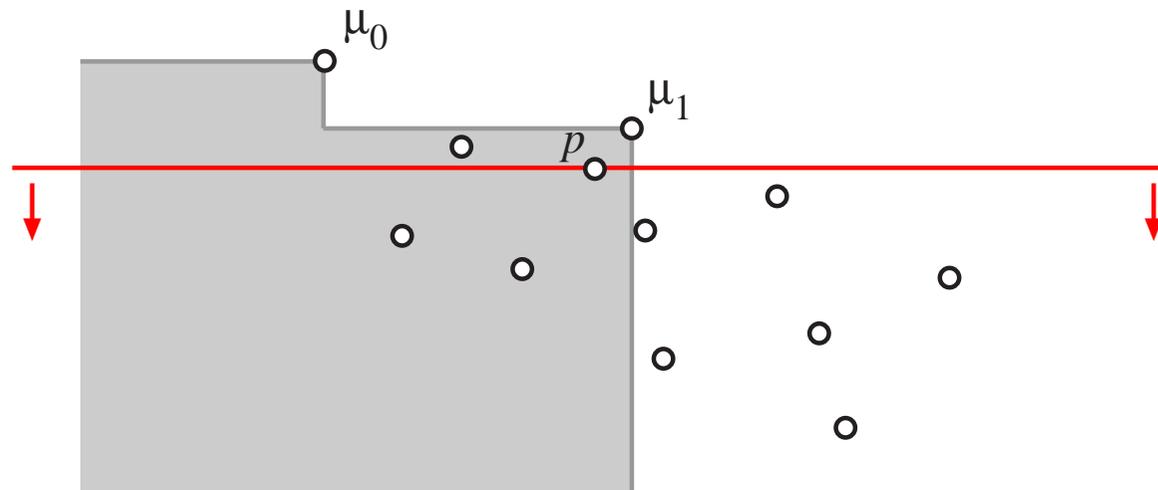


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$\mu_i$  : maximal  
points

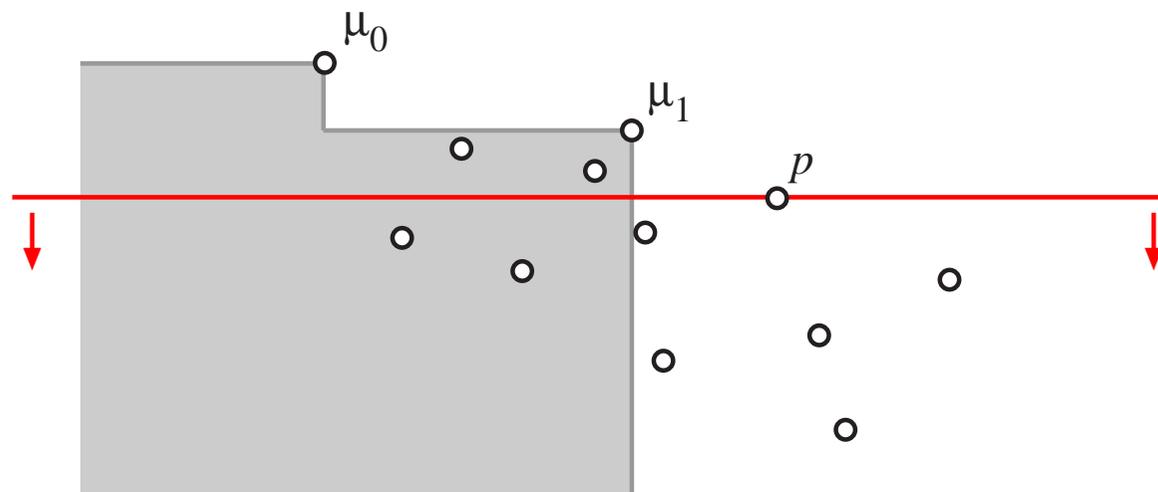


↑  
current

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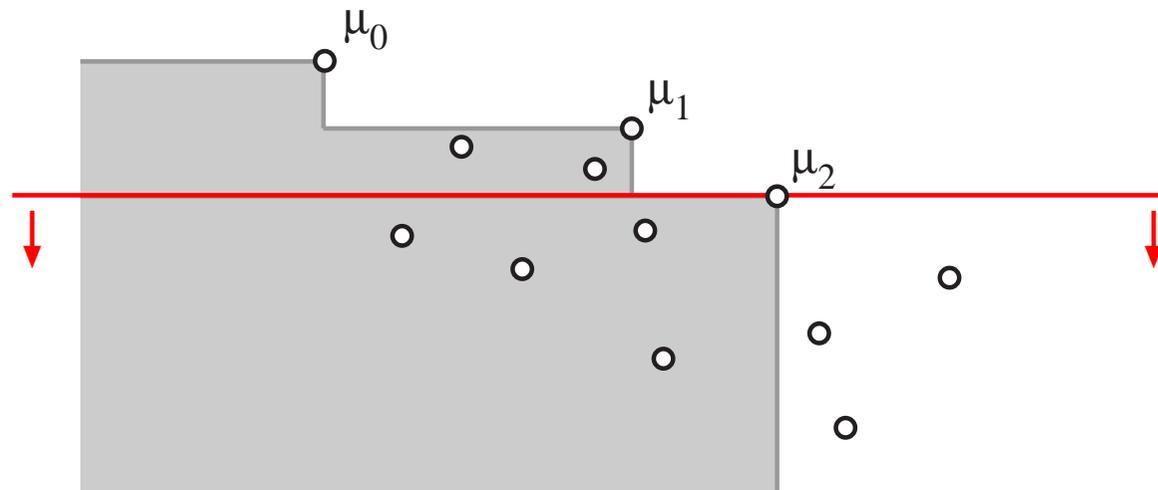


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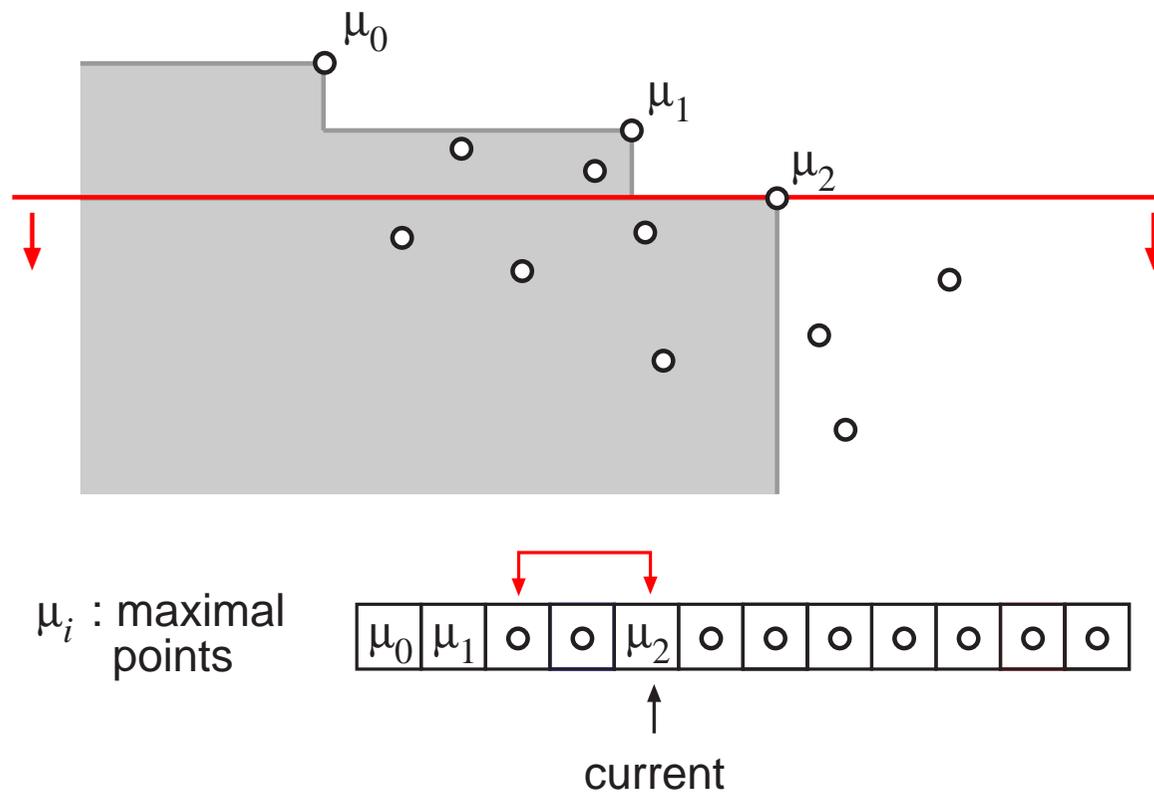


current

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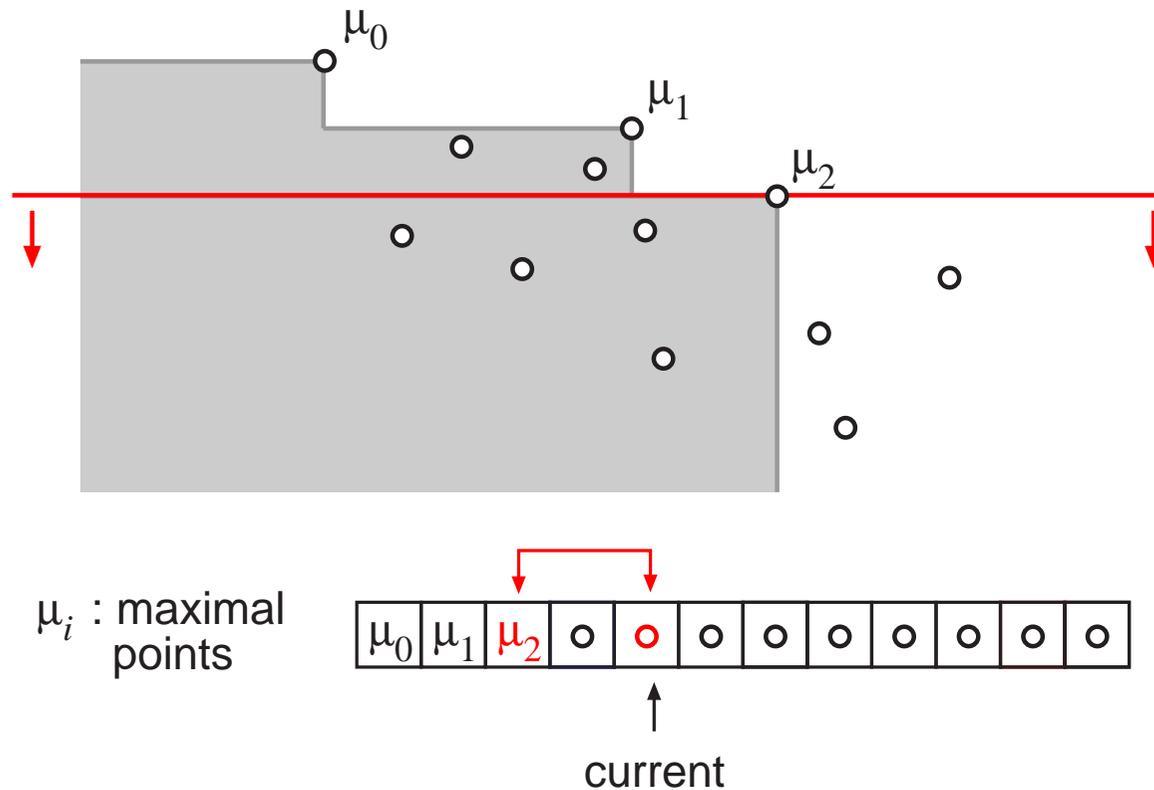
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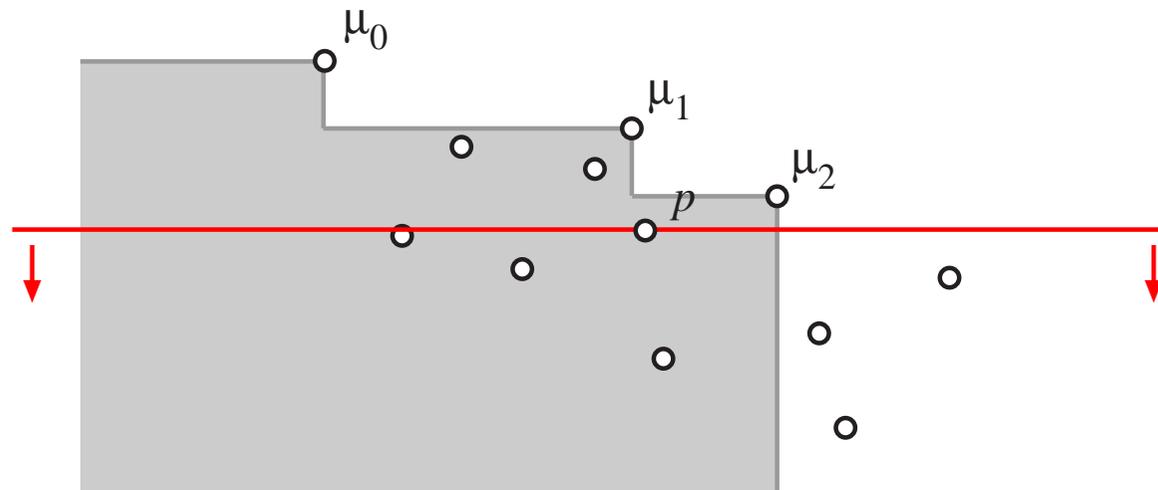
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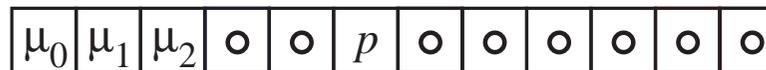
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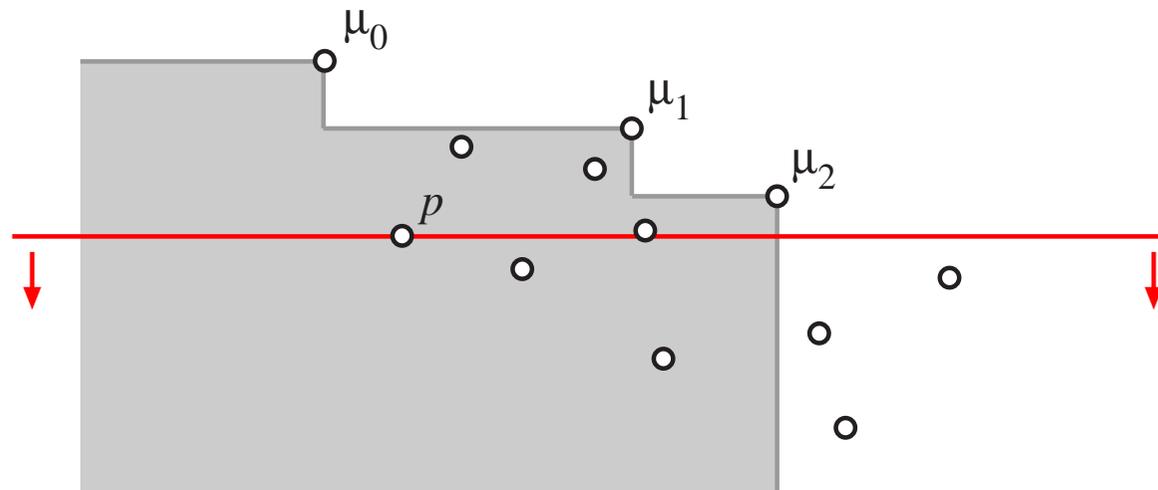


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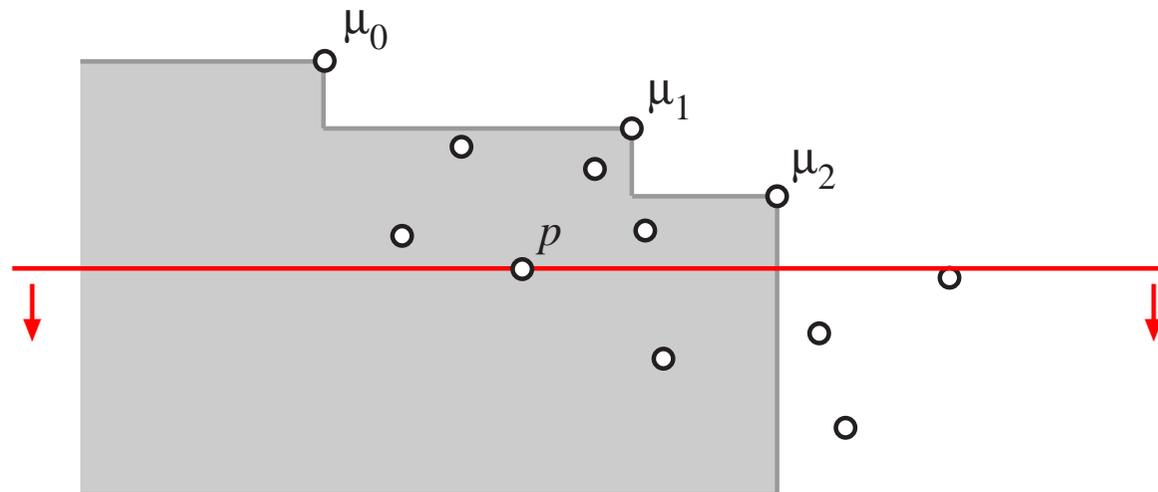


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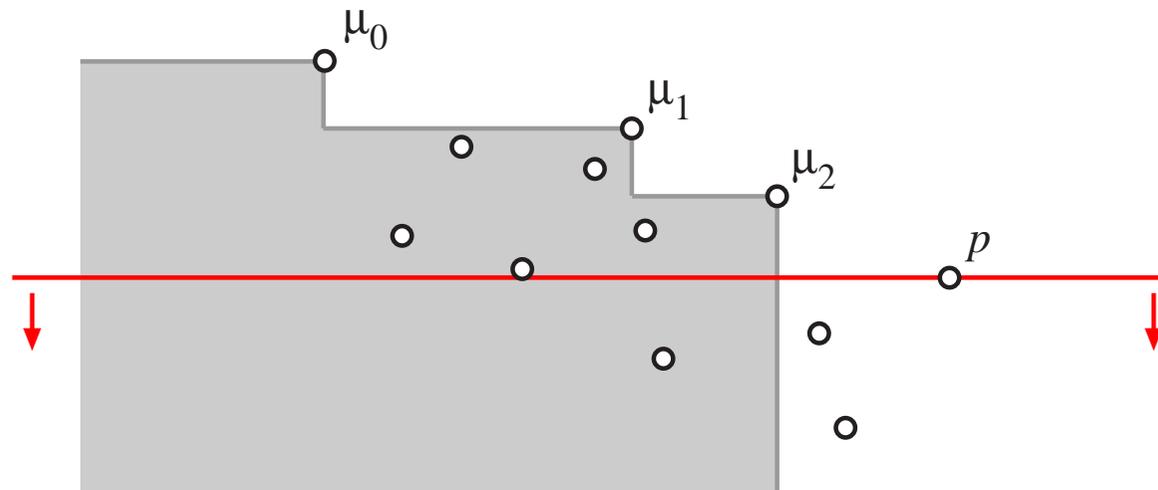


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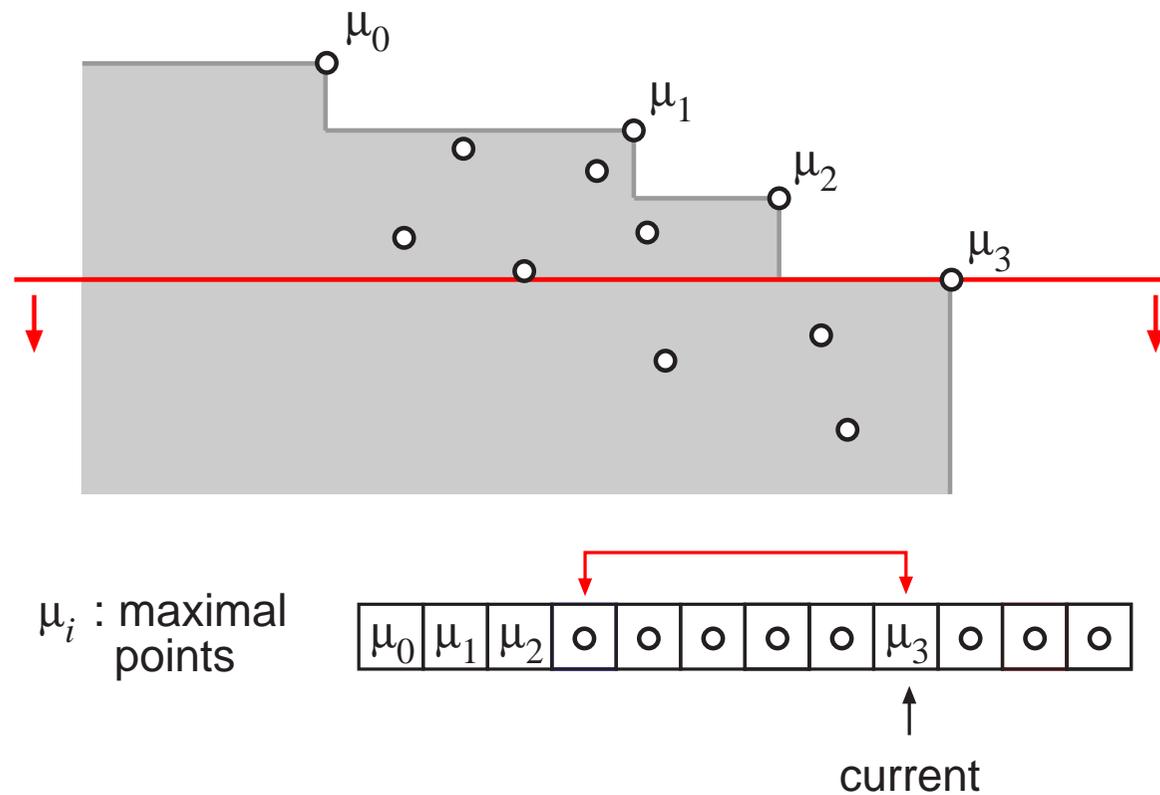


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current

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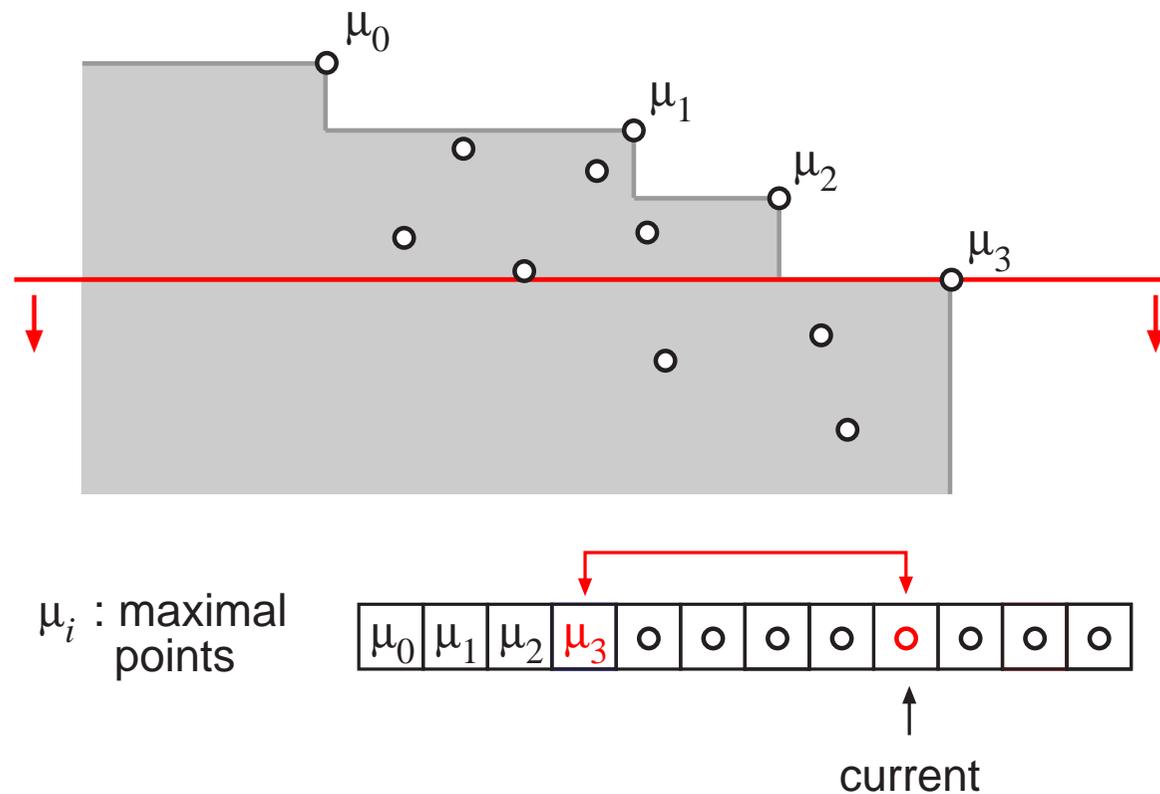
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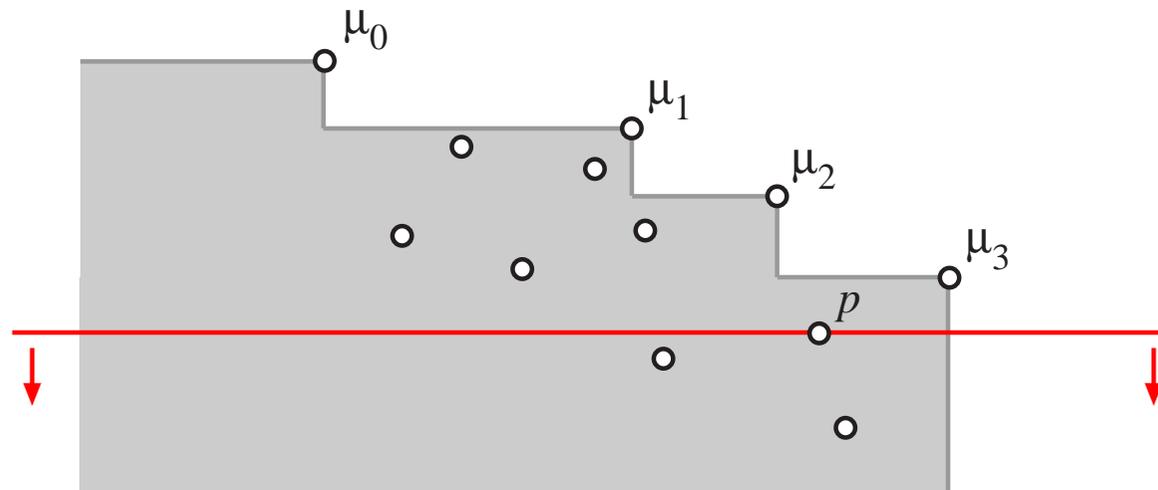
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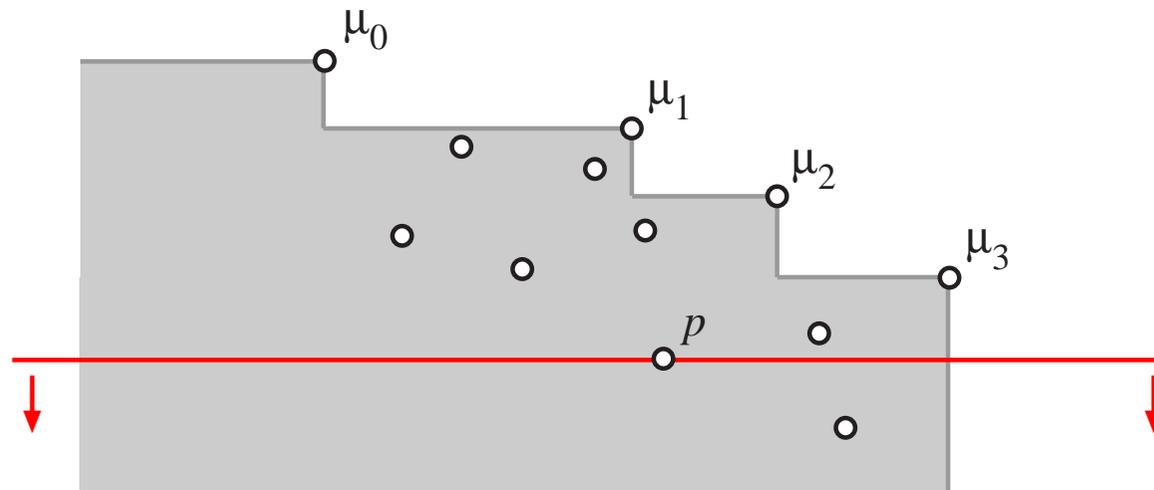


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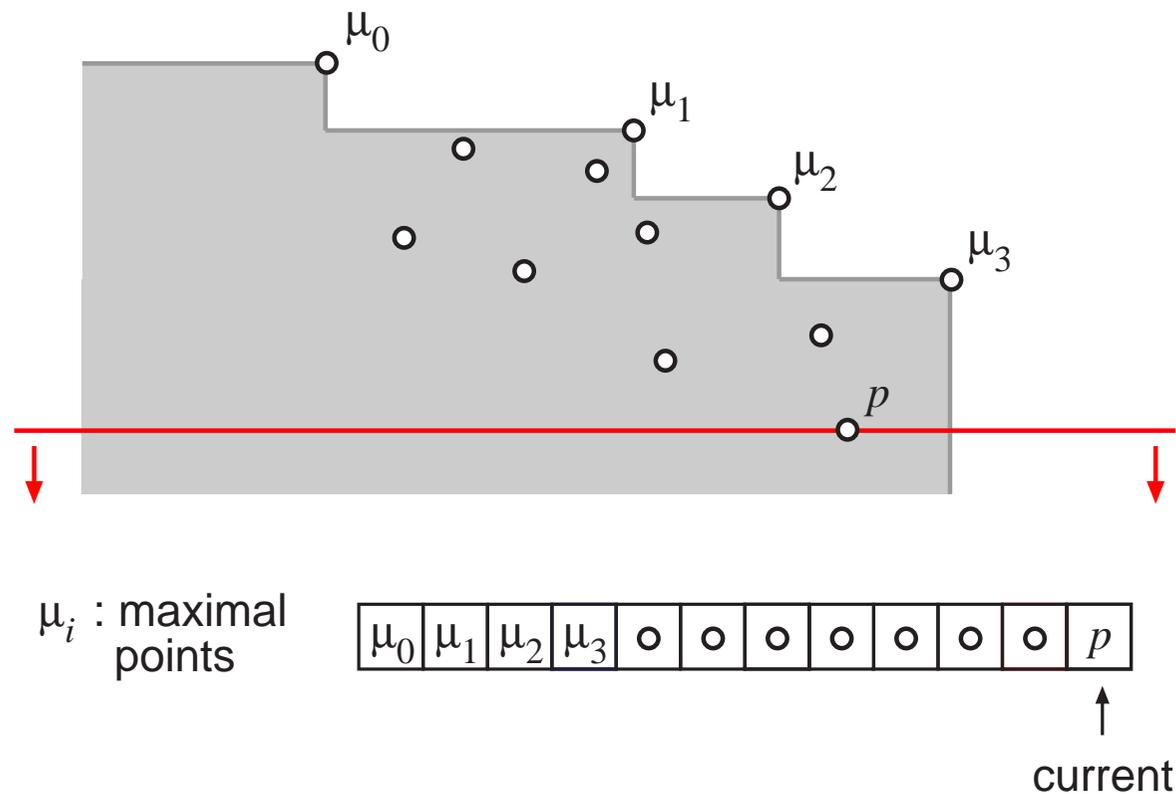


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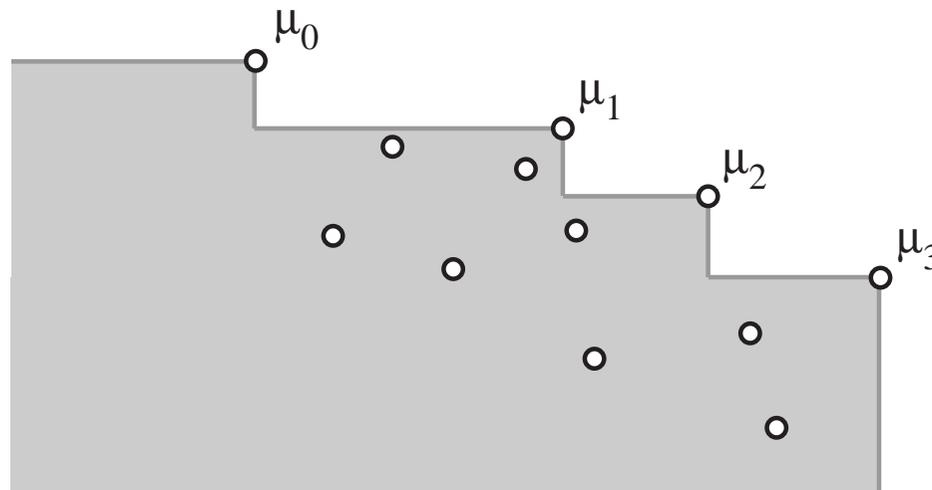


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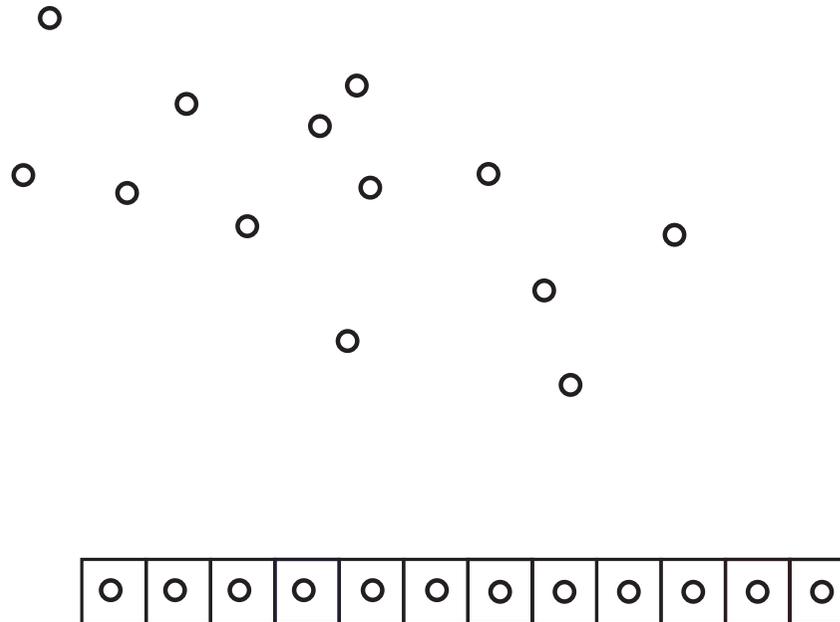


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# Computing the Convex Hull in 2D

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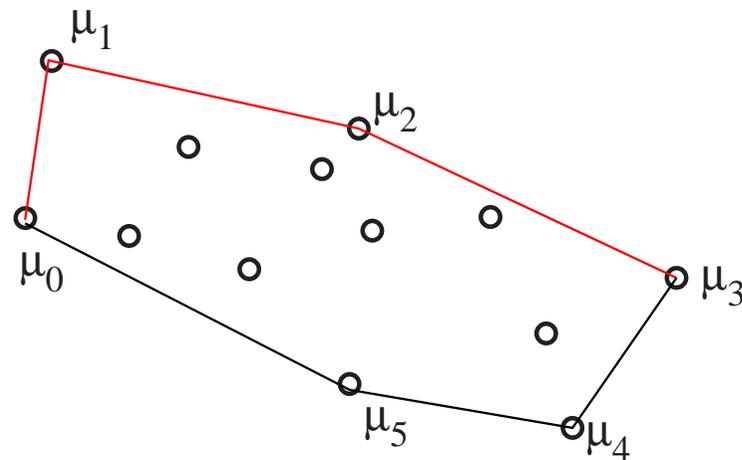
- Presort points lexicographically using, e.g., heapsort.



## Computing the Convex Hull in 2D

---

- Presort points lexicographically using, e.g., heapsort.
- Sweep left-right, maintain last two convex hull points seen so far.
  - **Invariant**: Point  $q$  **not** on upper convex hull iff  $(p, q, r)$  form a left-turn.
- Swap upper hull points to the front of the array; then compute lower hull ..



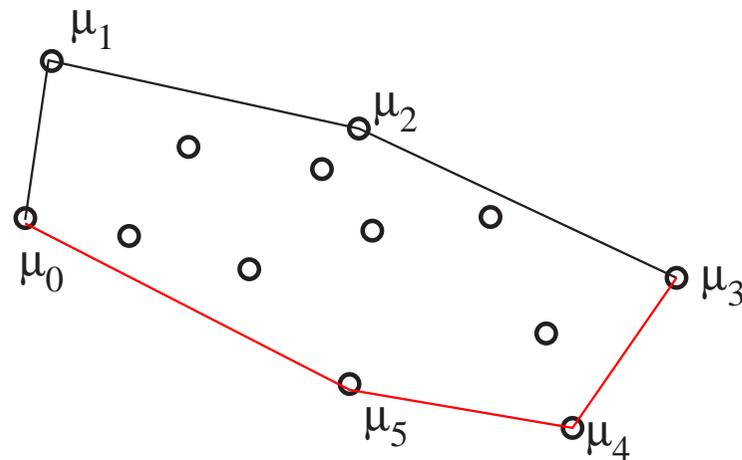
$\mu_i$  : convex hull points



## Computing the Convex Hull in 2D: Graham's Scan

---

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$\mu_i$  : convex hull points

$\mu_0$	$\mu_1$	$\mu_2$	$\mu_3$	$\mu_4$	$\mu_5$	○	○	○	○	○	○
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- Convex hull: In-place,  $\mathcal{O}(n \log n)$  (sort & scan) [Graham, 1972].

## Computing the Convex Hull in 2D output-sensitive [Chan, 1996]

---

### Chan's output-sensitive algorithm:

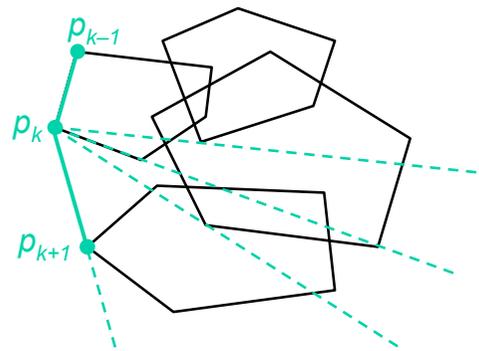
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  - Jarvis-march with  $CH(G_1), \dots, CH(G_H)$  (instead of points) as input-objects.
  - \* To find next CH-vertex  $p_k + 1$ : Compute tangents to  $G_1, \dots, G_H$ , each by binary search on a  $CH(G_i)$ .
  - $\Rightarrow$  Running time:  $\mathcal{O}(n/H \cdot H \cdot \log_2 H + H \cdot n/H \cdot \log_2 H) = \mathcal{O}(n \cdot \log_2 H)$

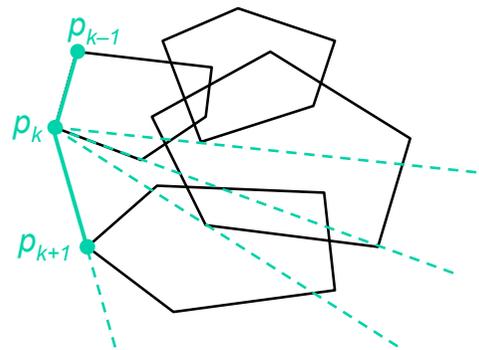


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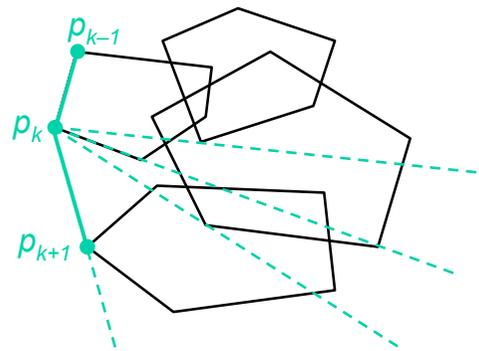
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 $\mathcal{O}\left(\sum_t^{\lceil \log_2 \log_2 h \rceil} n \cdot 2^t\right) = \mathcal{O}\left(n \cdot 2^{\lceil \log_2 \log_2 h \rceil + 1}\right) = \mathcal{O}(n \cdot \log_2 h)$ .



## How to run Chan's algorithm in-place?

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# Output-sensitive skyline computation

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**Idea applicable also to skyline problem?**

- Applicable:

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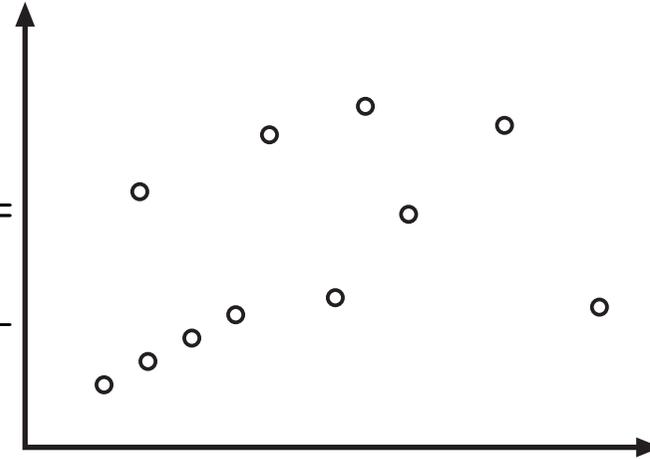
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# Computing Layers of Maxima

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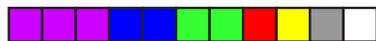
## Def. of 'Layers of Maxima':

- Compute 'skyline'  $\text{MAX}(\mathcal{P})$  of  $\mathcal{P}$ .
- If  $\mathcal{P} \setminus \text{MAX}(\mathcal{P})$  not empty, set  $\mathcal{P} := \text{MAX}(\mathcal{P})$  and repeat.
- Number of iterations (layers) can be linear in  $n$ .



## To achieve (in in-place setting):

- Group points by layer.
- In each layer, sort by  $x$ .

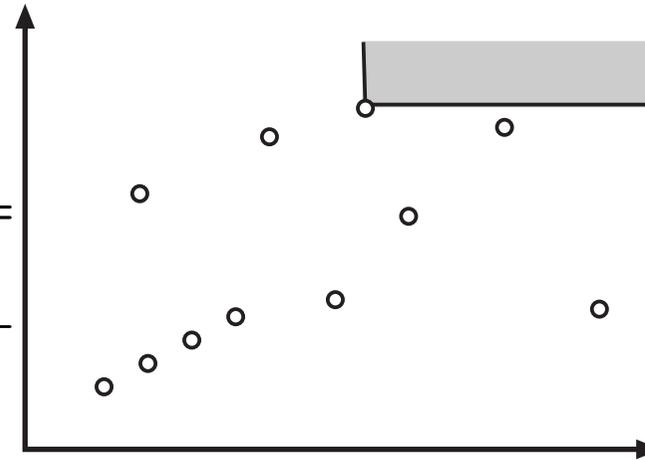


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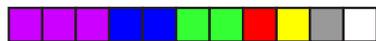
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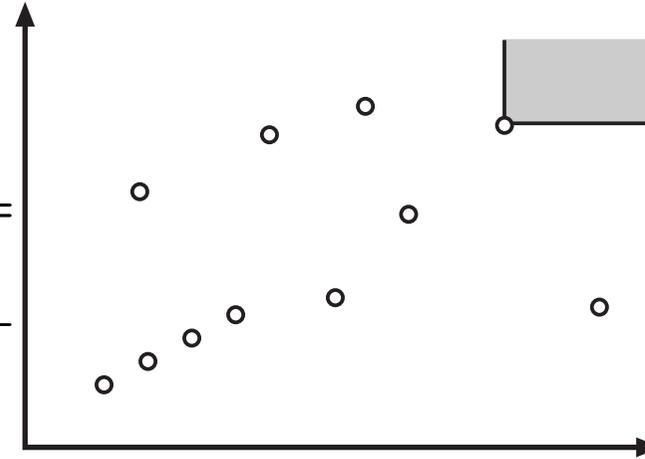


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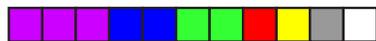
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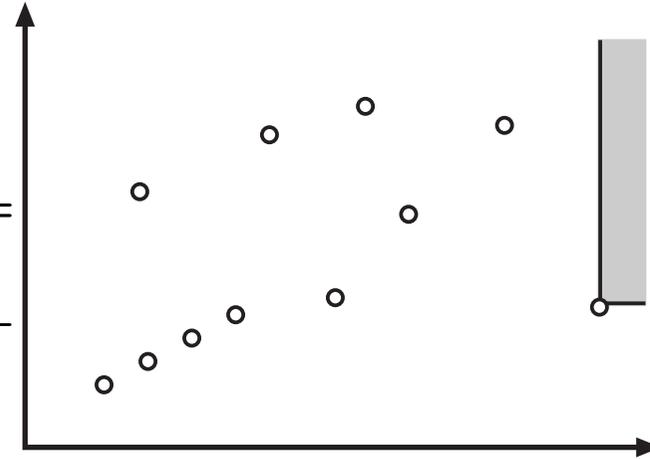


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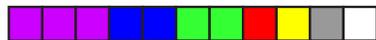
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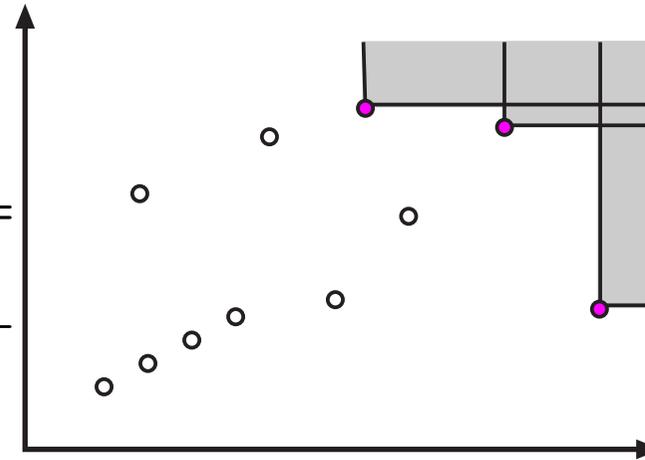


# Computing Layers of Maxima

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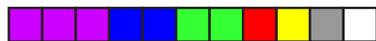
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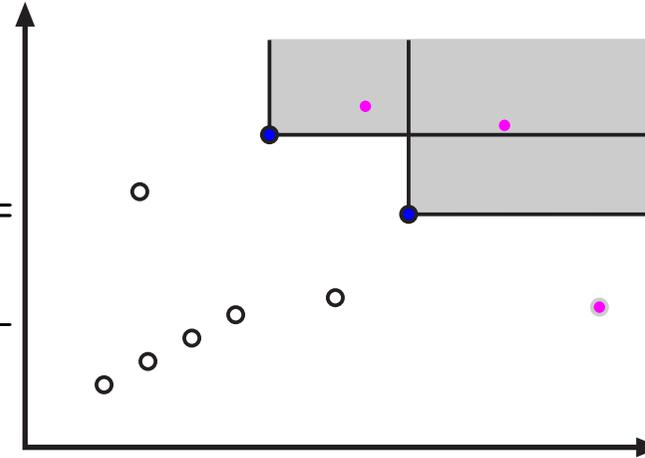


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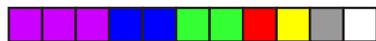
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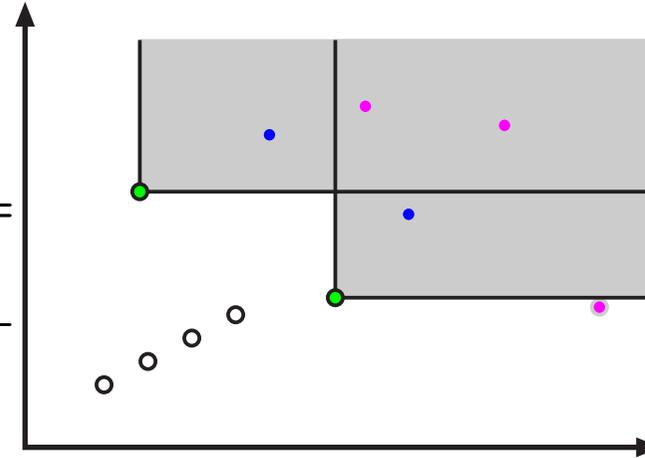


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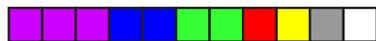
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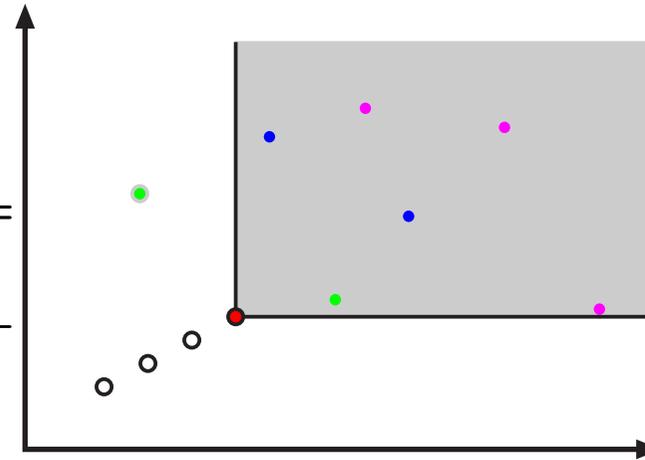


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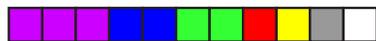
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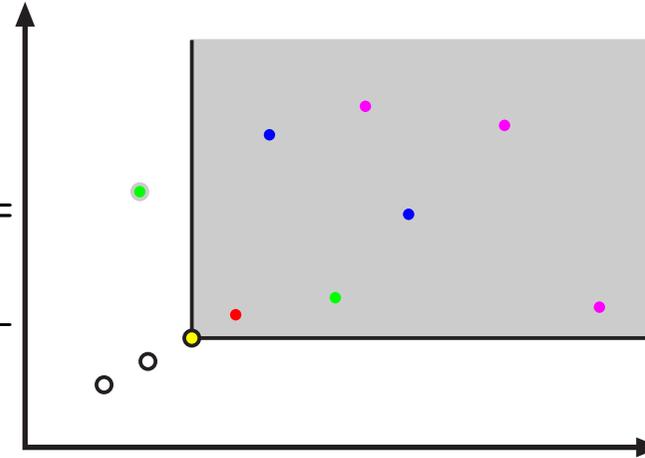


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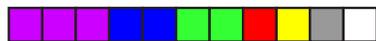
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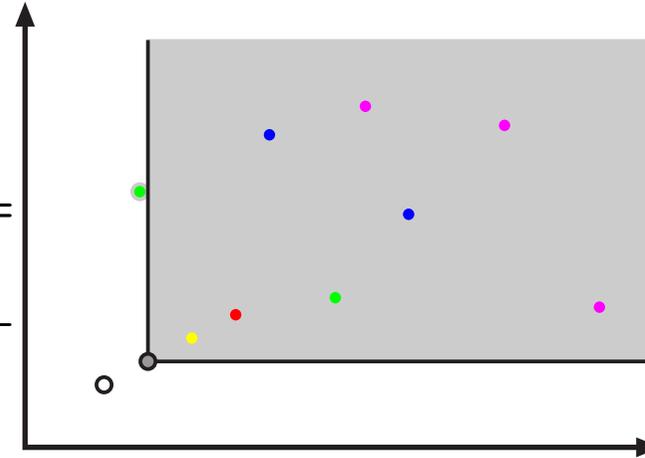


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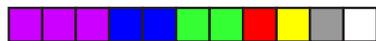
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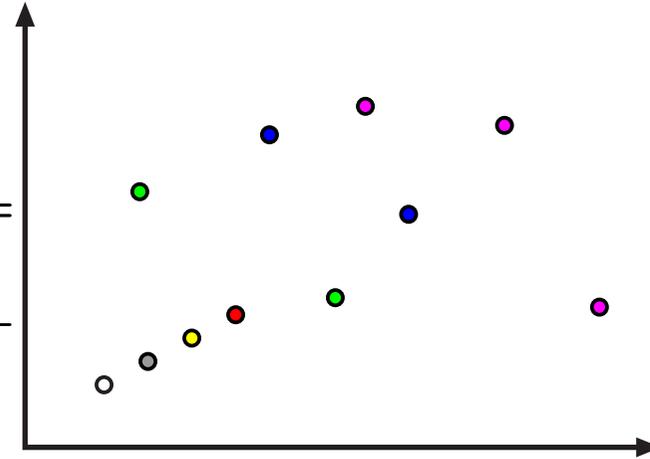


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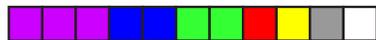
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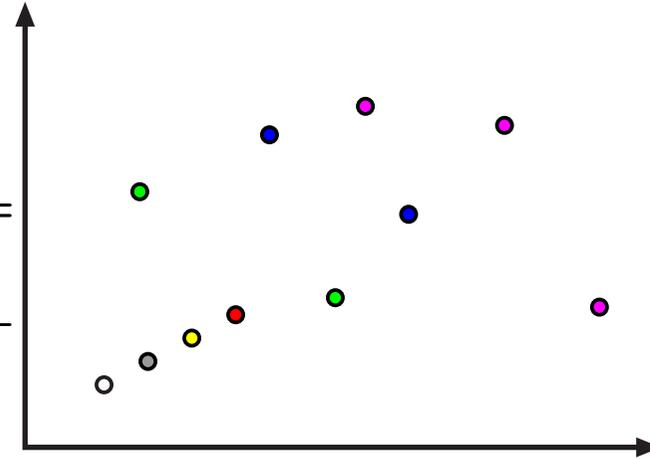


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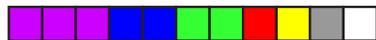
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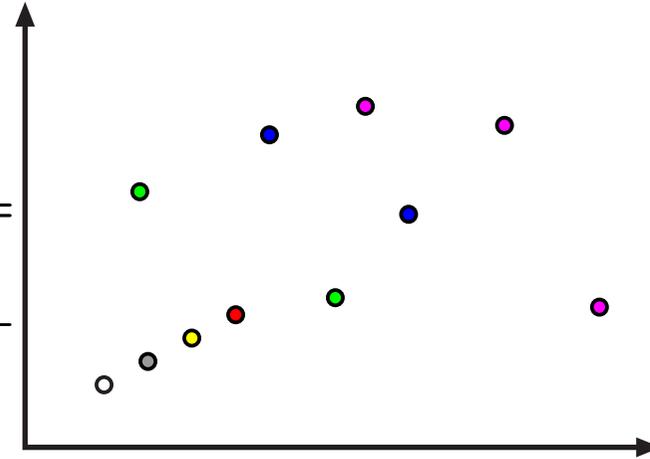


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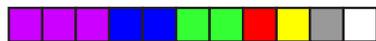
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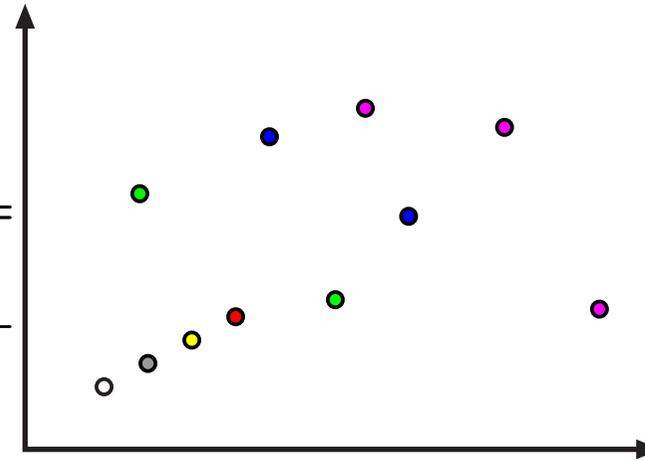
- Naïve approach: Iteratively compute skylines.

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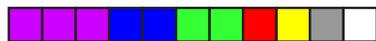
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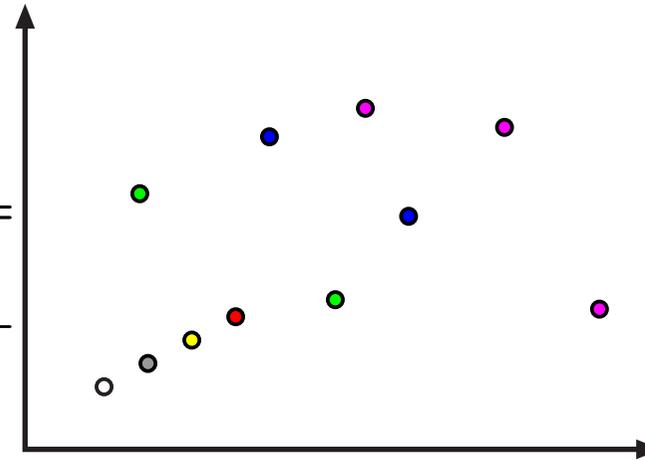
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# Computing Layers of Maxima

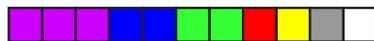
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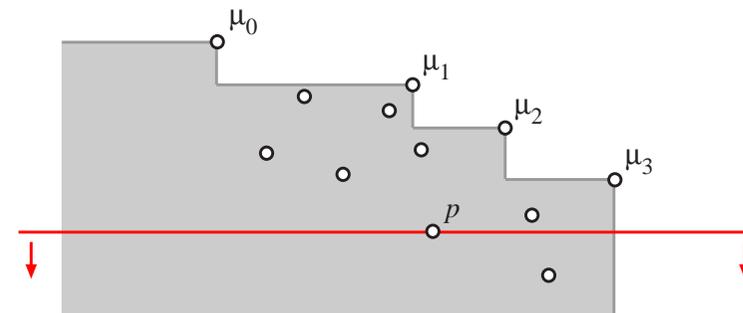
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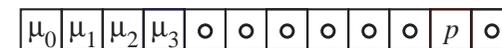


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$\mu_i$  : maximal points



current

# Computing Layers of Maxima in-place: Overview

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## Agenda:

- Compute (and arrange!) all points on each of the  $\mathcal{O}(n)$  layers in-place.

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- Process **multiple** layers at a time.
- Number of batches:  $\mathcal{O}(\log n)$ .
- Per batch:
  - Process  $\mathcal{O}(n/\log n)$  layers at a time by ...
  - sweeping the input array (similar to skyline sweep).
  - Maximum allowed cost:  $\mathcal{O}(n)$  time **per batch**, i.e., **no pre-sorting**.

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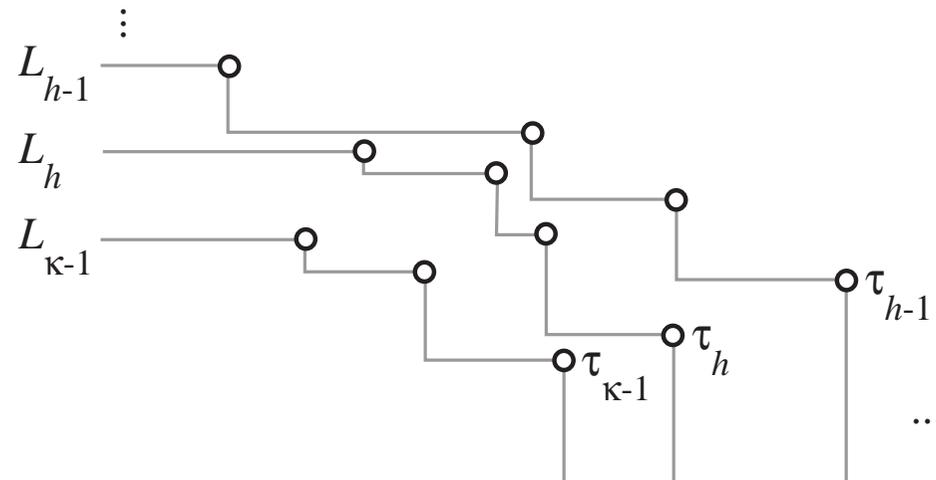
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- Charging scheme: Spend extra  $\mathcal{O}(\log n)$  time per point processed.

## For starters: Counting the Number of Layers

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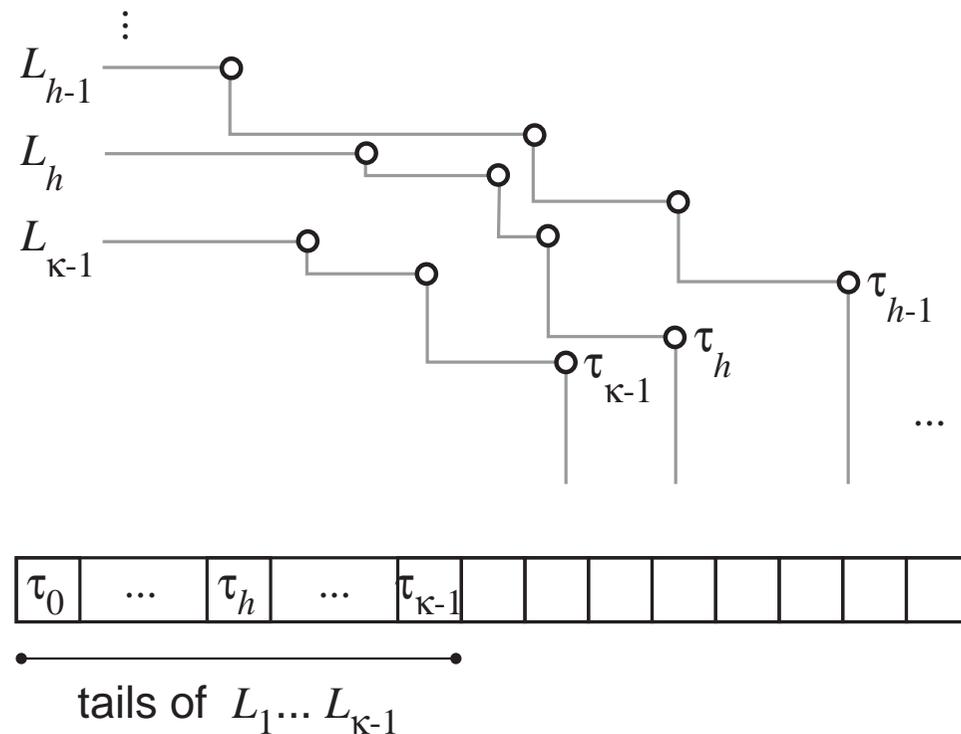
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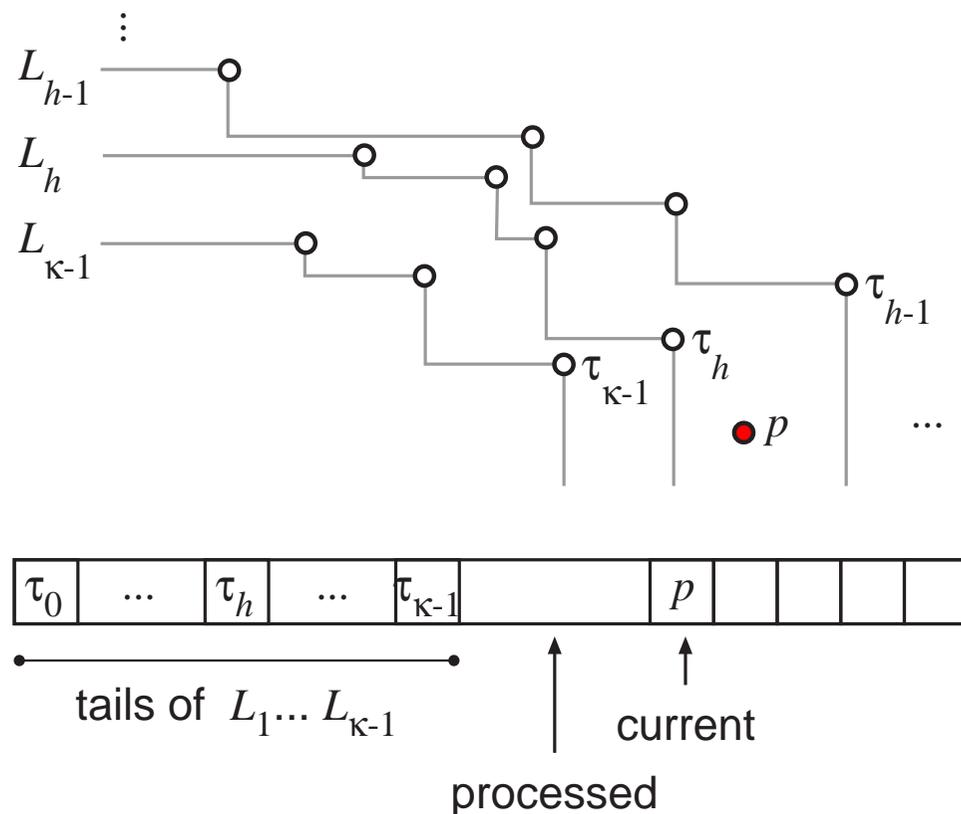
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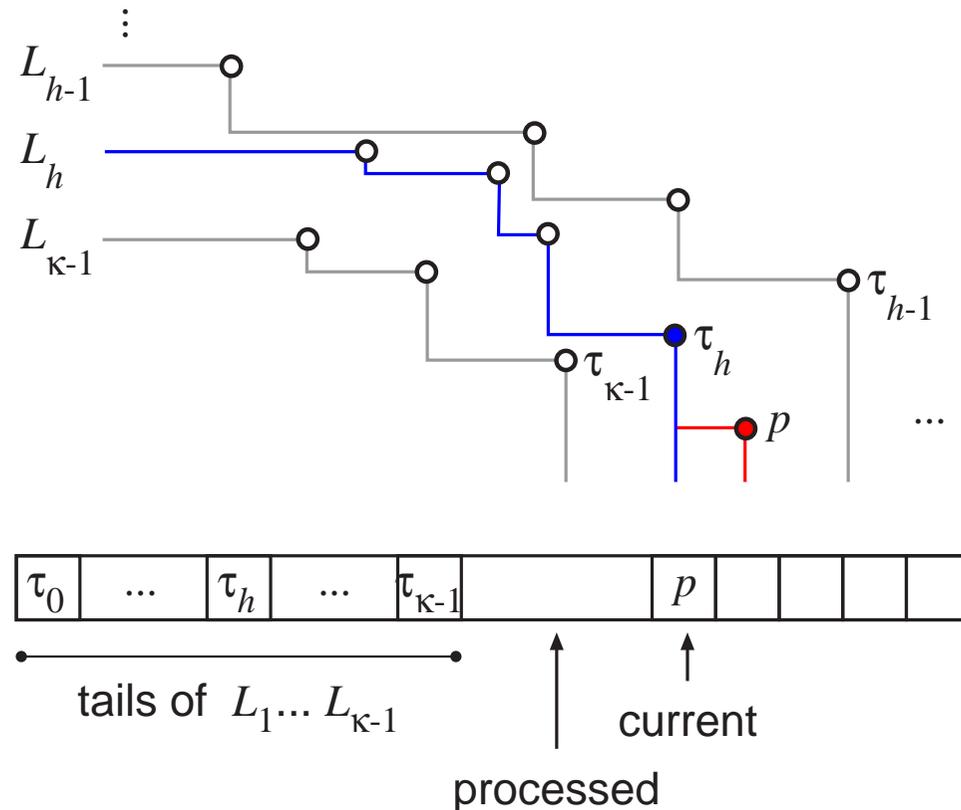
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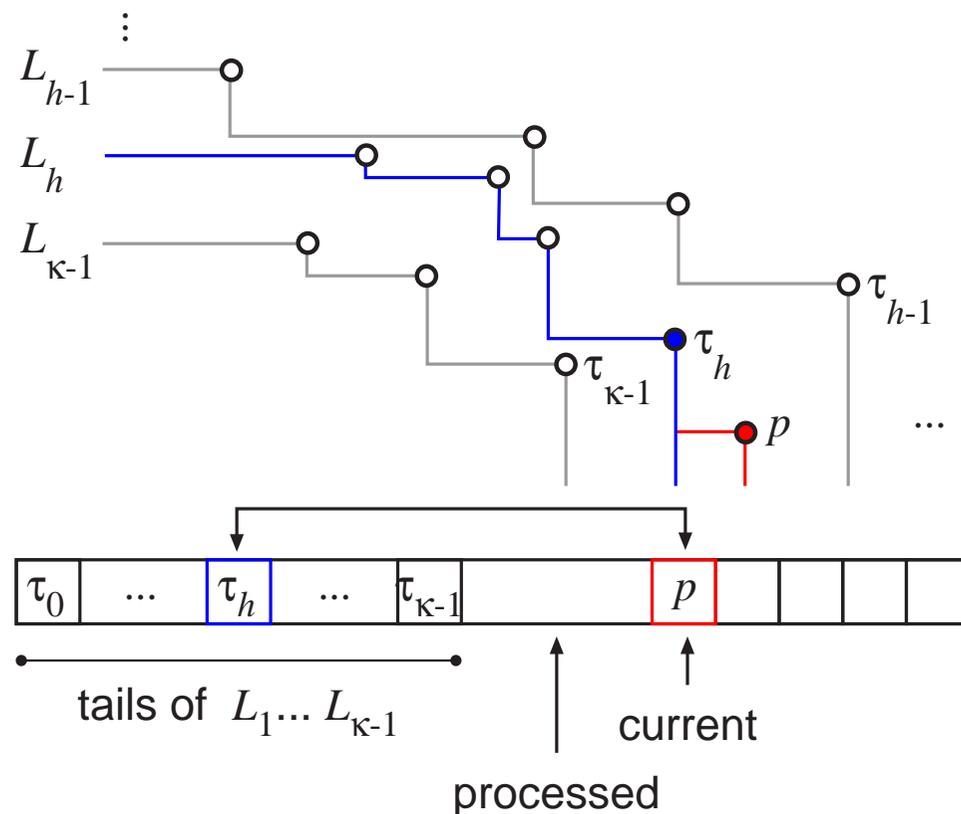
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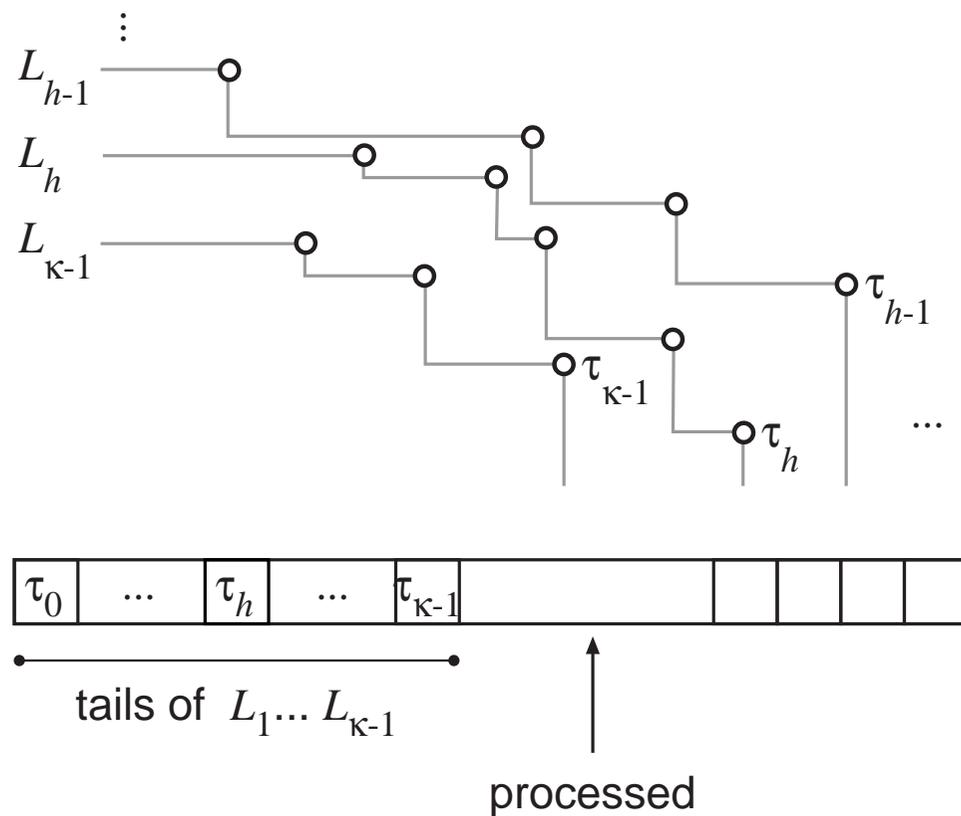
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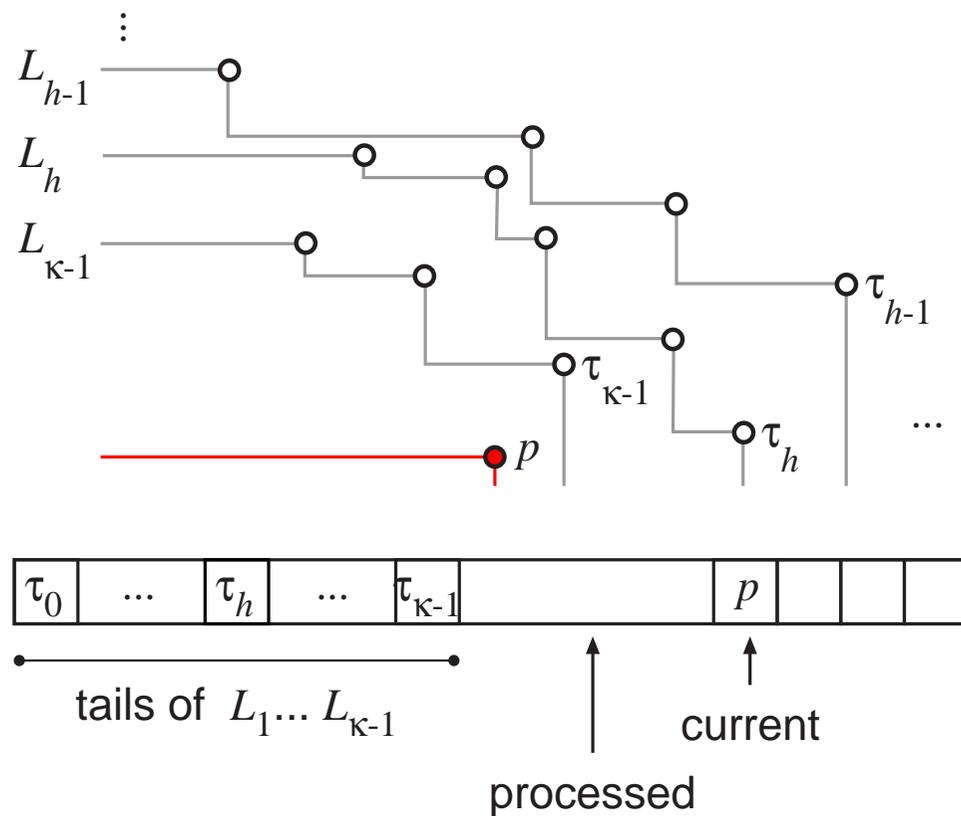
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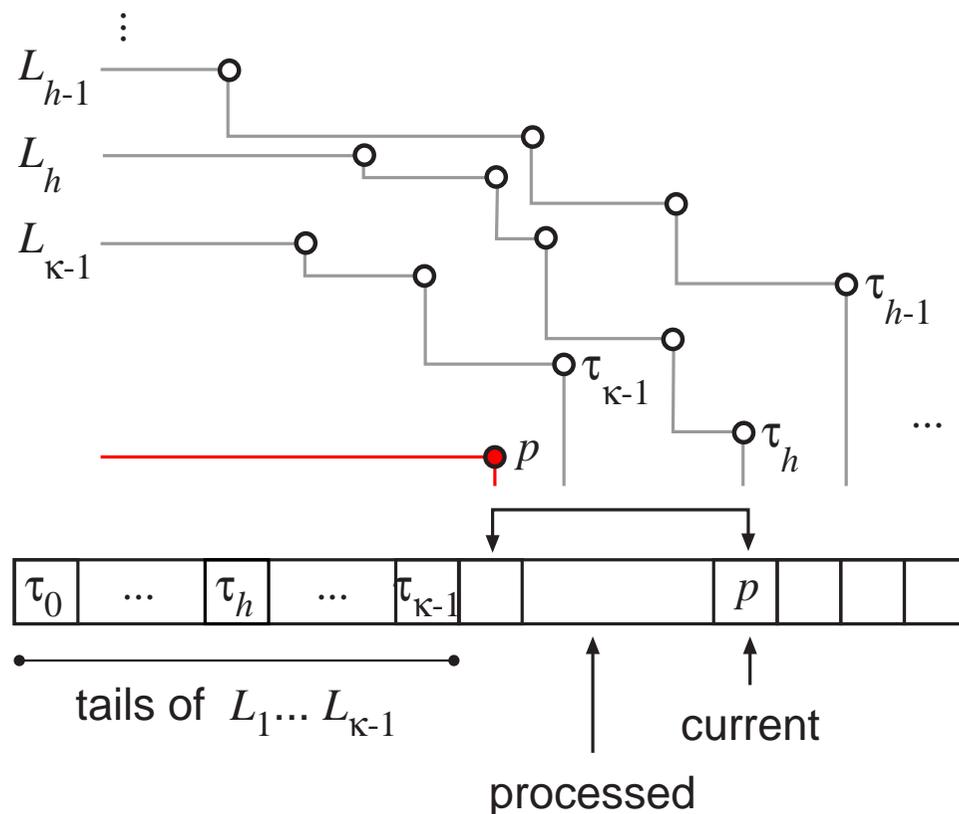
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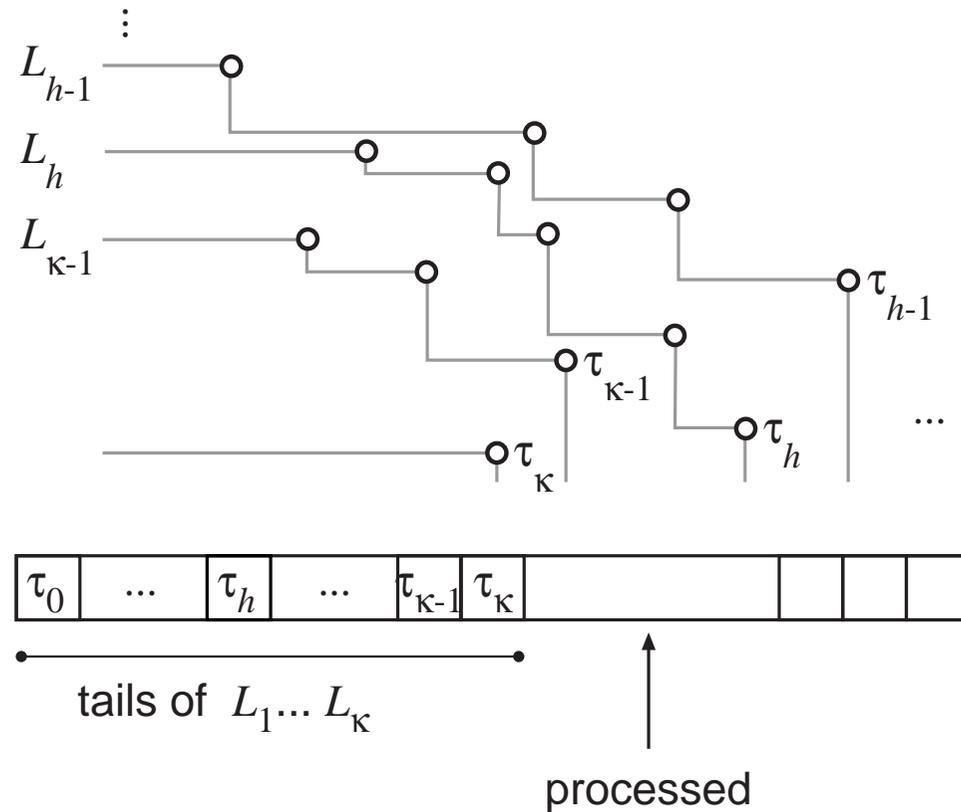
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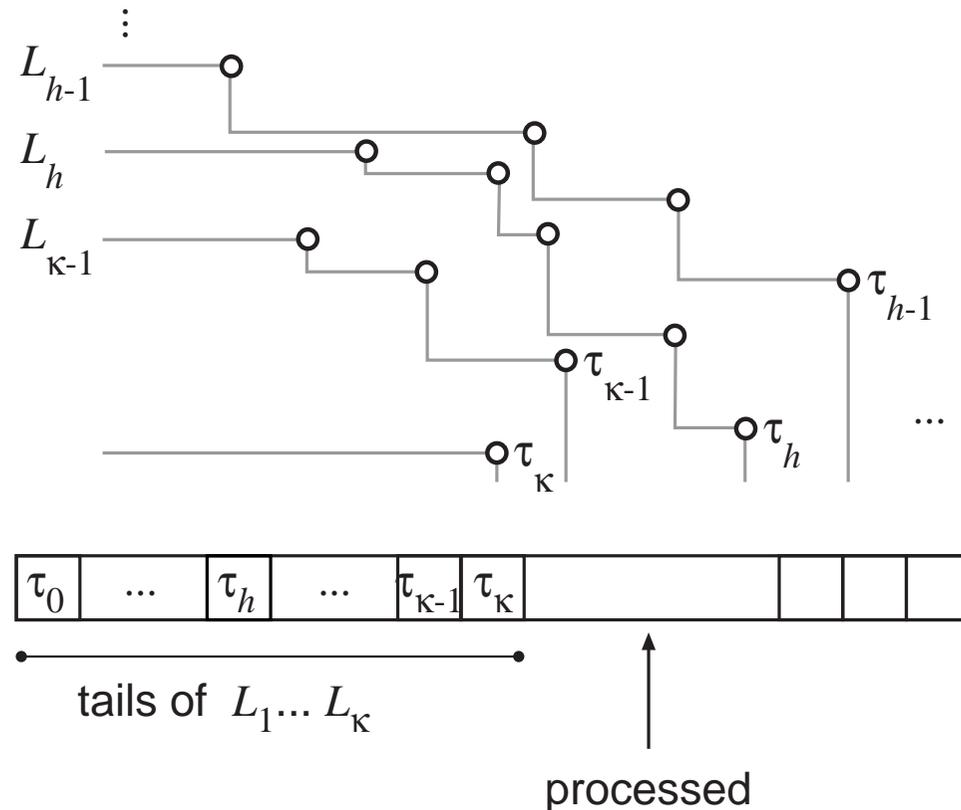
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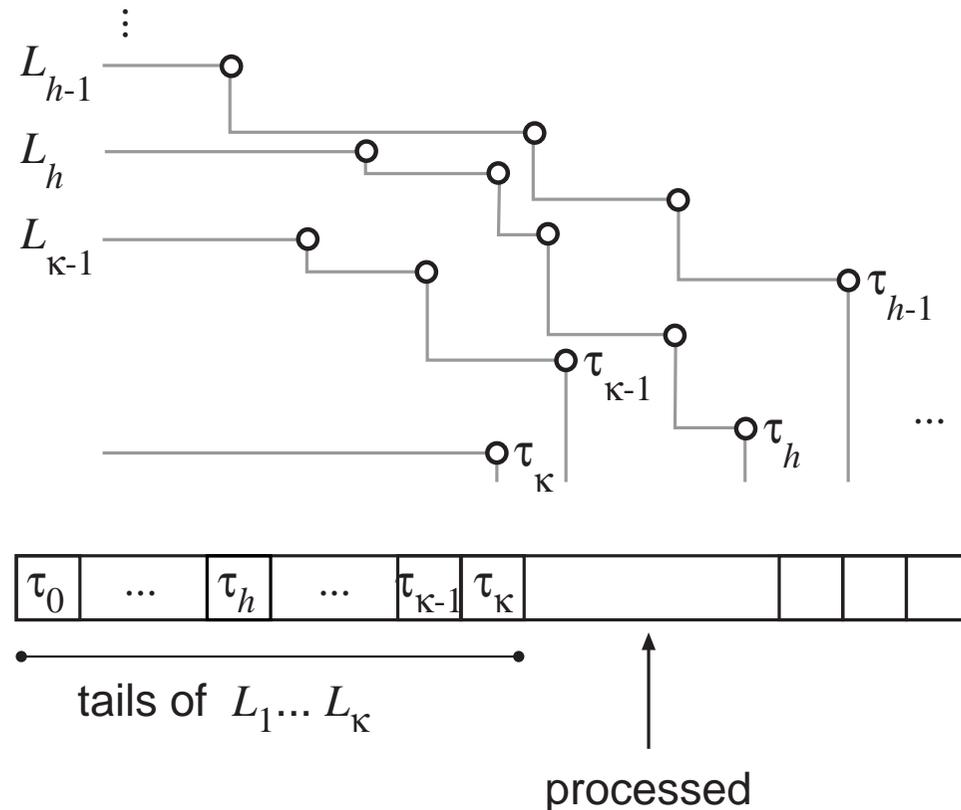
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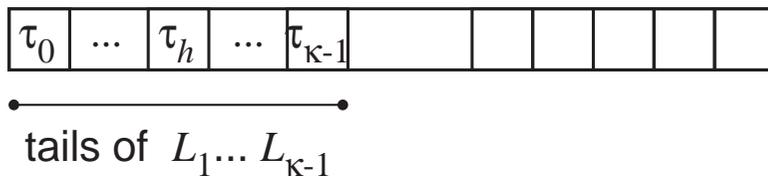
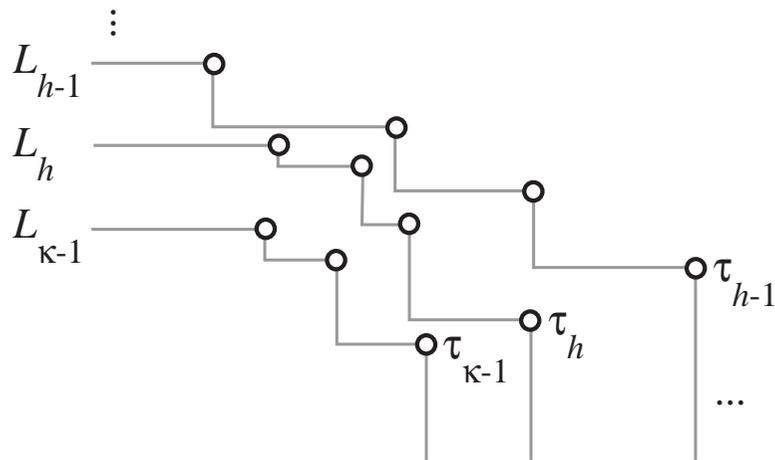


- In-place,  $\mathcal{O}(\log n)$  time per point  $\Rightarrow \mathcal{O}(n \log n)$  overall.
- Use this algorithm to count points on topmost layers.  $\Rightarrow$

## Counting the Points on the Topmost $\kappa$ Layers

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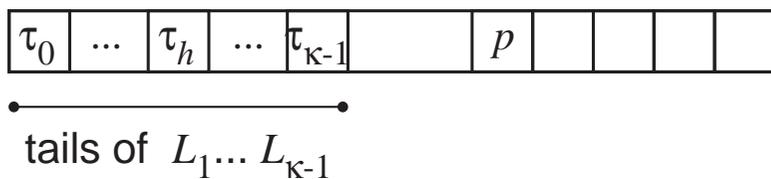
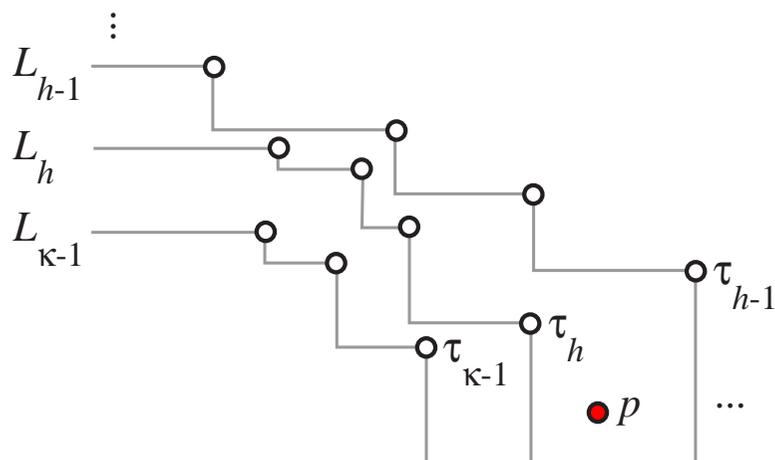
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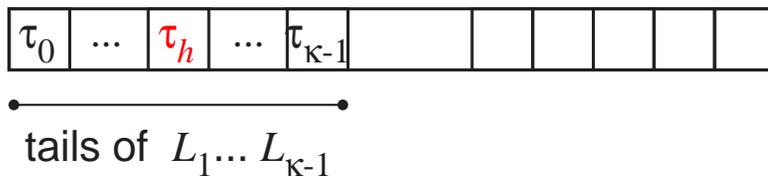
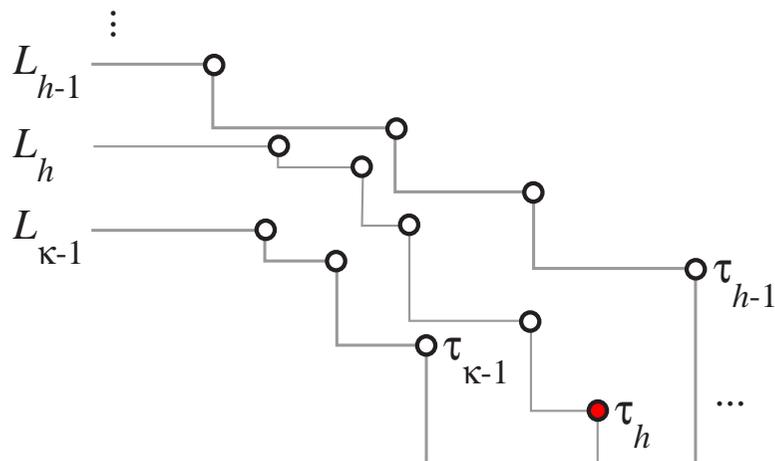




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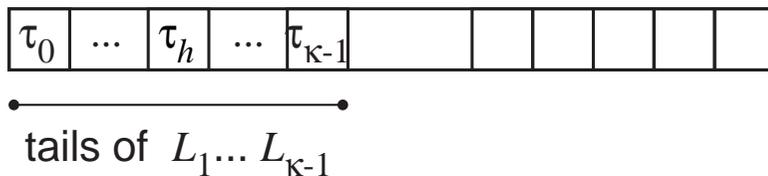
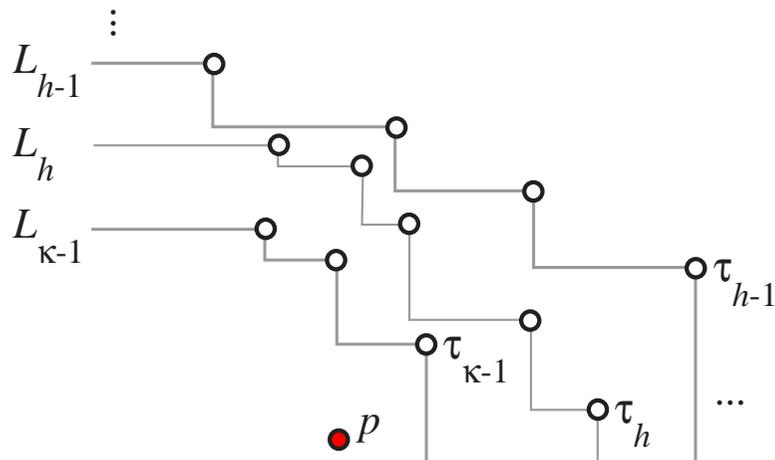
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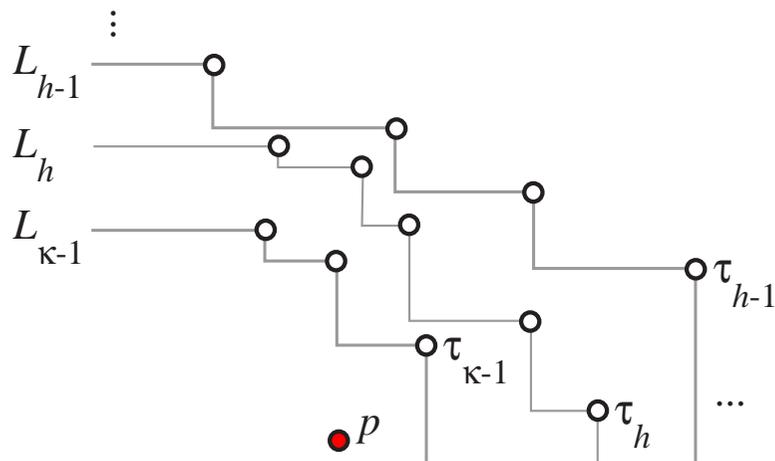
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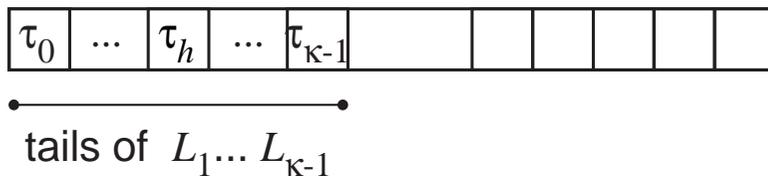
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- Sum:  $\mathcal{O}(n + \xi \log n)$ ,  $\xi = \sum_{i=0}^{\kappa-1} |L_i|$ .

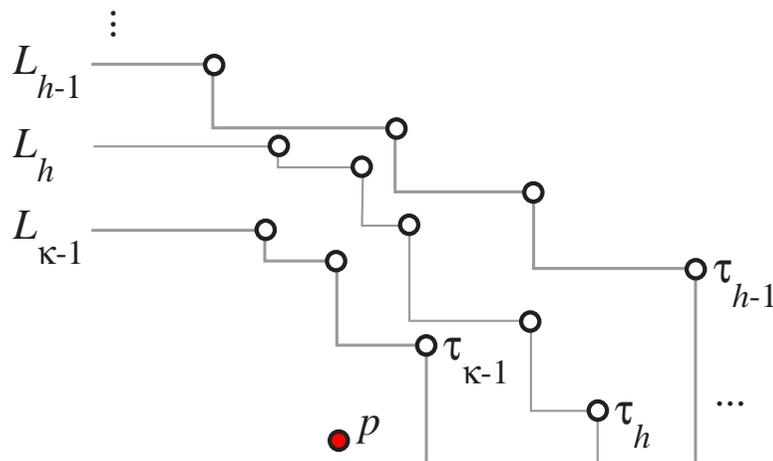


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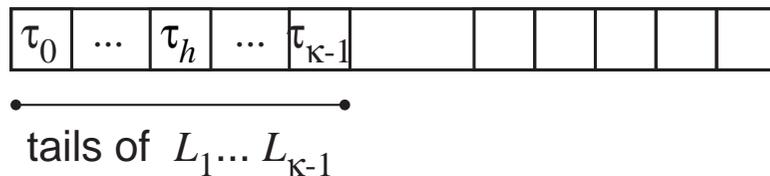
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### To compute each $|L_i| \dots$

- $\dots$  we need to increment a **counter**  $c_i$  for each update of  $\tau_i$ .

### Wait a minute!

- Did you say “ $\kappa \in \omega(1)$ ”?
- Where/how to store  $\kappa$  counters?



## Finding “extra” space

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**Space needed:**  $\kappa \in \omega(1)$  counters.

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**Bit-encoding technique [Munro, 1986]:**

- Use permutation of two adjacent elements to encode one bit.
- $p <_y q$ :  $pq \equiv 0$ ,  $qp \equiv 1$ . Counter:  $2 \lceil \log_2 n \rceil$  elements.

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- Set  $\kappa = \frac{1}{6}n / \log_2 n \Rightarrow \kappa$  counters need  $\frac{1}{3}n$  representing points.

## Finding “extra” space

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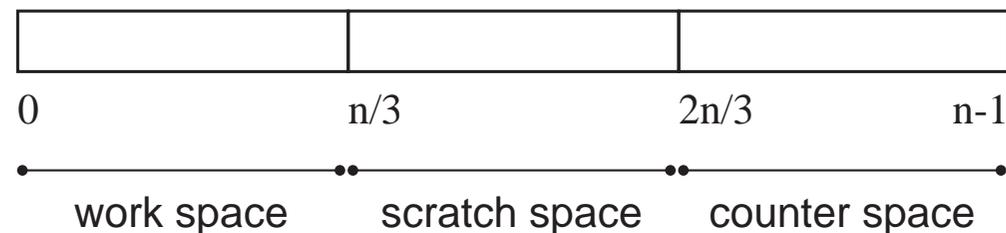
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- Set  $\kappa = \frac{1}{6}n / \log_2 n \Rightarrow \kappa$  counters need  $\frac{1}{3}n$  representing points.

### Partitioning the input array:

- Start working on the first  $\frac{1}{3}n$  entries.



## Finding “extra” space

---

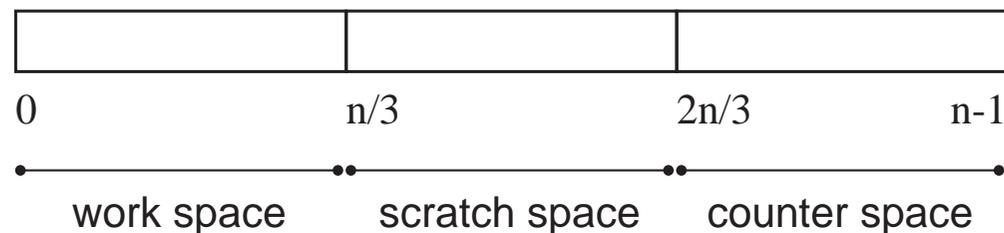
**Space needed:**  $\kappa \in \omega(1)$  counters, i.e.,  $\kappa \cdot \lceil \log_2 n \rceil$  bits.

### Bit-encoding technique [Munro, 1986]:

- Use permutation of two adjacent elements to encode one bit.
- $p <_y q$ :  $pq \equiv 0$ ,  $qp \equiv 1$ . Counter:  $2 \lceil \log_2 n \rceil$  elements.
- Set  $\kappa = \frac{1}{6}n / \log_2 n \Rightarrow \kappa$  counters need  $\frac{1}{3}n$  representing points.

### Partitioning the input array:

- Start working on the first  $\frac{1}{3}n$  entries.
- Use last  $\frac{1}{3}n$  entries for counters.

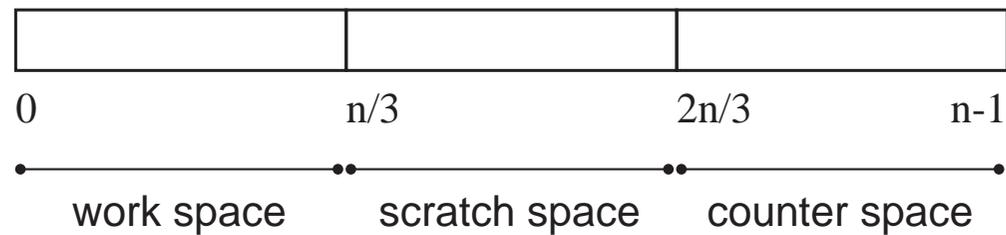


## Extracting the Topmost $\kappa$ Layers

---

### Setup:

- Compute size  $c_i$  of  $i$ -th layer,  $0 \leq i < \kappa = \frac{1}{6}n / \log_2 n$ .

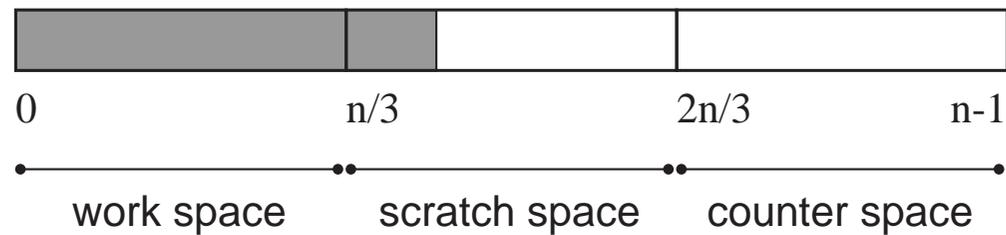


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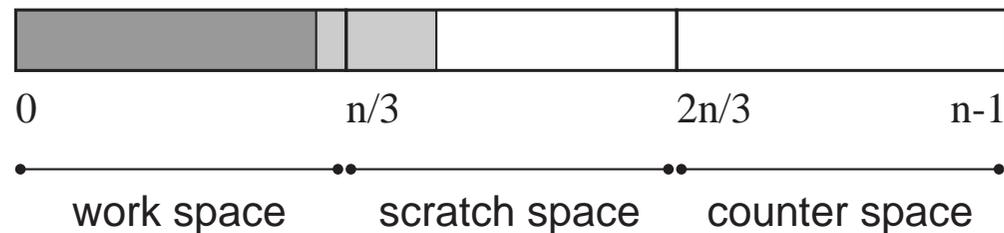


## Extracting the Topmost $\kappa$ Layers

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- Compute size  $c_i$  of  $i$ -th layer,  $0 \leq i < \kappa = \frac{1}{6}n / \log_2 n$ .
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## Extracting the Topmost $\kappa$ Layers

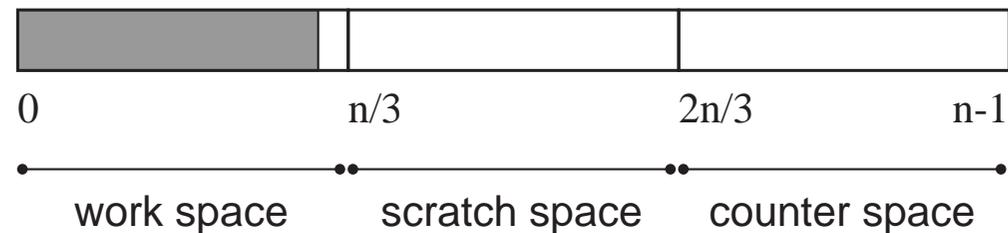
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### Extracting the topmost $j$ layers:

- Combine extraction with *counting sort*.



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### Extracting the topmost $j$ layers:

- Combine extraction with *counting sort*.
- Maintain “tails” in “work space”; construct layers *in sorted order* in “scratch space”.



## Extracting the Topmost $\kappa$ Layers

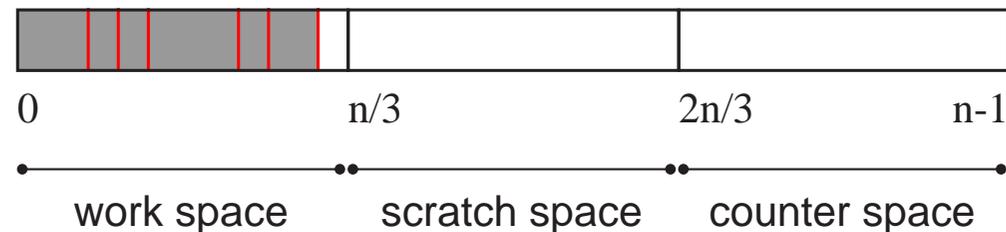
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### Extracting the topmost $j$ layers:

- Combine extraction with *counting sort*.
- Maintain “tails” in “work space”; construct layers *in sorted order* in “scratch space”.
- Move constructed layers to front.

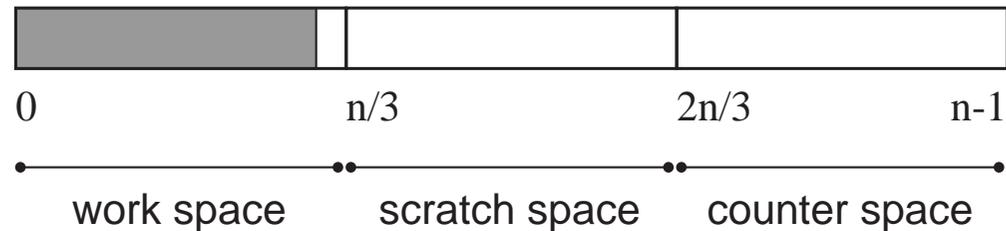


## Extracting All Layers—I

---

First phase, i.e., for earlier iterations:

- Construct (groups of  $\frac{1}{6} \cdot \frac{n}{\log n}$ ) layers in first part of the array.

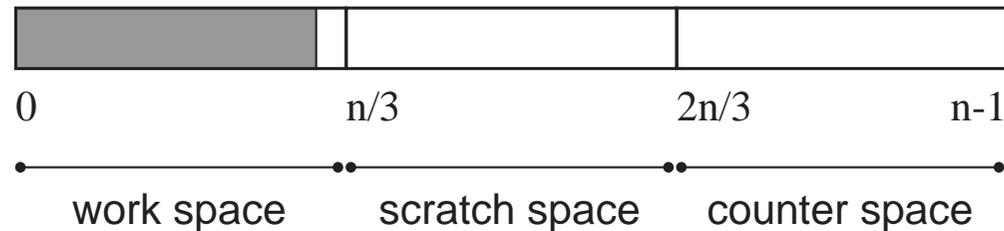


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**Analysis:**

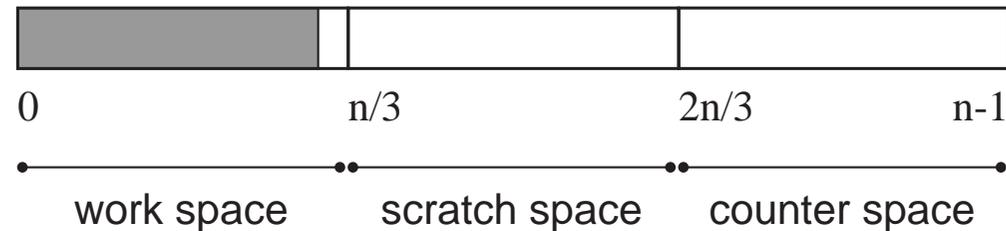
- Cost per iteration that processes all  $\xi$  points on  $\frac{1}{6} \cdot \frac{n}{\log n}$  layers:  
 $\mathcal{O}(n + \xi \log n)$ .
- Invariant: Keep unprocessed(!) points in sorted  $<_y$ -order.

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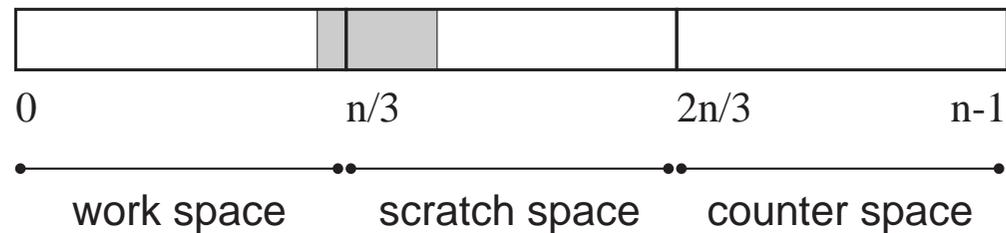
- Cost per iteration that processes all  $\xi$  points on  $\frac{1}{6} \cdot \frac{n}{\log n}$  layers:  $\mathcal{O}(n + \xi \log n)$ .
- Invariant: Keep unprocessed(!) points in sorted  $<_y$ -order.
- No more than  $\mathcal{O}(\log n)$  such iterations, i.e.,  $\mathcal{O}(n \log n)$  global cost.

## Extracting All Layers–II

---

### Second phase (with a grain of salt):

- Construct (in  $\mathcal{O}(n \log n)$  time) one layer crossing the boundary between work and scratch space using the [skyline](#) algorithm.

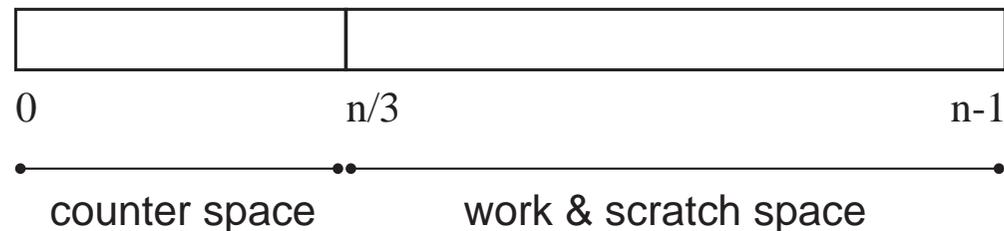


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### Second phase (with a grain of salt):

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### Third phase i.e., for later iterations:

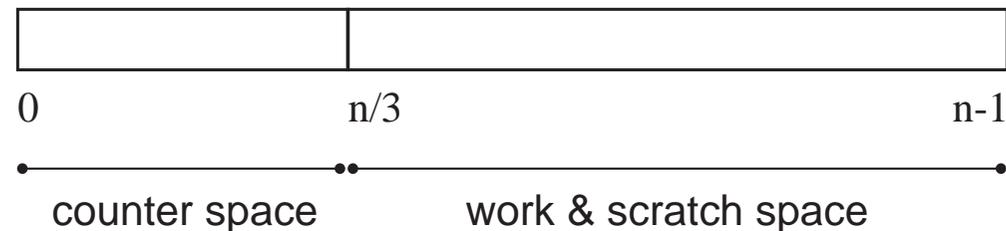
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## Extracting All Layers–II

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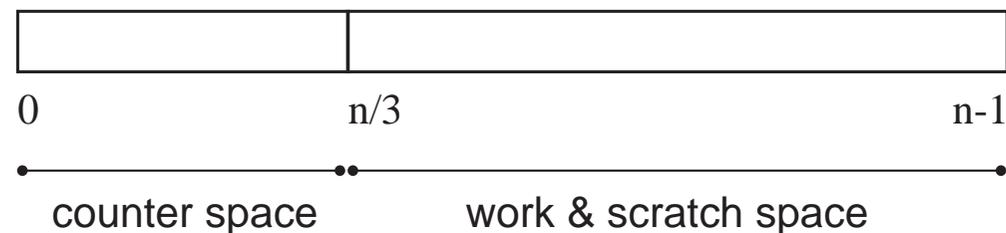
- Construct (groups of  $\frac{1}{6} \cdot \frac{n}{\log n}$ ) layers in second part of the array.
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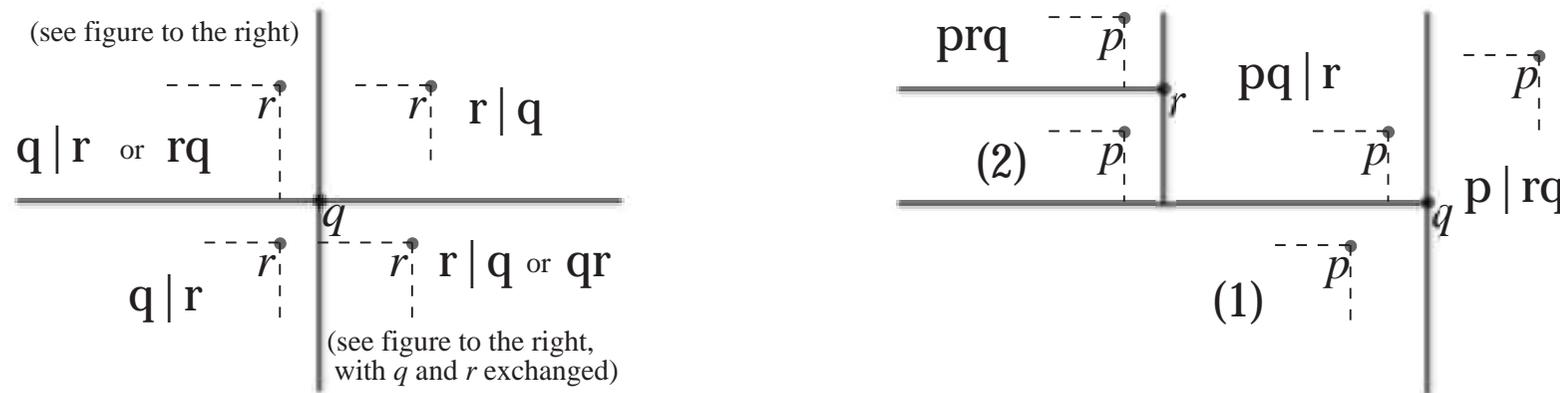
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- $\mathcal{O}(n + \xi \log n)$  time to process  $\frac{1}{6} \cdot \frac{n}{\log n}$  layers with  $\xi$  points.
- Whenever scratch space is too small, perform [skyline](#) computations on subarrays of [geometrically decreasing size](#)  $\Rightarrow \mathcal{O}(n \log n)$ .

## Repairing the Layer Order

---

### Finishing up:

- Bit-encoding corrupts layer order (locally).
- Repairing after last iteration by linear time sweep:
- Each bit-neighbour pair  $(q, r)$  can be correctly ordered by only looking at  $q$ ,  $r$  and predecessor  $p$ :



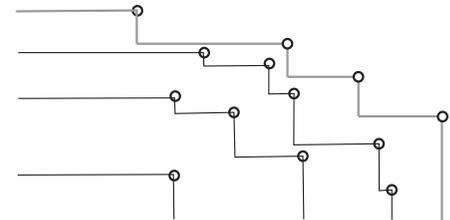
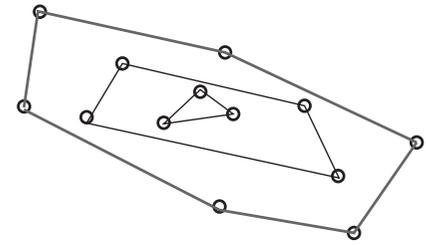
- $\Rightarrow$  Layer order repairable by linear scan.
  - $\Rightarrow \mathcal{O}(n \cdot \log_2 n)$  in-place computation of layers of maxima.
-

# Convex layers computation

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**Ideas applicable also to convex layers problem?**

- Applicable:

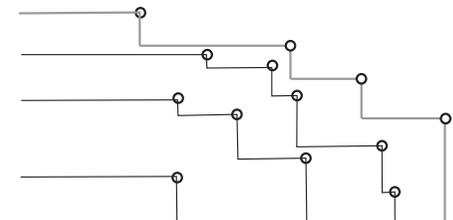
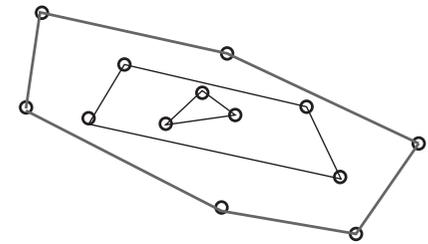


# Convex layers computation

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**Ideas applicable also to convex layers problem?**

- Applicable:
  - Sweep-framework.

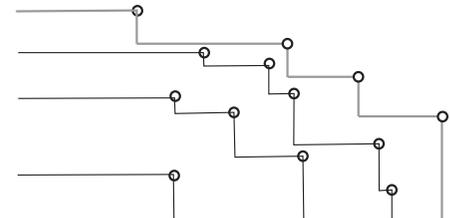
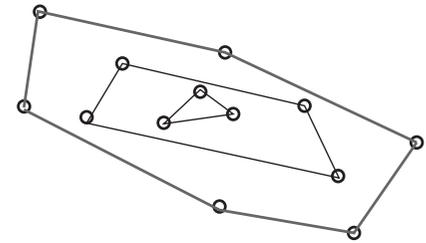


# Convex layers computation

---

## Ideas applicable also to convex layers problem?

- Applicable:
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  - Maintenance of tails for each layer.



# Convex layers computation

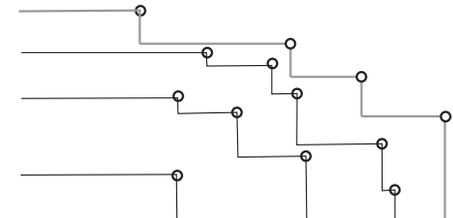
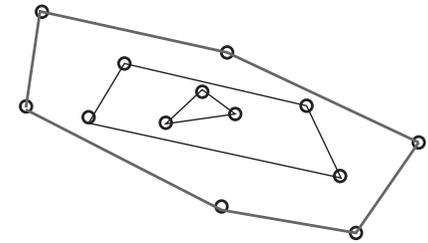
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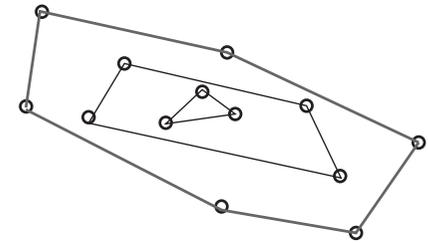
## Problem:

- A point changes its convex layer  $\mathcal{O}(n)$  times during sweep.



# Convex layers computation

---

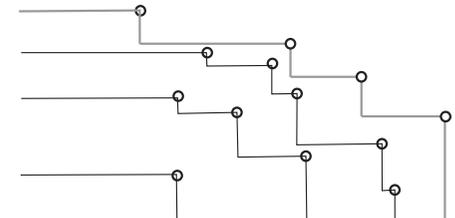


## Ideas applicable also to convex layers problem?

- Applicable:
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## Problem:

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## Solutions (for 2D layers and 3D hull)?

- for 2D convex layers?
- for 3D convex hull?

## Computing the skyline in 3D

---

### Time-Optimal algorithm [Kung et al., 1975]:

- Do divide-and-conquer along  $z$ .
- For each conquer-step:
  - Problem broken down to 2D ...
  - Divide in upper and lower part.
  - Simultaneous  $y$ -sweep over upper and lower maxima and exploit:
  - For each maximum of  $\mathcal{P}_{|z>\zeta}$ : on skyline (of whole input).
  - For each maximum of  $\mathcal{P}_{|z\leq\zeta}$ : on skyline  $\Rightarrow x$ -larger than actual tail.

...	Maxima of $\mathcal{P}_{ z\leq\zeta}$		Maxima of $\mathcal{P}_{ z>\zeta}$		...
	$l_b$	$l'_b$	$\lfloor (l_b + l_e)/2 \rfloor$	$l'_e$	$l_e$

⇓

...	Maxima of $\mathcal{P}_{ z\leq\zeta} \cup \mathcal{P}_{ z>\zeta}$	...
	$l_b$	$l_e$

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### Making it in-place:

- Use in-place recursion framework [Bose et al., 2006].

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⇓

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	$l_b$	$l'$	$l_e$

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	$\ell_b$	$\ell'_b$	$\lfloor (\ell_b + \ell_e) / 2 \rfloor$	$\ell'_e$	$\ell_e$

⇓

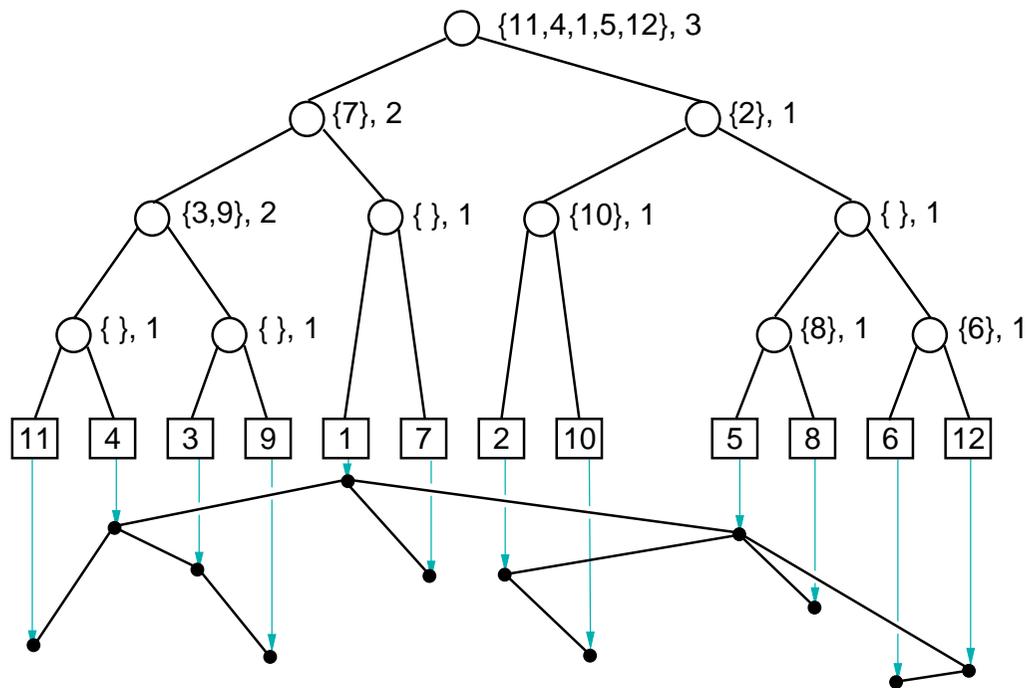
...	Maxima of $\mathcal{P}_{ z\leq\zeta} \cup \mathcal{P}_{ z>\zeta}$	...
	$\ell_b$	$\ell_e$

# Convex hull and layers computation

---

## Solutions (for 2D layers and 3D hull):

- Build recursively defined hull data structure ...

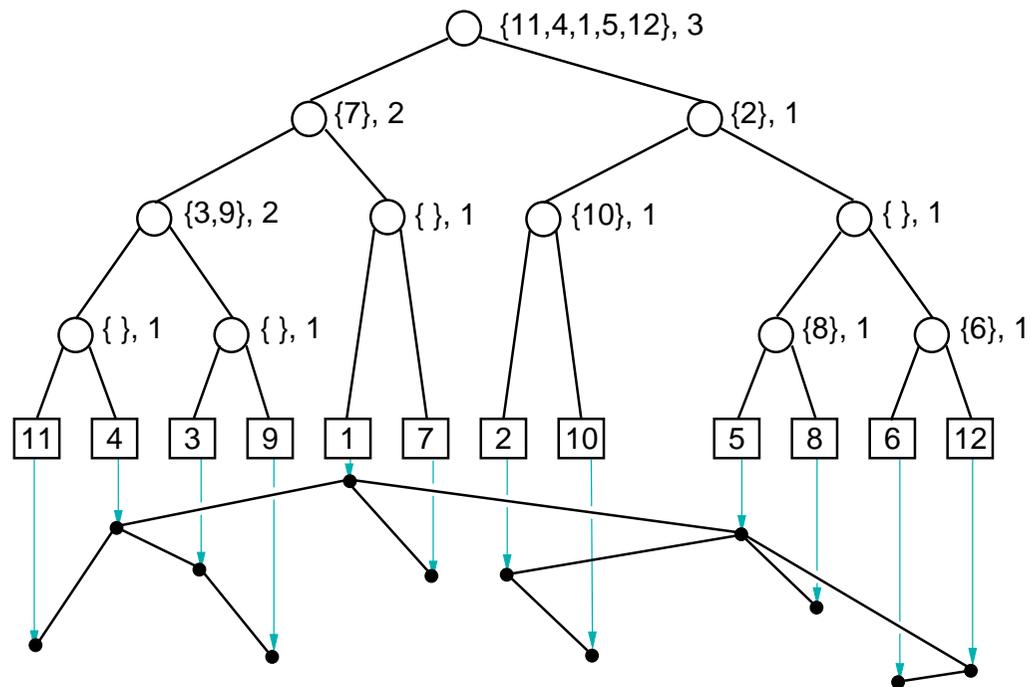


# Convex hull and layers computation

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## Solutions (for 2D layers and 3D hull):

- Build recursively defined hull data structure ...
- ... then remove points iteratively.

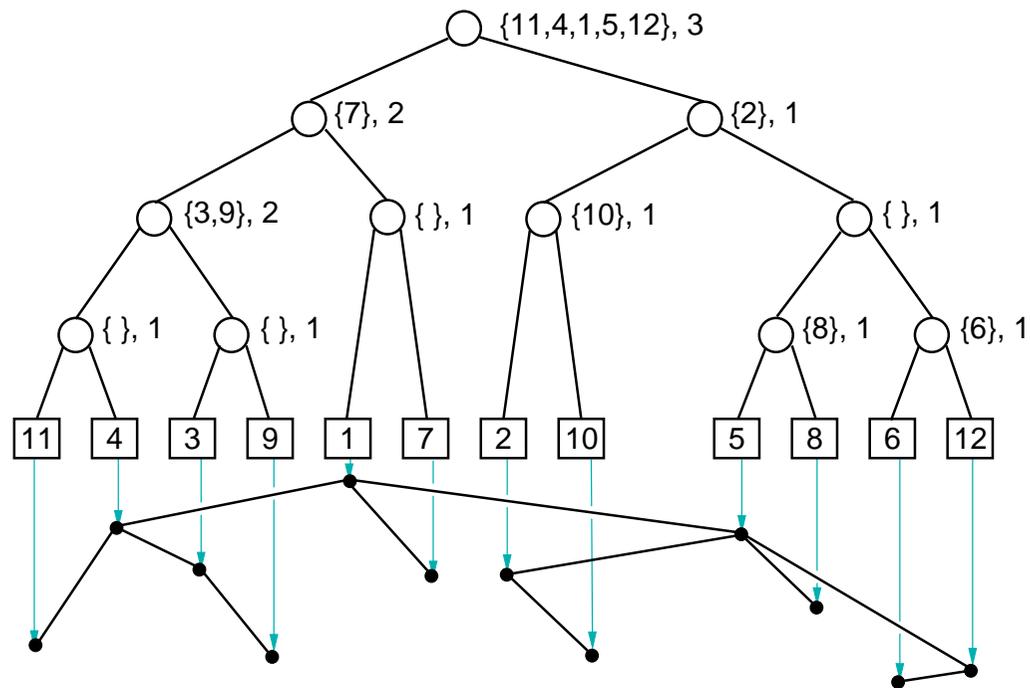


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- $\Rightarrow$  2D Convex layers in  $\mathcal{O}(n \log_2 n)$  time [Chazelle, 1985].

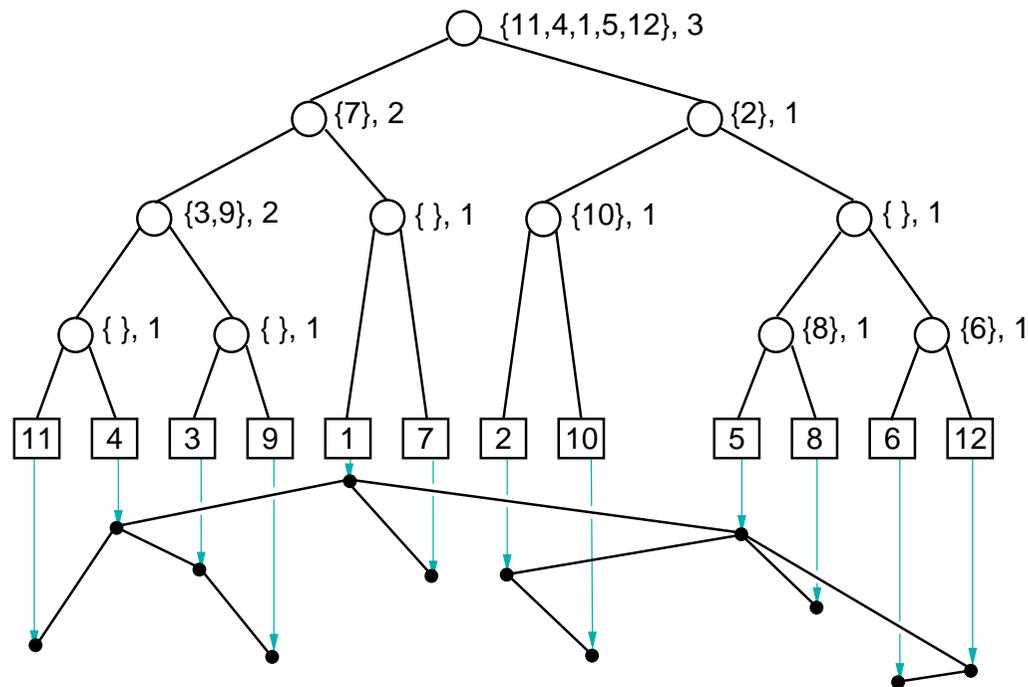


# Convex hull and layers computation

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- $\Rightarrow$  3D Convex hull in  $\mathcal{O}(n \log_2^3 n)$  time and  $\mathcal{O}(1)$  space [Brönnimann et al., 2004a].



# Overview

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1. Introduction: Motivation for implicit computation
2. Skylines and convex hulls

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