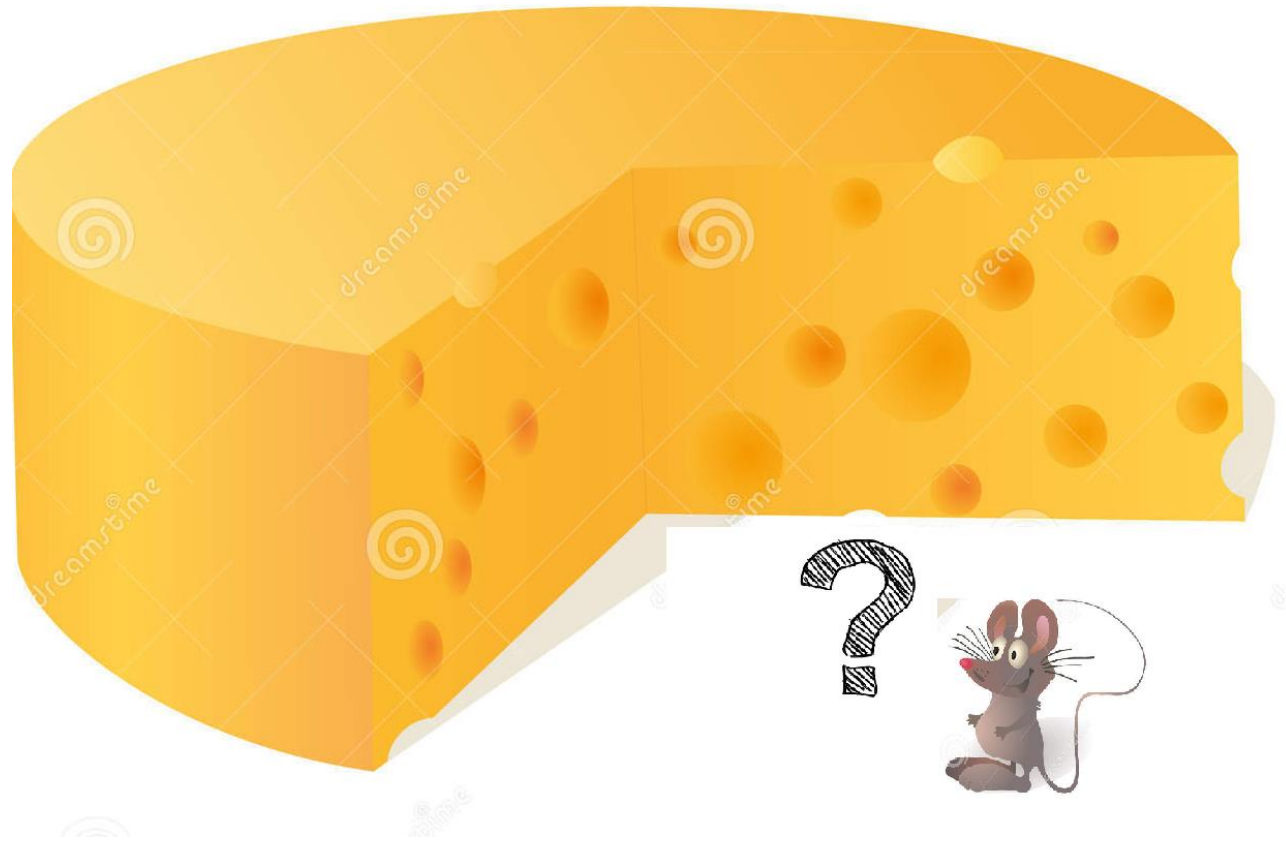


Big Data Class



LECTURER: DAN FELDMAN

TEACHING ASSISTANTS:

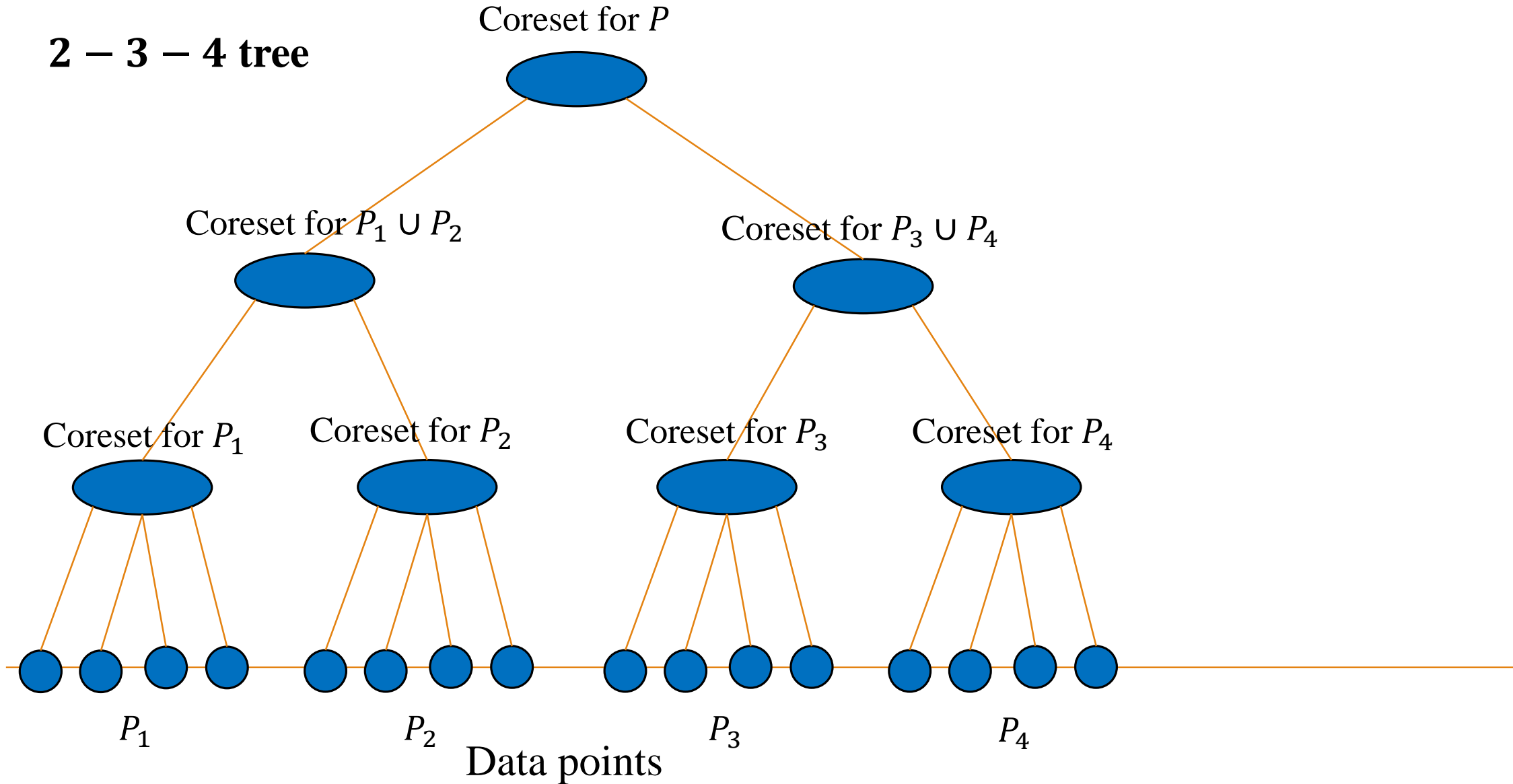
IBRAHIM JUBRAN

ALAA MAALOUF



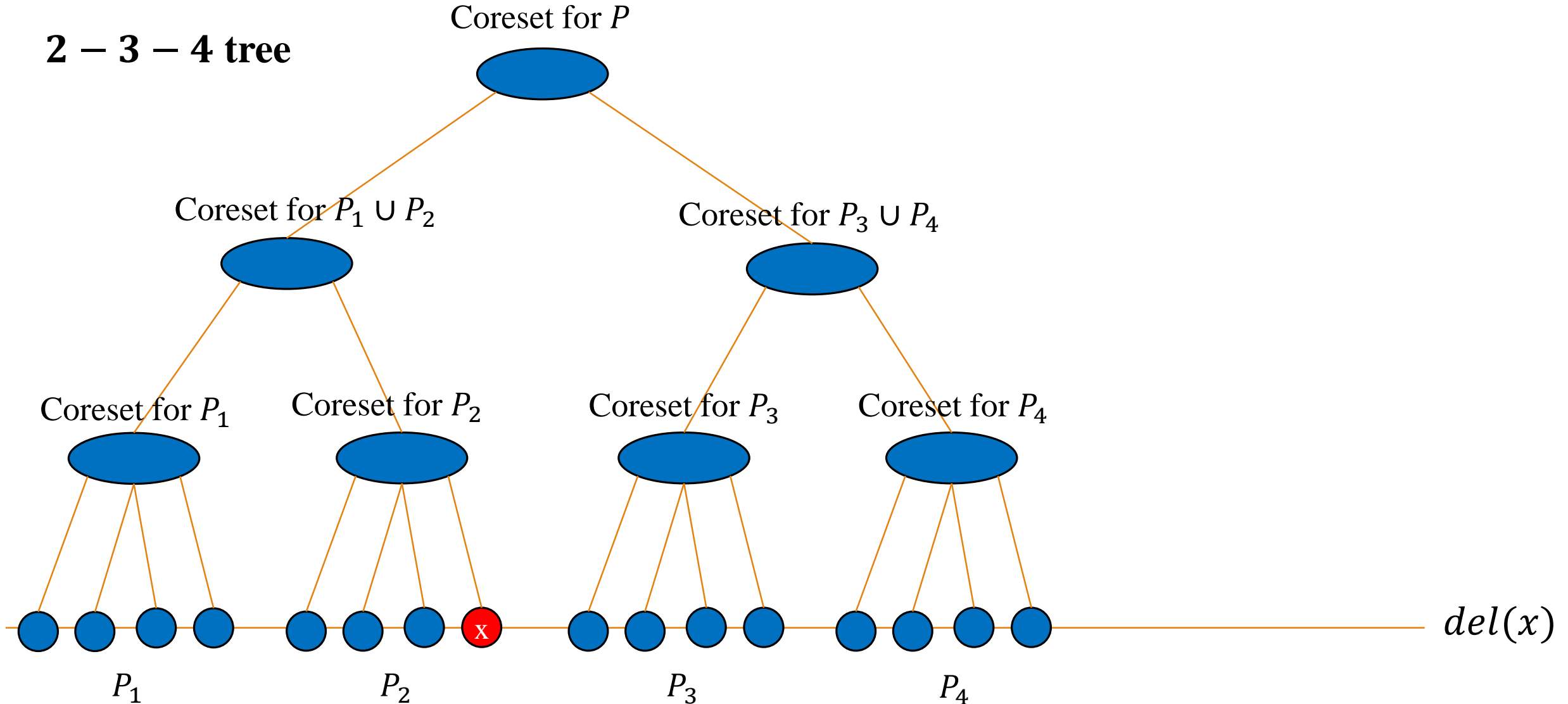
Dynamic Data with Insertions and Deletions

2 – 3 – 4 tree



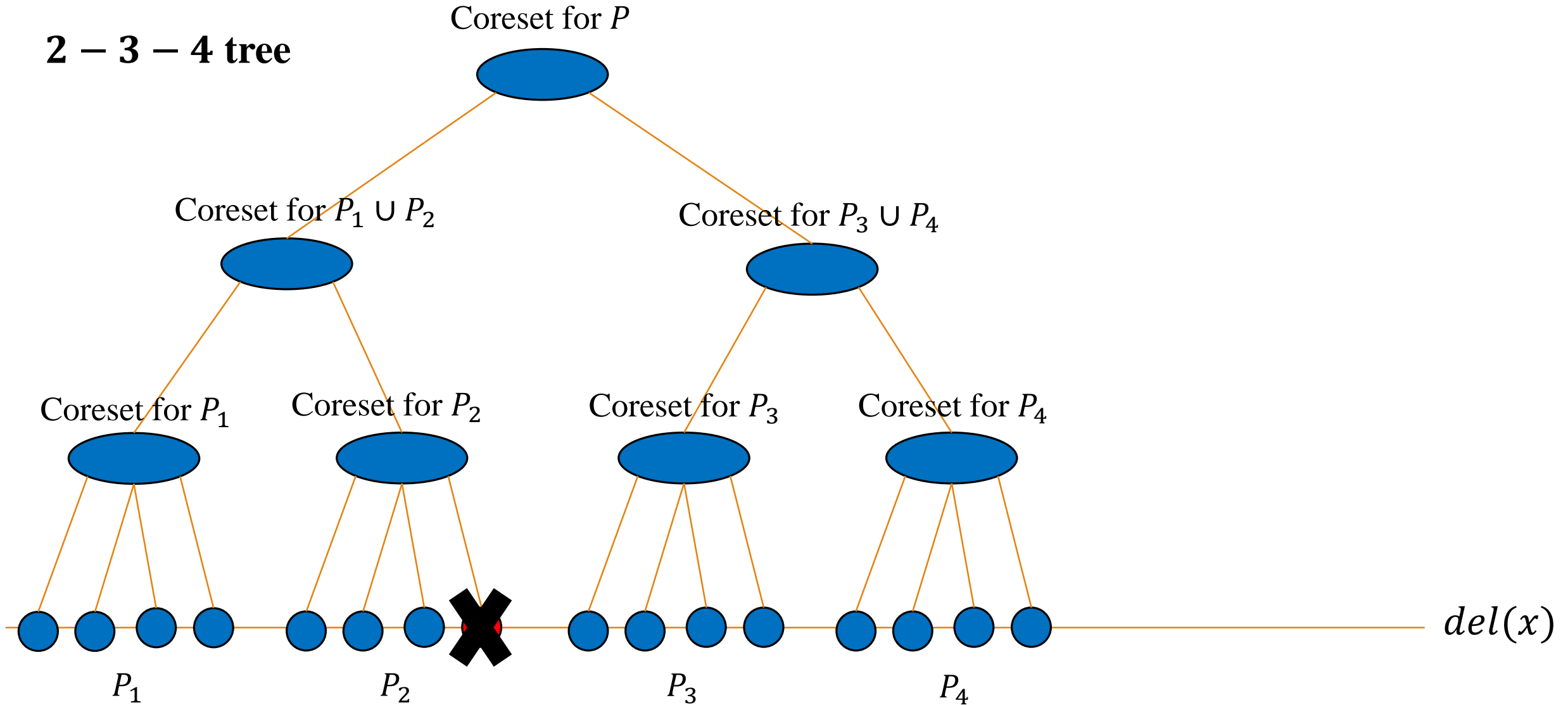
Dynamic Data with Insertions and Deletions

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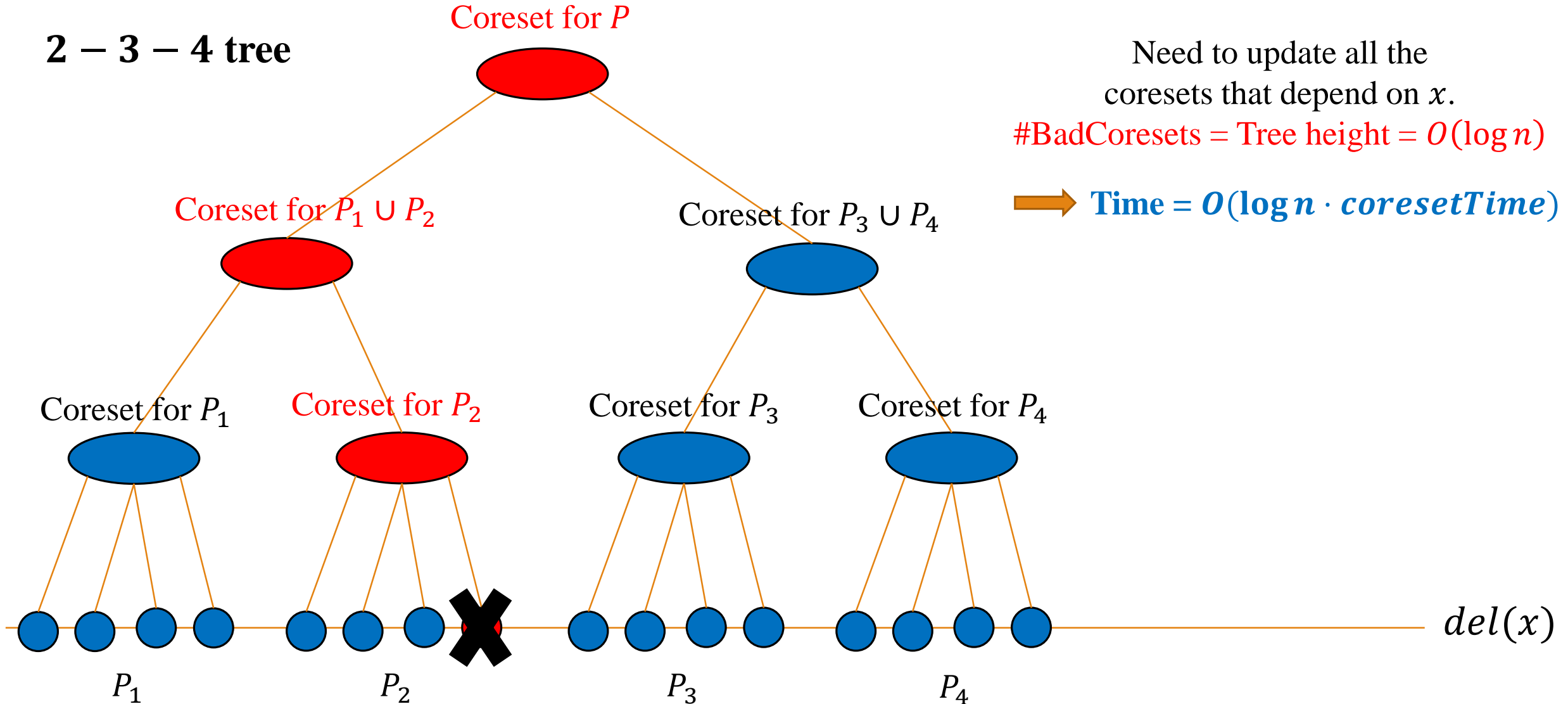
Dynamic Data with Insertions and Deletions

2 – 3 – 4 tree



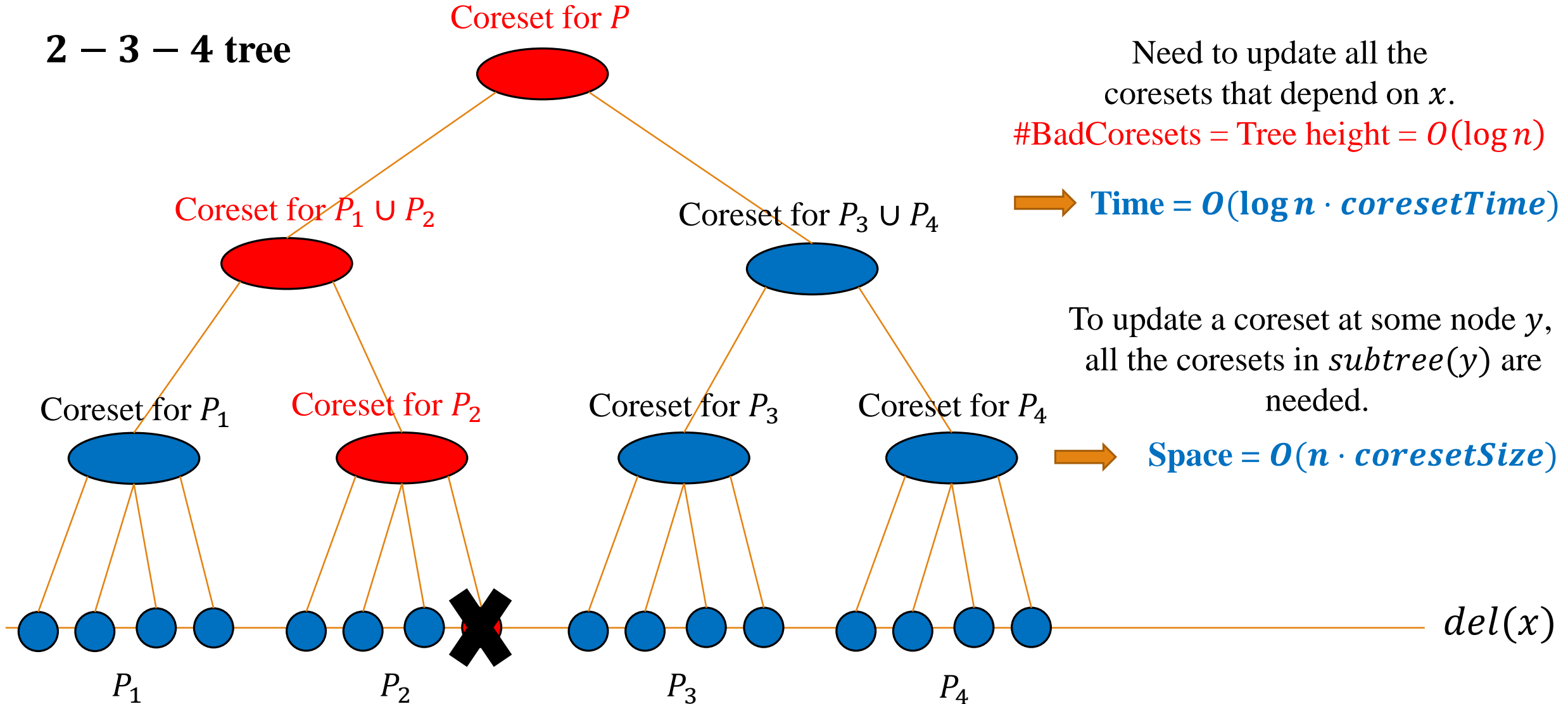
Dynamic Data with Insertions and Deletions

2 – 3 – 4 tree



Dynamic Data with Insertions and Deletions

2 – 3 – 4 tree

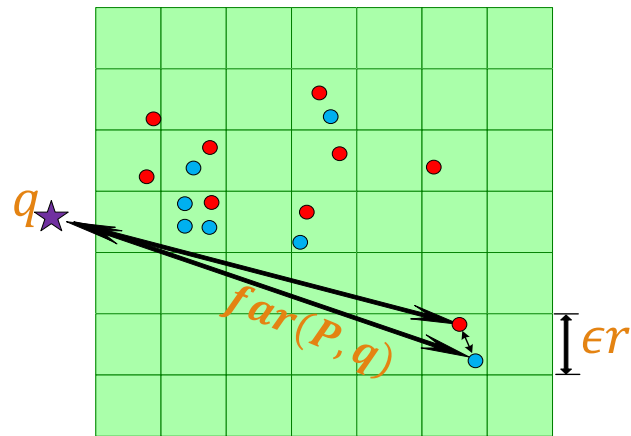


Re-use of the *coreset* for 1-center

Reminder:

- We learned about coreset for 1-center.
- Given P, Q in R^d , such coreset $C \subseteq P$ guarantee that for every $q \in Q$:

$$\max_{p \in P} \|p - q\| \leq \max_{c \in C} \|c - q\| + O(\epsilon) \cdot \max_{p \in P} \|p - q\|$$

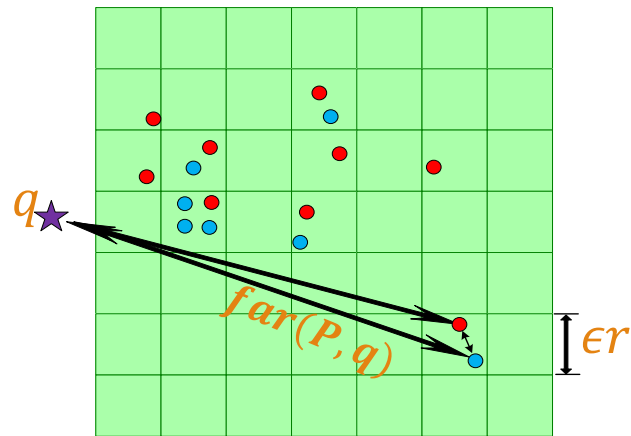


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Question:

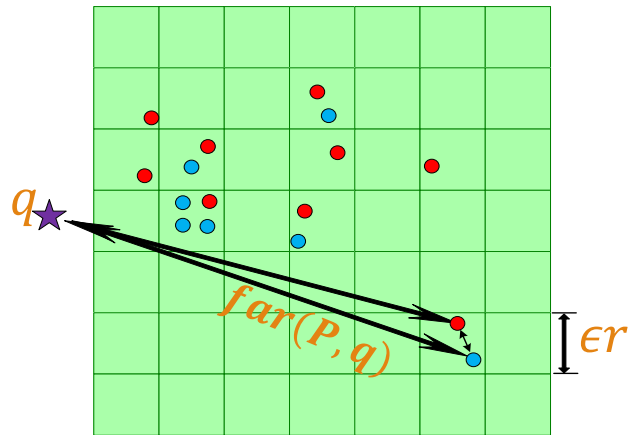
Can we use the same coreset for other problems/functions?

Re-use of the *coreset* for 1-center

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Question:

Can we use the same
coreset for
Sum of distances ?

Question:

Can we use the same
coreset for other
problems/functions?

Re-use of the *coreset* for 1-center

Re

Question:

Can we use the same
coreset for
**Sum of squared
distances ?**

center.

Let $C \subseteq P$ guarantee that for every $q \in Q$:

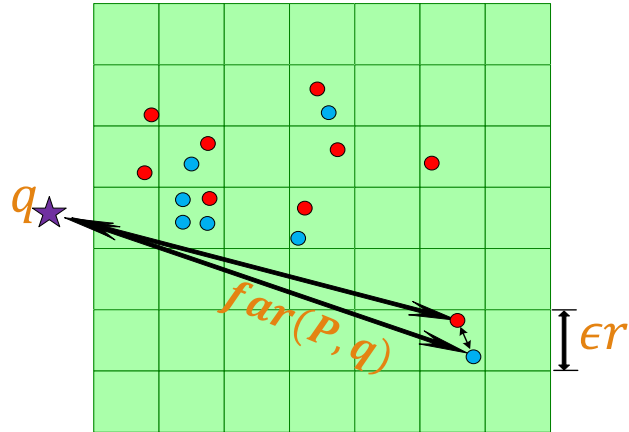
$$\|q - c^*\| \leq \max_{c \in C} \|c - q\| + O(\epsilon) \cdot \max_{p \in P} \|p - q\|$$

Question:

Can we use the same
coreset for
Sum of distances ?

Question:

Can we use the same
coreset for other
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Re-use of *coreset* for 1 – center

Coreset for sum of distances ?

- Given coreset for 1 – center, what error we get if we use it to measure sum, instead of max, of distances ?
- c_p := The representative of p
- $\forall c \in C, \quad \omega(c) := |\{p \in P \mid c_p = c\}|$

Claim:

$$\forall q \in Q: \quad \sum_{p \in P} \|p - q\| \leq \sum_{c \in C} \omega(c) \|c - q\| + n \cdot O(\epsilon) \cdot \max_{p \in P} \|p - q\|$$

Re-use of the *coreset* for 1-center

Coreset for sum of distances - Proof

- $c_p :=$ The representative of p
- $\forall c \in C, \quad \omega(c) := |\{p \in P \mid c_p = c\}|$
- coreset for 1 – center implies that

$$\forall p \in P, q \in Q: \quad \|p - q\| \leq \|c_p - q\| + O(\epsilon) \cdot \max_{p \in P} \|p - q\|$$

Re-use of the *coreset* for 1-center

Coreset for sum of distances - Proof

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$$\forall p \in P, q \in Q: \quad \|p - q\| \leq \|c_p - q\| + O(\epsilon) \cdot \max_{p \in P} \|p - q\|$$

$$\begin{aligned} \forall q \in Q: \quad \sum_{p \in P} \|p - q\| &\leq \sum_{p \in P} \left(\|c_p - q\| + O(\epsilon) \cdot \max_{p \in P} \|p - q\| \right) \\ &= \sum_{p \in P} \|c_p - q\| + n \cdot O(\epsilon) \cdot \max_{p \in P} \|p - q\| \\ &= \sum_{c \in C} \omega(c) \|c - q\| + n \cdot O(\epsilon) \cdot \max_{p \in P} \|p - q\| \end{aligned}$$



Re-use of the *coreset* for 1-center

Coreset for sum of distances - Proof

- $c_p :=$ The representative of p
- $\forall c \in C, \omega(c) := |\{p \in P : c_p = c\}|$
- coreset for 1-center

Question:

Can we use the same
coreset for
Sum of distances ?



$$\forall p \in P, q \in Q$$

$$\max_{p \in P} \|p - q\|$$

$$\begin{aligned} \forall q \in Q: \sum_{p \in P} \|p - q\| &\leq \sum_{p \in P} \left(\|c_p - q\| + O(\epsilon) \cdot \max_{p \in P} \|p - q\| \right) \\ &= \sum_{p \in P} \|c_p - q\| + n \cdot O(\epsilon) \cdot \max_{p \in P} \|p - q\| \\ &= \sum_{c \in C} \omega(c) \|c - q\| + n \cdot O(\epsilon) \cdot \max_{p \in P} \|p - q\| \end{aligned}$$



Re-use of the *coreset* for 1-center

Coreset for sum of squared distances ?

- Given coreset for 1 – center, what error we get if we use it to measure sum of squared, instead of max, distances ?

- c_p := The representative of p

- Let's look at the error:

$$\begin{aligned} \forall p \in P, q \in Q: & \left| \|p - q\|^2 - \|c_p - q\|^2 \right| \\ &= \left| \|p\|^2 + \|q\|^2 - 2 \cdot p^T q - \|c_p\|^2 - \|q\|^2 + 2 \cdot c_p^T q \right| \\ &\leq \left| \|p\|^2 - \|c_p\|^2 + 2 \cdot (c_p - p)^T q \right| \\ &\leq ?? \end{aligned}$$

Re-use of the *coreset* for 1-center

Coreset for sum of squared distances ?

- Given coreset for 1 – center of squared, instead of max, distance measure sum

- c_p := The representative

- Let's look at the error:

$$\begin{aligned} \forall p \in P, q \in Q: & \left| \|p\|^2 - \|c_p\|^2 - 2 \cdot p^T q + \|q\|^2 \right| \\ & = \left| \|p\|^2 + \|q\|^2 - 2 \cdot p^T q - \|c_p\|^2 - \|q\|^2 + 2 \cdot c_p^T q \right| \\ & \leq \left| \|p\|^2 - \|c_p\|^2 + 2 \cdot (c_p - p)^T q \right| \\ & \leq ?? \end{aligned}$$

Question:

Can we use the same coreset for

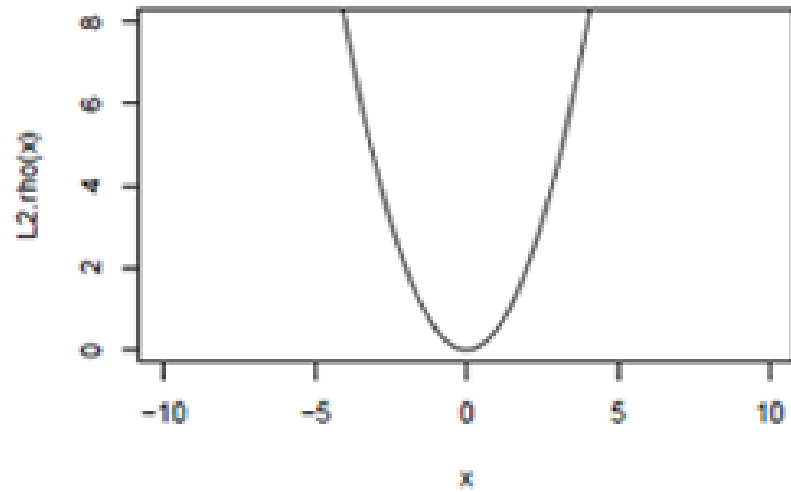
Sum of squared distances ?



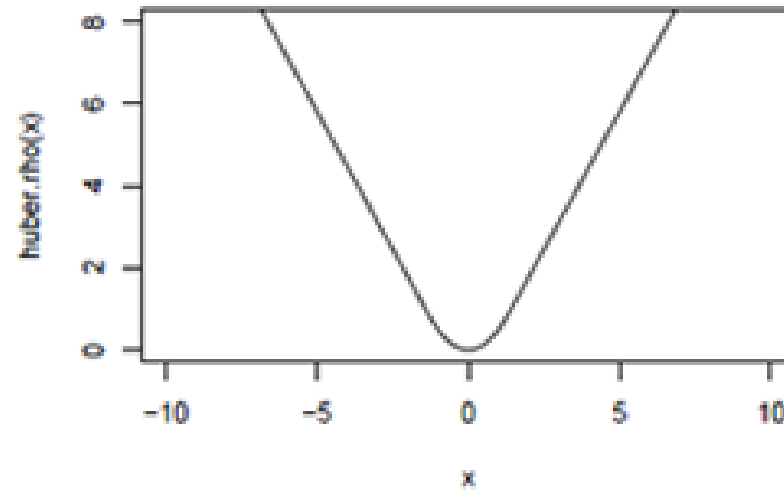
Motivation

M-estimators:

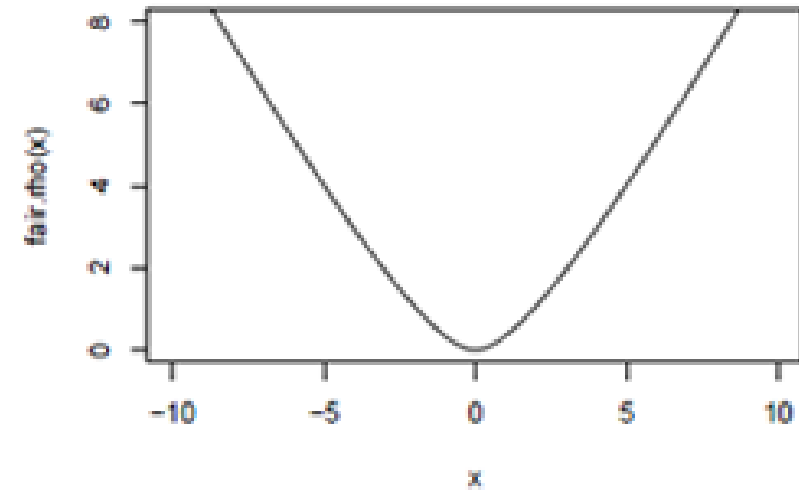
L2



Huber



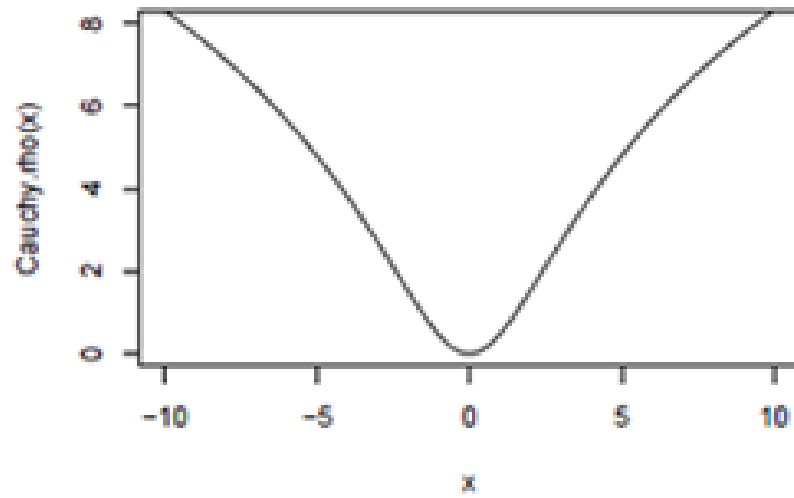
Fair



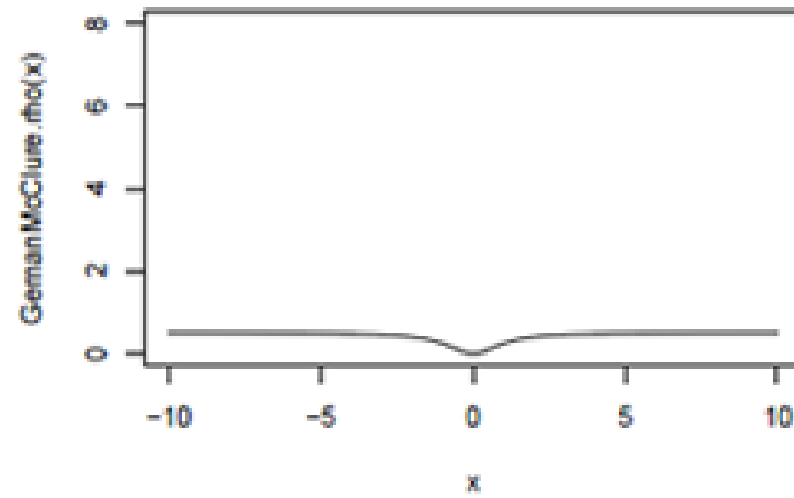
Motivation

M-estimators:

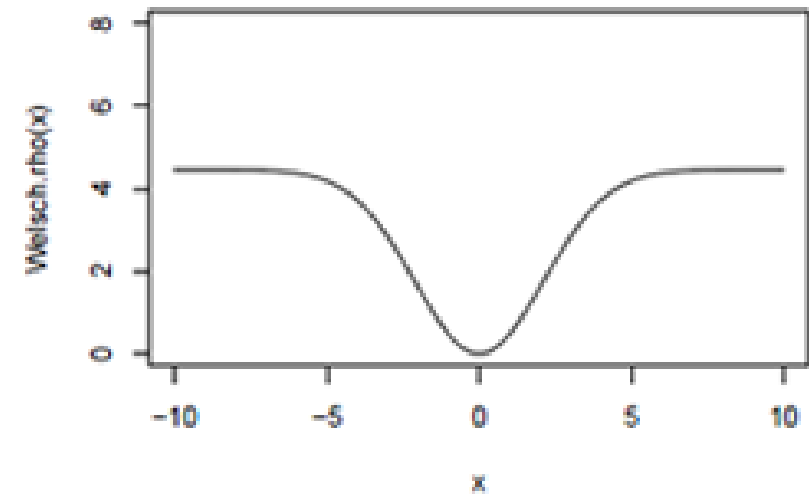
Cauchy



GemanMcClure

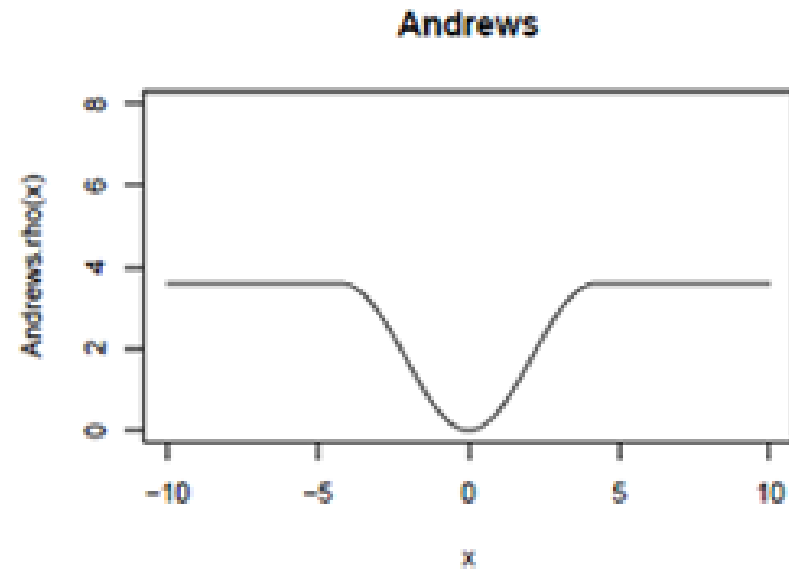
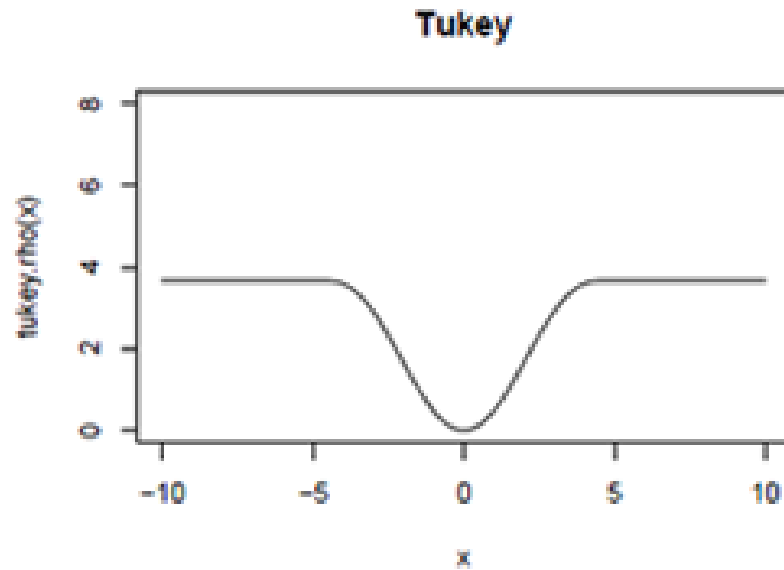


Welsch



Motivation

M-estimators:



Distance Function (Metric)

- A **distance function** is a function that defines a distance between each pair of elements of a **set** X

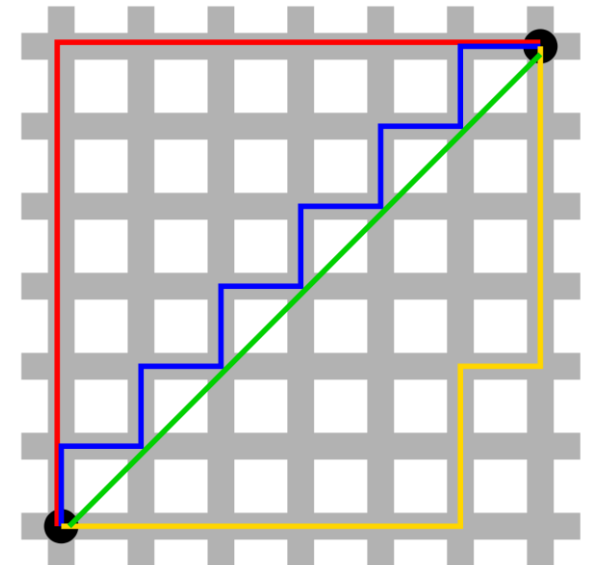
$$d: X \times X \rightarrow [0, \infty)$$

- A **distance function** satisfies the following conditions for every $x, y, z \in X$:

1) $d(x, y) \geq 0$ and $d(x, y) = 0 \leftrightarrow x = y$ non-negativity axiom.

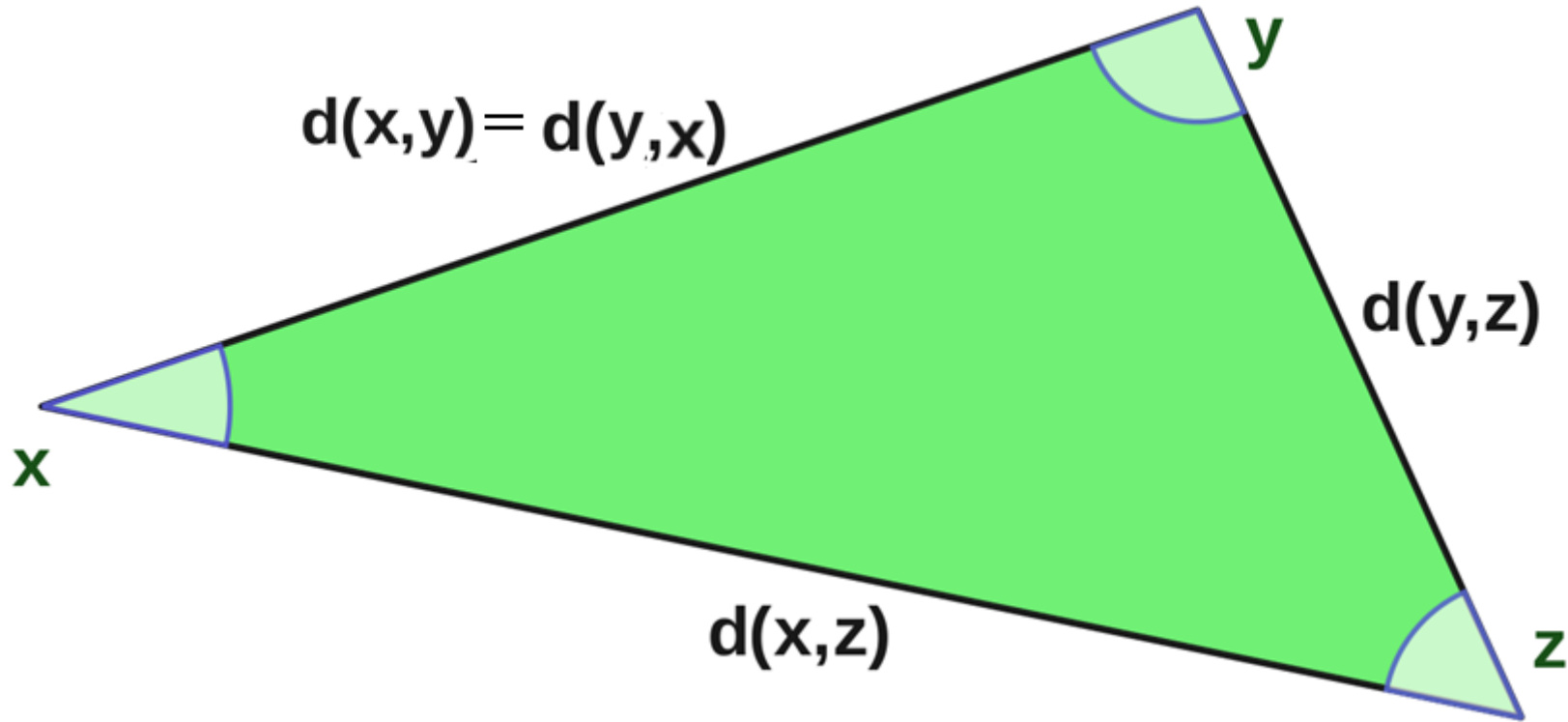
2) $d(x, y) = d(y, x)$ symmetry.

3) $d(x, z) \leq d(x, y) + d(y, z)$ triangle-inequality.



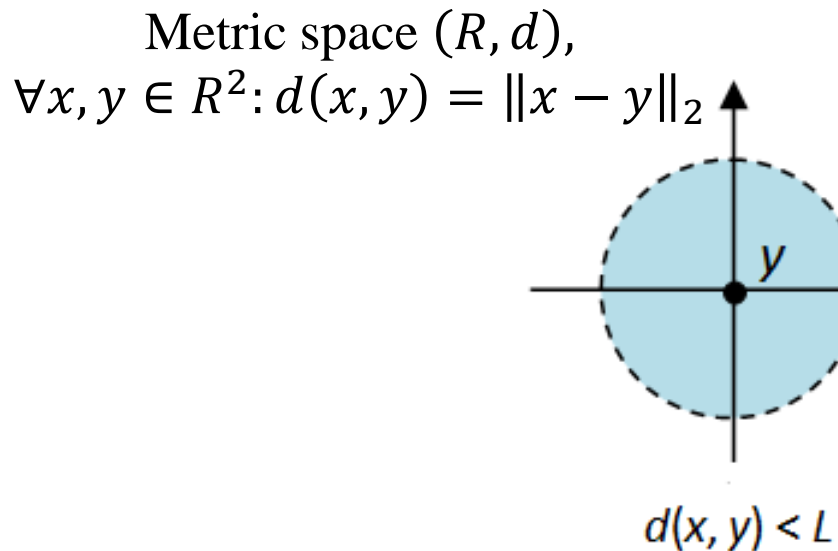
Distance Function (Metric)

- Illustration:

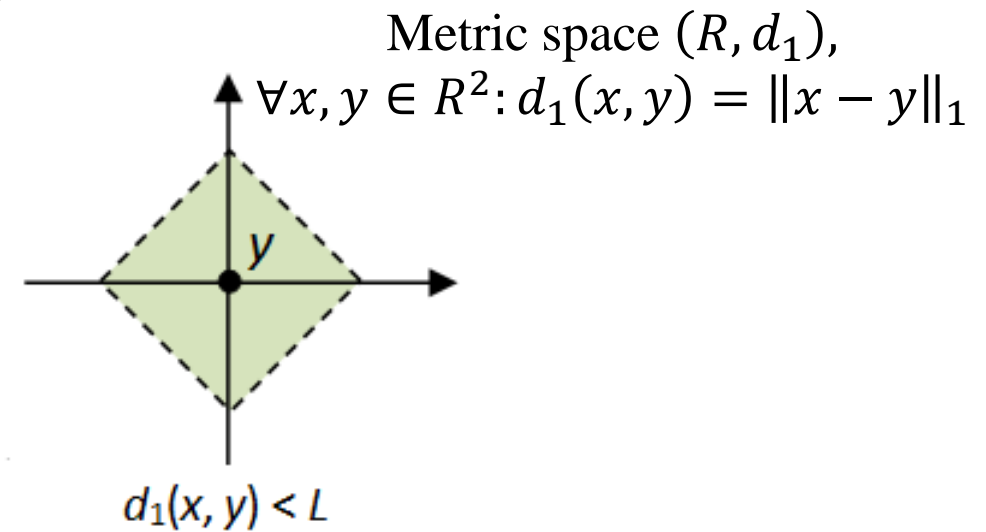
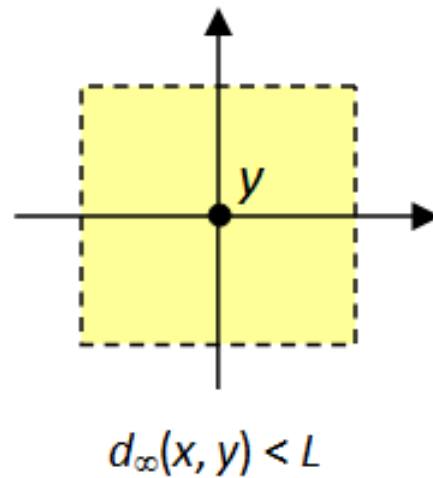


Metric Space

- A **metric space** is an ordered pair (X, d) where X is a set and $d: X \times X \rightarrow [0, \infty)$ is a distance function on the set X .



Metric space (R, d_∞) ,
 $\forall x, y \in R^2: d_\infty(x, y) = \|x - y\|_\infty$



Definitions

1) Log-Log Lipschitz:

A **monotonic non-decreasing** function $D: [0, \infty) \rightarrow [0, \infty)$ satisfies the **Log-Log Lipschitz** condition if there is $r > 0$ such that for every $x > 0$ and $\Delta > 1$ it holds that:

$$D(\Delta x) \leq \Delta^r D(x)$$

Lipschitz constant

2) Weak triangle inequality:

Let $D: X \times X \rightarrow [0, \infty)$. The function D satisfies the **weak triangle inequality** if there is $\rho > 0$ such that for every $(p, p', c) \in X^3$ the following holds:

$$D(p, c) \leq \rho(D(p, p') + D(p', c))$$

Definitions

3) Property 1:

Let $D: X \times X \rightarrow [0, \infty)$. For every $\psi \in \left(0, \frac{1}{2}\right)$ there is a real $\phi \geq 0$ such that for every $(p, p', c) \in X^3$ it holds that

$$|D(p, c) - D(p', c)| \leq \phi D(p, p') + \psi D(p, c)$$

Main Claims

Let $(X, dist)$ be a metric space and let $f: [0, \infty) \rightarrow [0, \infty)$ be a function that satisfies the *Log-Log Lipschitz* condition.

Define $far: X^2 \rightarrow [0, \infty)$ to be a mapping from every $p, c \in X$ to

$$far(p, c) = f(dist(p, c))$$

- **Claim 1:**

The function far satisfies the *weak triangle inequality* for $\rho = \max\{2^{r-1}, 1\}$, i.e., for every $p, q, c \in X^3$:

$$far(p, q) \leq \rho(far(p, c) + far(c, q))$$

Main Claims

- **Proof of Claim 1:**

Let $x = \text{dist}(p, c)$, $y = \text{dist}(c, q)$, $z = \text{dist}(p, q)$. Need to prove for $\rho = \max\{2^{r-1}, 1\}$ it holds that:

$$\text{far}(p, q) = \mathbf{f(z)} \leq \rho \cdot (\mathbf{f(x)} + \mathbf{f(y)}) = \rho \cdot (\text{far}(p, c) + \text{far}(c, q))$$

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- **Proof of Claim 1:**

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$$\text{far}(p, q) = f(z) \leq \rho \cdot (f(x) + f(y)) = \rho \cdot (\text{far}(p, c) + \text{far}(c, q))$$

By the triangle inequality and the fact that $f(\Delta x) \leq \Delta^r f(x)$, for every $\omega \in (0, 1)$ it holds that:

$$f(z) \leq f(x + y) = \omega \cdot f(x + y) + (1 - \omega) \cdot f(x + y)$$

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Log-Log Lipschitz $\leq \omega \cdot f(x) \left(\frac{x+y}{x}\right)^r + (1 - \omega) f(y) \left(\frac{x+y}{y}\right)^r$

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Log-Log Lipschitz

$$\begin{aligned} &\leq \omega \cdot f(x) \left(\frac{x+y}{x}\right)^r + (1 - \omega) f(y) \left(\frac{x+y}{y}\right)^r \\ &= (x + y)^r \left(\frac{\omega \cdot f(x)}{x^r} + \frac{(1-\omega)f(y)}{y^r}\right) \end{aligned}$$

Main Claims

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Log-Log Lipschitz

$$\leq \omega \cdot f(x) \left(\frac{x+y}{x}\right)^r + (1 - \omega) f(y) \left(\frac{x+y}{y}\right)^r$$

$$= (x + y)^r \left(\frac{\omega \cdot f(x)}{x^r} + \frac{(1 - \omega) f(y)}{y^r} \right)$$

By substituting $\omega = \frac{x^r}{x^r + y^r}$

$$= \left(\frac{(x+y)^r}{x^r + y^r} \right) \cdot (f(x) + f(y))$$

ρ ←

Main Claims

Let $(X, dist)$ be a metric space and let $f: [0, \infty) \rightarrow [0, \infty)$ be a function that satisfies the *Log-Log Lipschitz* condition.

Define $far: X^2 \rightarrow [0, \infty)$ to be a mapping from every $p, c \in X$ to

$$far(p, c) = f(dist(p, c))$$

- **Claim 2:**

The function far satisfies **property 1** for every $\psi \in \left(0, \frac{1}{2}\right)$ and $\phi = \max\left\{\left(\frac{r}{\psi}\right)^r, 1\right\}$

Main Claims

- **Proof of Claim 2:**

Let $x = \text{dist}(p, c)$, $y = \text{dist}(c, q)$, $z = \text{dist}(p, q)$, $\psi \in \left(0, \frac{1}{2}\right)$ and $\phi = \left(\frac{r}{\psi}\right)^r$.

Need to prove that:

$$\text{far}(p, c) - \text{far}(c, q) = f(x) - f(y) \leq \phi f(z) + \psi f(x) = \phi \text{far}(p, q) + \psi \text{far}(p, c)$$

Assume $f(x) > \phi f(z)$, otherwise Claim 2 holds trivially.

Main Claims

- **Proof of Claim 2:**

Let $x = \text{dist}(p, c)$, $y = \text{dist}(c, q)$, $z = \text{dist}(p, q)$, $\psi \in \left(0, \frac{1}{2}\right)$ and $\phi = \left(\frac{r}{\psi}\right)^r$.

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Assume $f(x) > \phi f(z)$, otherwise Claim 2 holds trivially.

By the Log-Log Lipschitz it holds that $f(x) = f\left(y \cdot \frac{x}{y}\right) \leq \left(\frac{x}{y}\right)^r \cdot f(y)$

Main Claims

- **Proof of Claim 2:**

Let $x = \text{dist}(p, c)$, $y = \text{dist}(c, q)$, $z = \text{dist}(p, q)$, $\psi \in \left(0, \frac{1}{2}\right)$ and $\phi = \left(\frac{r}{\psi}\right)^r$.

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Assume $f(x) > \phi f(z)$, otherwise Claim 2 holds trivially.

By the Log-Log Lipschitz it holds that $f(x) = f\left(y \cdot \frac{x}{y}\right) \leq \left(\frac{x}{y}\right)^r \cdot f(y)$
 $\rightarrow f(y) \geq f(x) \cdot \left(\frac{y}{x}\right)^r$

Main Claims

- **Proof of Claim 2:**

Let $x = \text{dist}(p, c)$, $y = \text{dist}(c, q)$, $z = \text{dist}(p, q)$, $\psi \in \left(0, \frac{1}{2}\right)$ and $\phi = \left(\frac{r}{\psi}\right)^r$.

Need to prove that:

$$f_{ar}(p, c) - f_{ar}(c, q) = f(x) - f(y) \leq \phi f(z) + \psi f(x) = \phi f_{ar}(p, q) + \psi f_{ar}(p, c)$$

Assume $f(x) > \phi f(z)$, otherwise Claim 2 holds trivially.

By the Log-Log Lipschitz it holds that $f(x) = f\left(y \cdot \frac{x}{y}\right) \leq \left(\frac{x}{y}\right)^r \cdot f(y)$
 $\rightarrow f(y) \geq f(x) \cdot \left(\frac{y}{x}\right)^r$

Hence, $f(x) - f(y) \leq f(x) \cdot \left(1 - \left(\frac{y}{x}\right)^r\right)$.

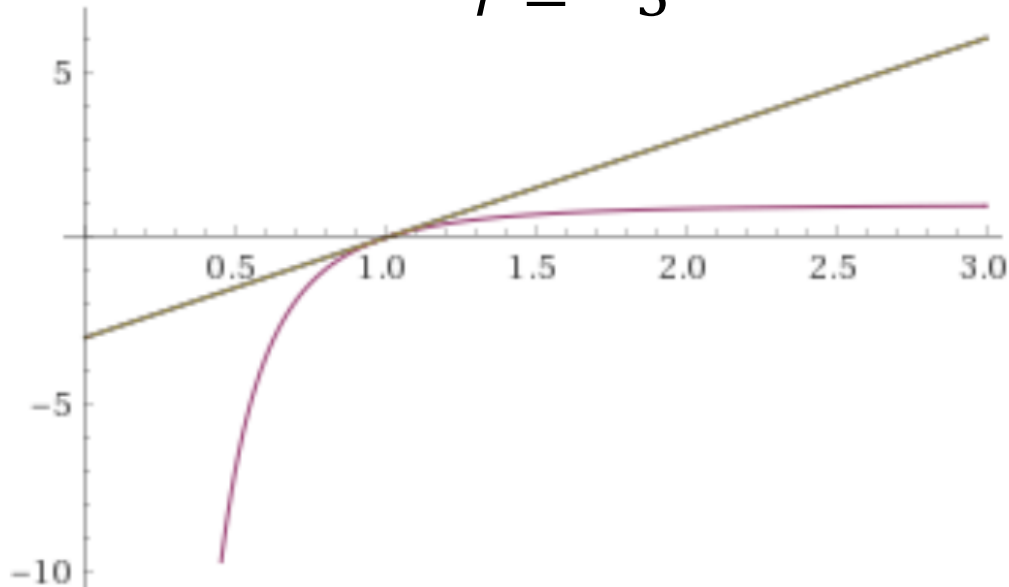
Main Claims

- **Proof of Claim 2:**

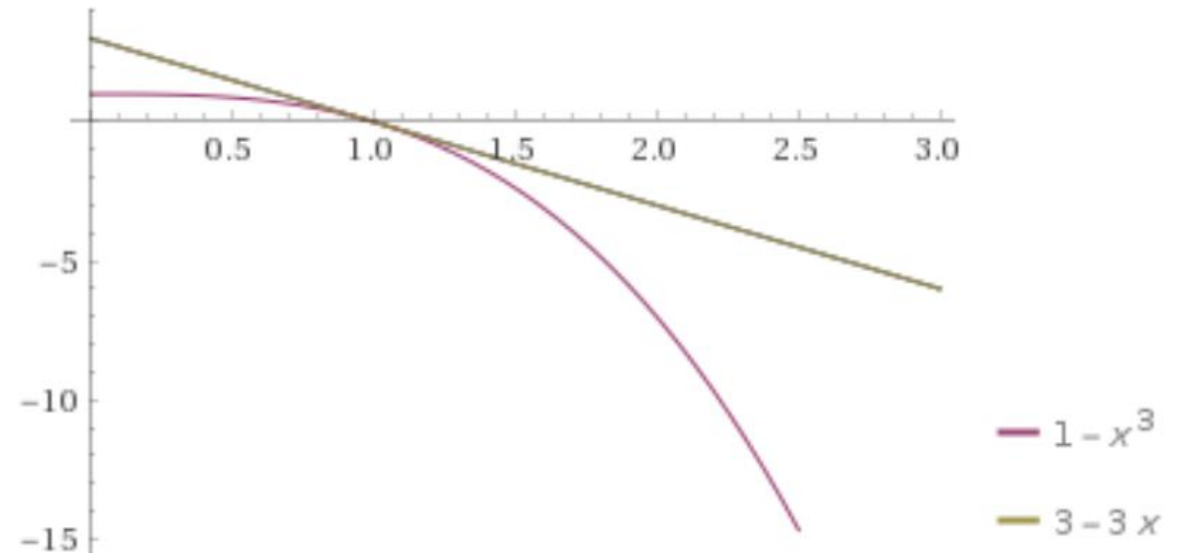
Hence, $f(x) - f(y) \leq f(x) \cdot \left(1 - \left(\frac{y}{x}\right)^r\right)$.

For every $\omega \geq 0$ it holds that $1 - \omega^r \leq r(1 - \omega)$.

$r = -3$



$r = 3$



Main Claims

- **Proof of Claim 2:**

Hence, $f(x) - f(y) \leq f(x) \cdot \left(1 - \left(\frac{y}{x}\right)^r\right)$.

For every $\omega \geq 0$ it holds that $1 - \omega^r \leq r(1 - \omega)$.

$$\rightarrow f(x) - f(y) \leq f(x) \cdot \left(1 - \left(\frac{y}{x}\right)^r\right) \leq f(x) \cdot r \left(1 - \frac{y}{x}\right)$$

Main Claims

- **Proof of Claim 2:**

Hence, $f(x) - f(y) \leq f(x) \cdot \left(1 - \left(\frac{y}{x}\right)^r\right)$.

For every $\omega \geq 0$ it holds that $1 - \omega^r \leq r(1 - \omega)$.

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*Triangle
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Assumption:

$$\begin{aligned} &\phi f(z) < f(x) \quad \star \\ &\rightarrow f\left(\frac{z}{\phi^{\frac{1}{r}}}\right) \leq \phi f(z) < f(x) \end{aligned}$$

$\rightarrow \frac{z}{\phi^{\frac{1}{r}}} \leq z < x$ since f is non-decreasing

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Main Claims

Let $(X, dist)$ be a metric space and let $f: [0, \infty) \rightarrow [0, \infty)$ be a function that satisfies the *Log-Log Lipschitz* condition.

Define $far: X^2 \rightarrow [0, \infty)$ to be a mapping from every $p, c \in X$ to

$$far(p, c) = f(dist(p, c))$$

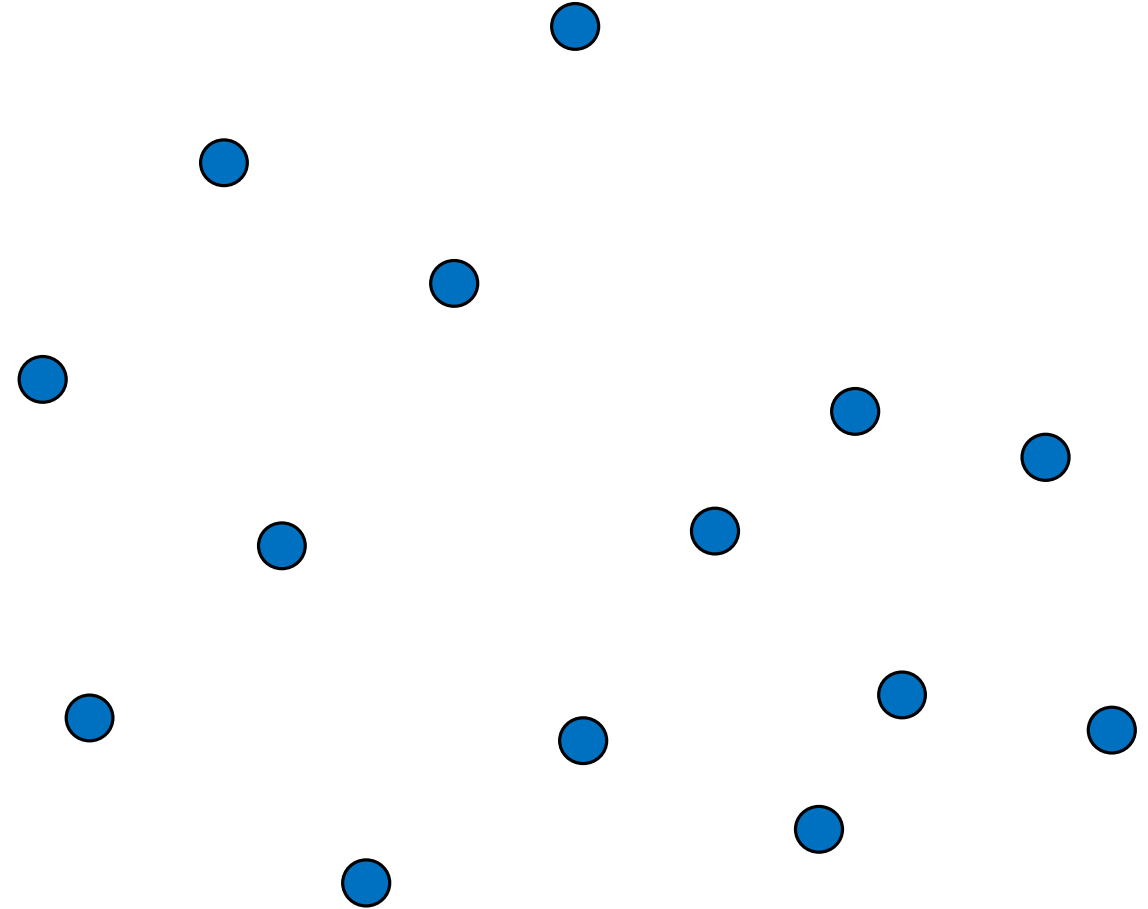
- **Claim 3:** (Tighter bound than in Claim 2)

The function far satisfies **property 1** for every $\psi \in (0, \frac{1}{2})$ and

$$\phi = \max \left\{ \left(\frac{r-1}{\psi} \right)^{r-1}, 1 \right\} \text{ if } r > 1.$$

General Bi-criteria Algorithm

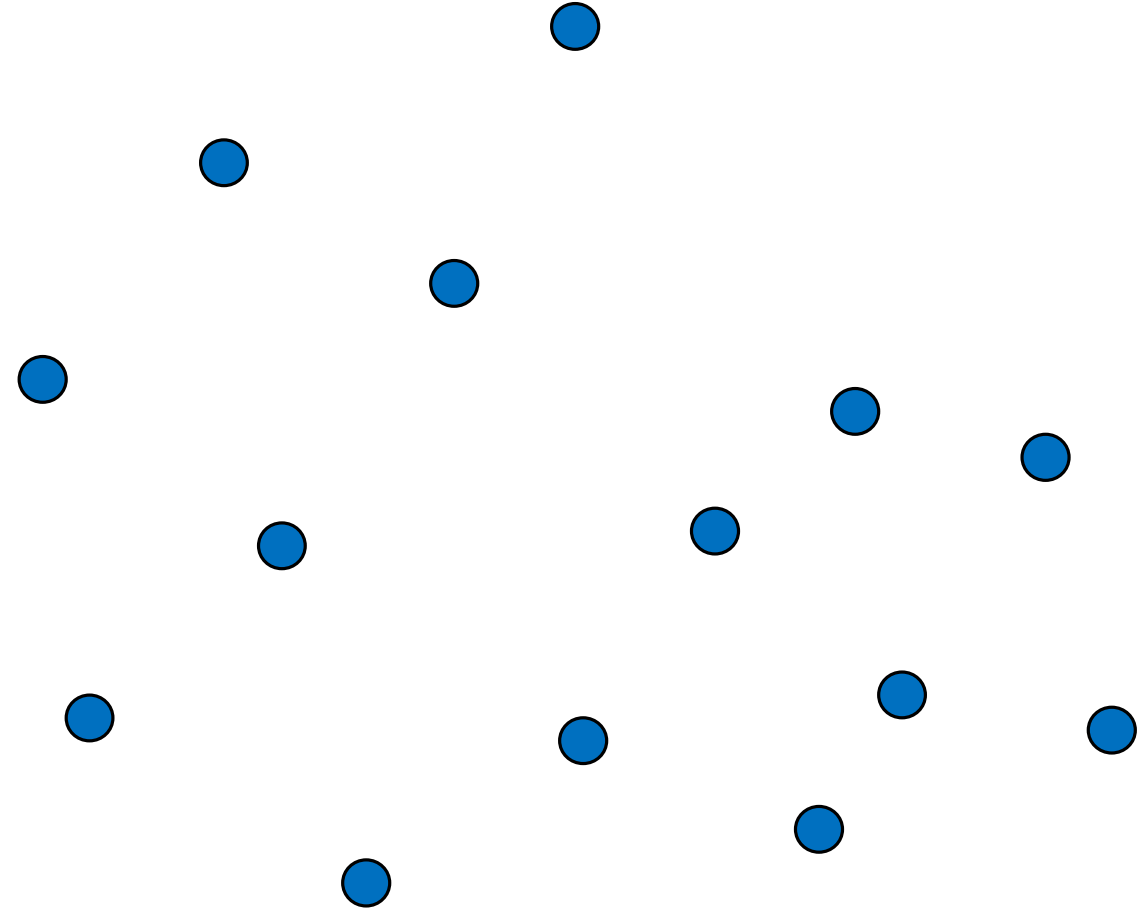
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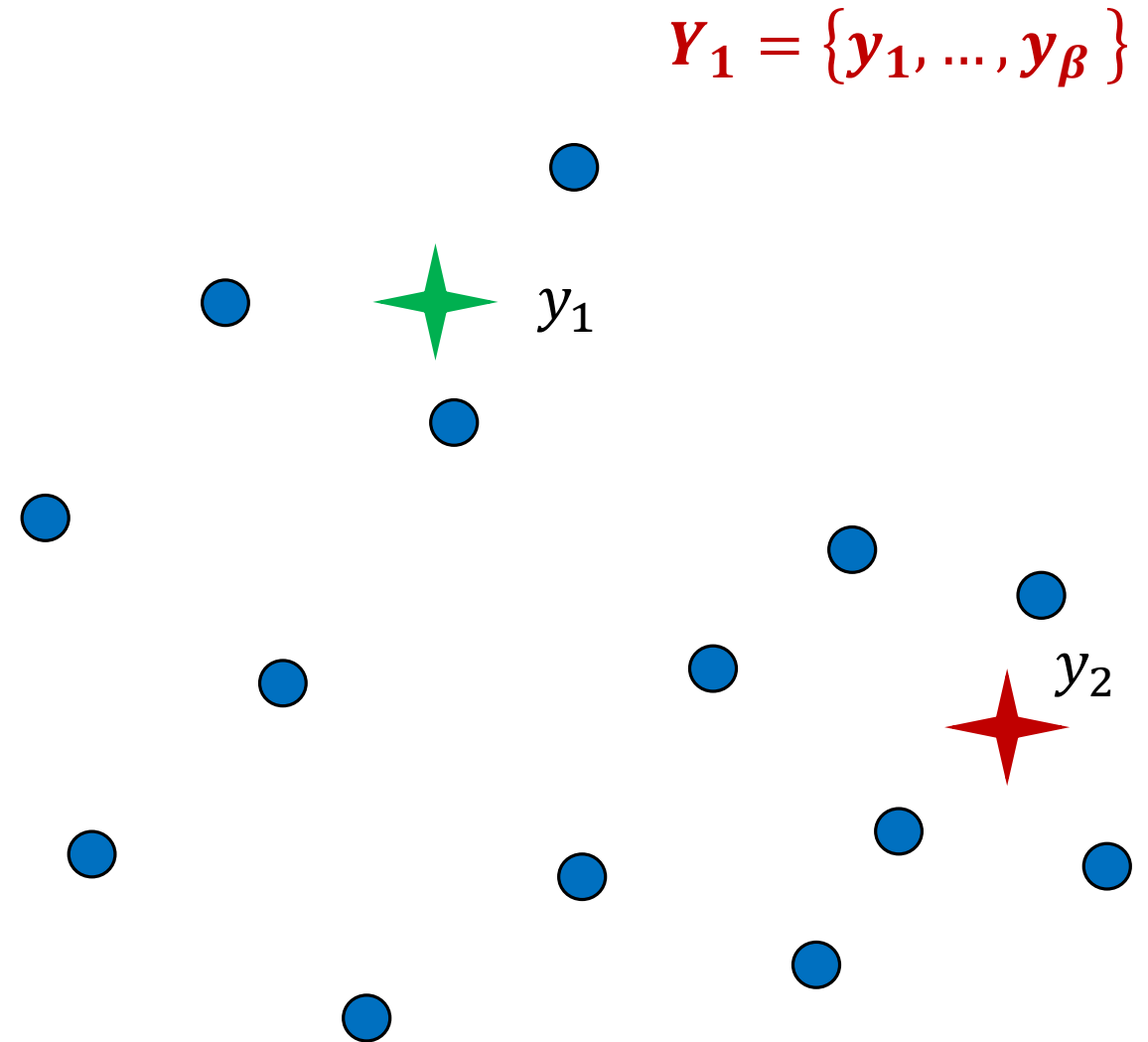
- 1) Compute Y_i : a $\left(\frac{3}{4}, \frac{1}{2}, \alpha, \beta\right)$ -approx for the specific problem $(P_i, dist)$.



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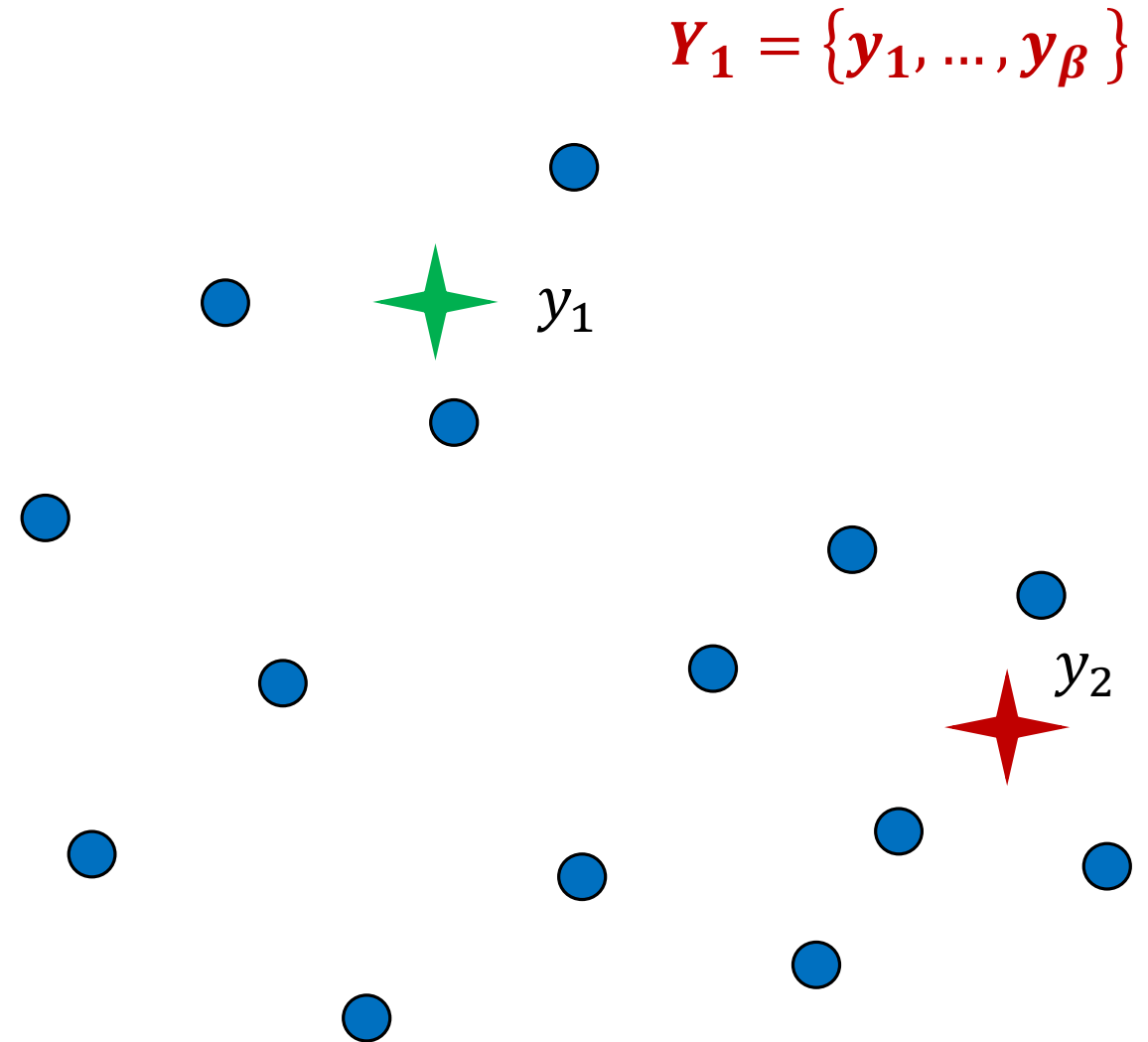
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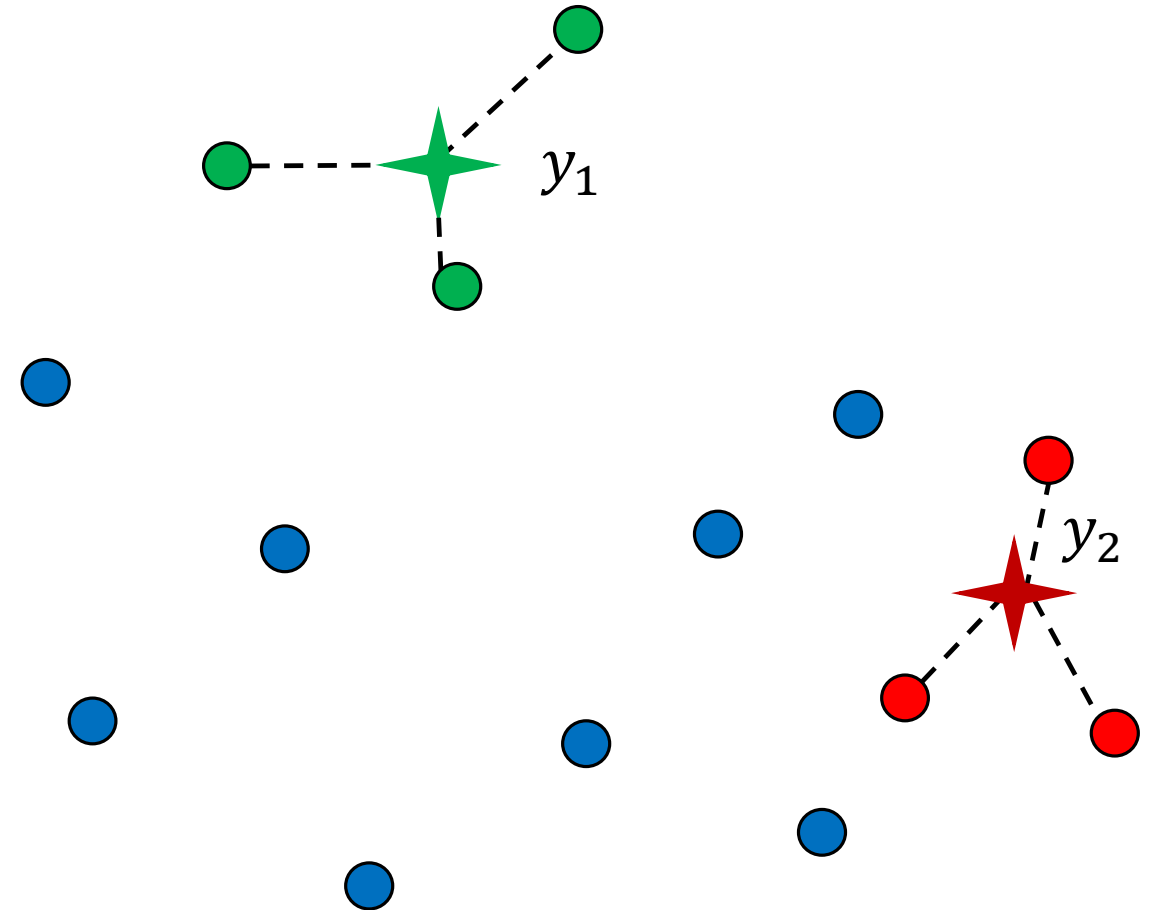
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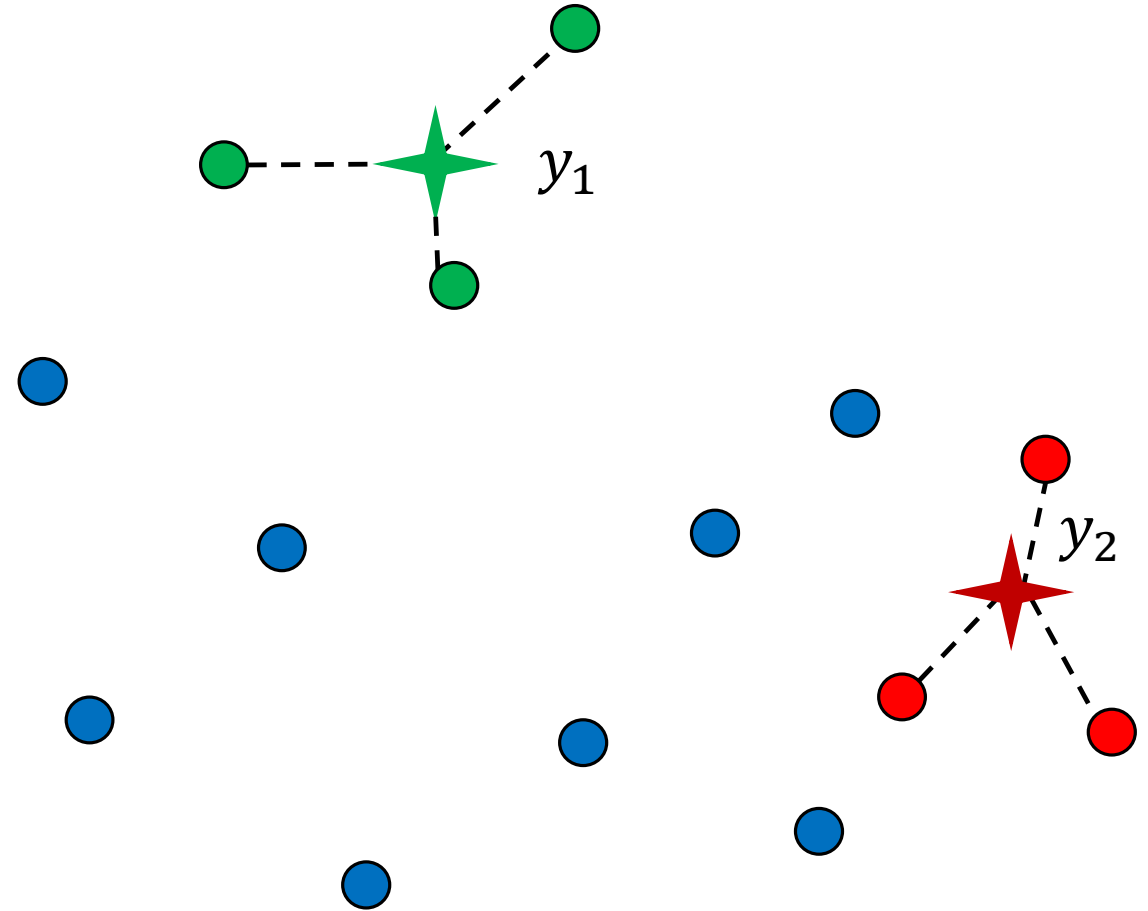


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$$Y_1 = \{y_1, \dots, y_\beta\}$$

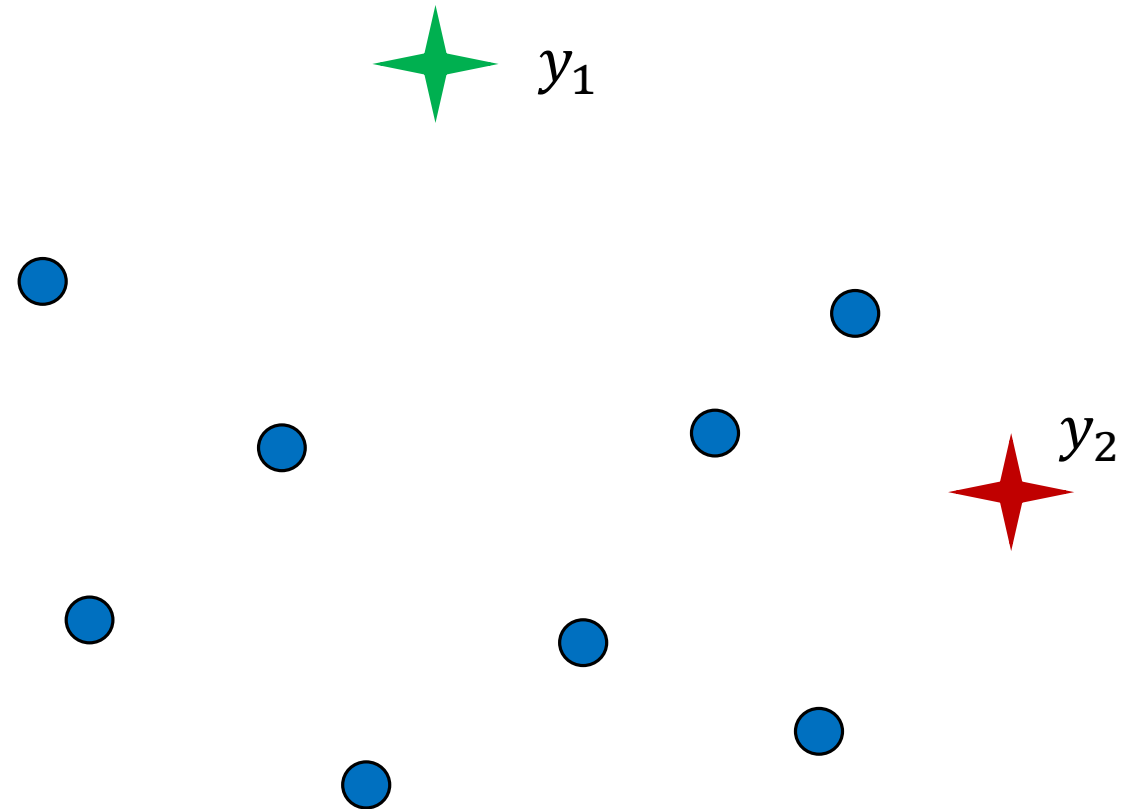


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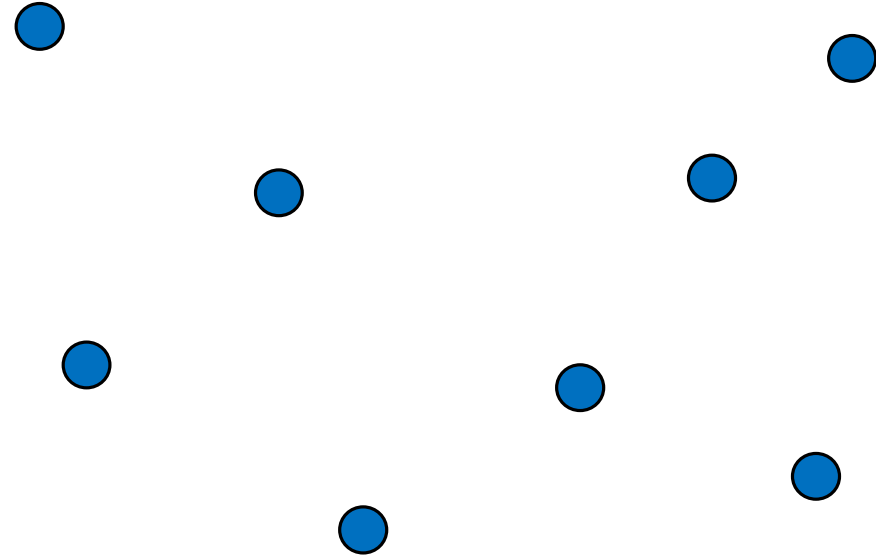
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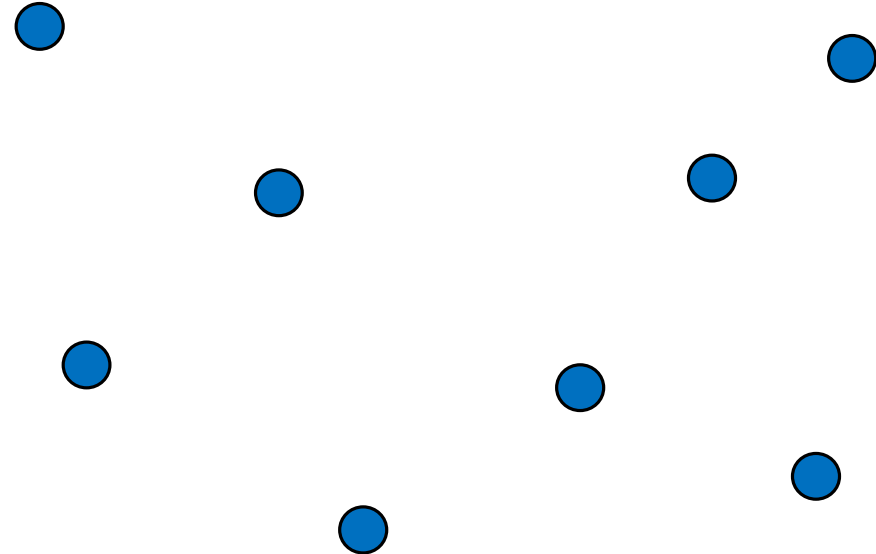
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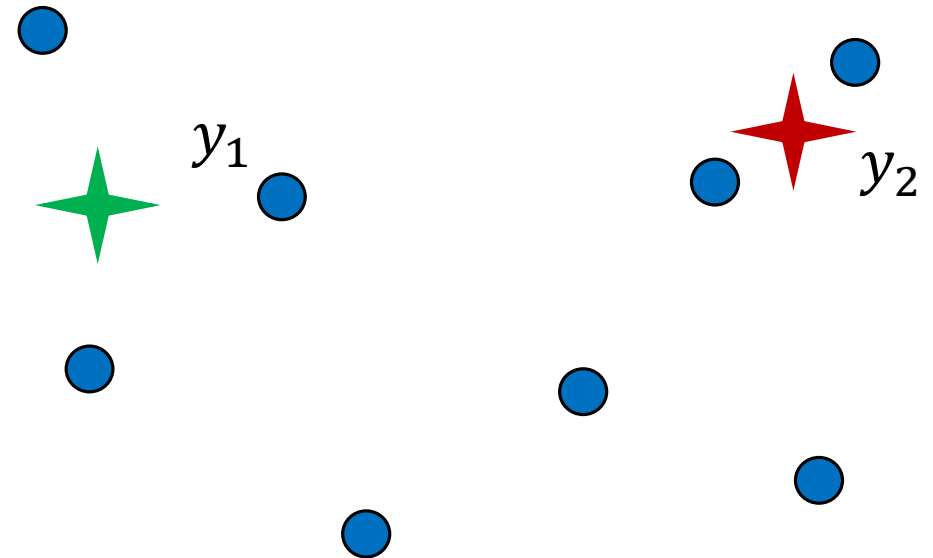


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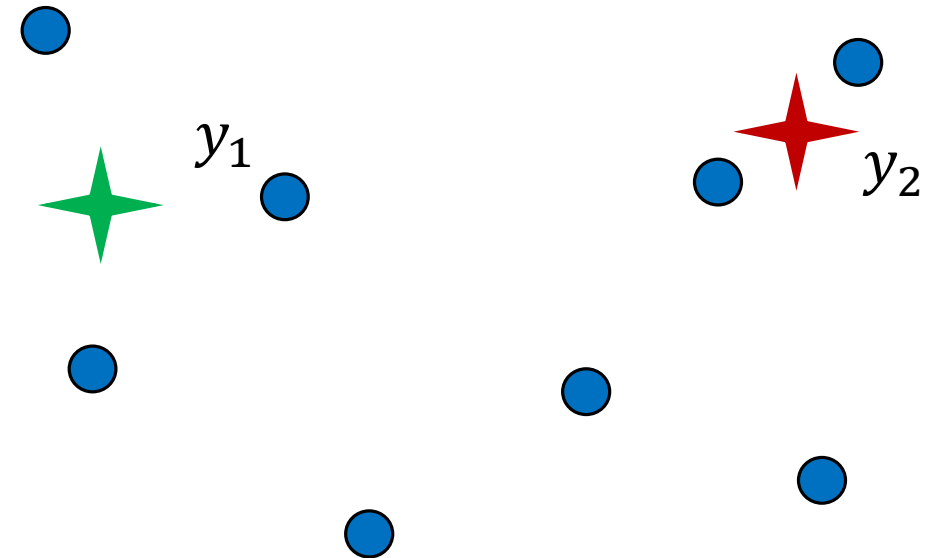


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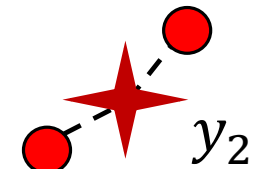
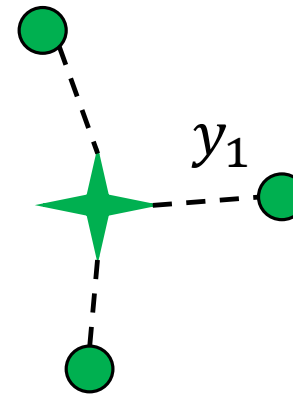


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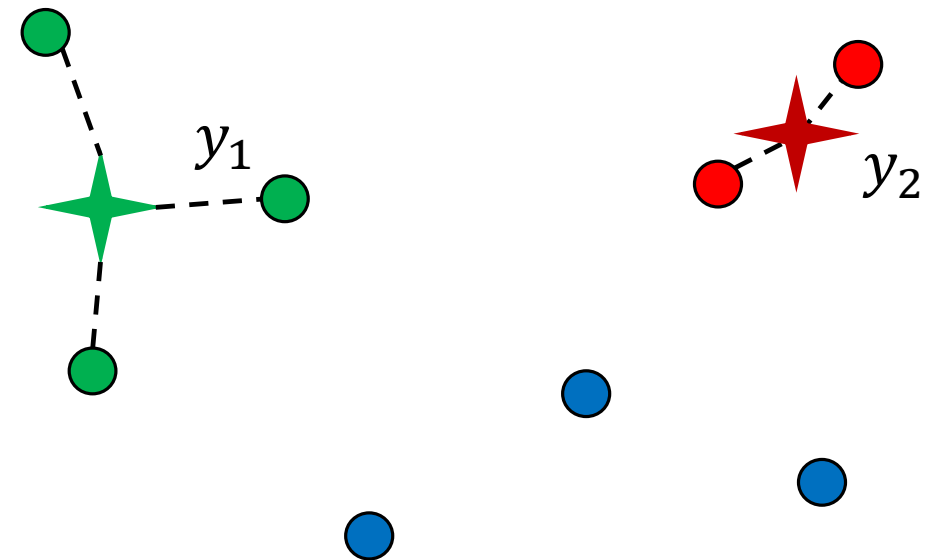


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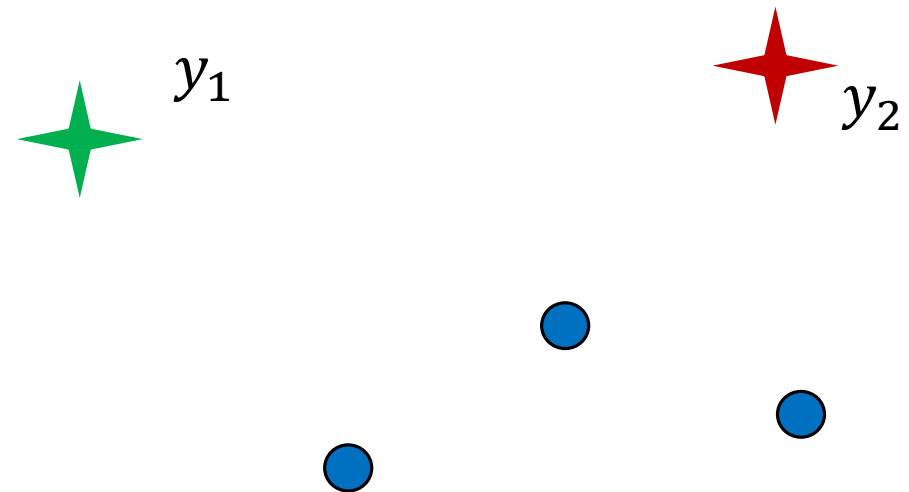


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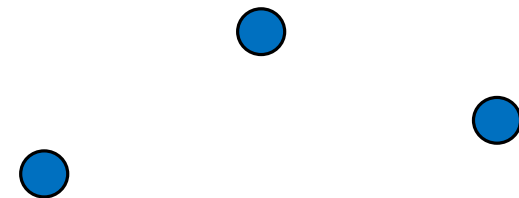


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$$Y = Y_1 \cup Y_2 \cup \dots \cup Y_i$$



General Bi-criteria Algorithm

- Claim:

The algorithm ***BICRITERIA***($P, dist, \epsilon, \alpha, \beta$) returns an $(O(\alpha), O(\beta \log n))$ -approximation.

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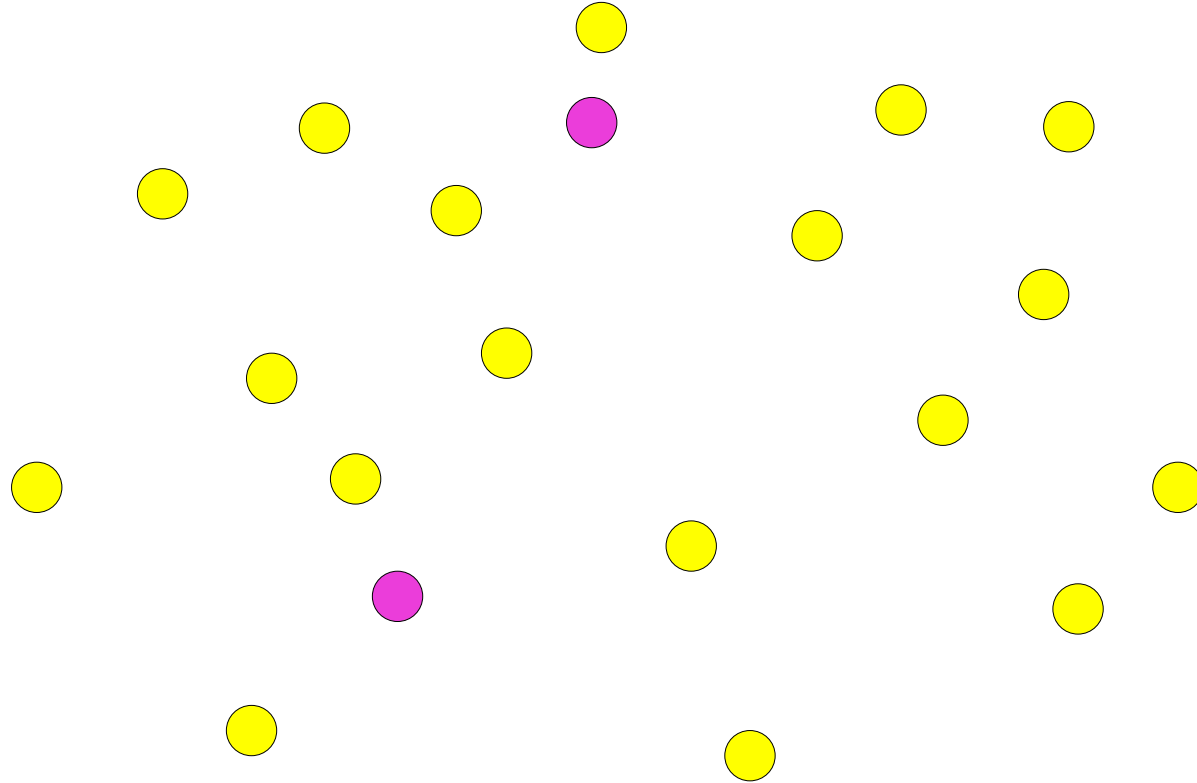
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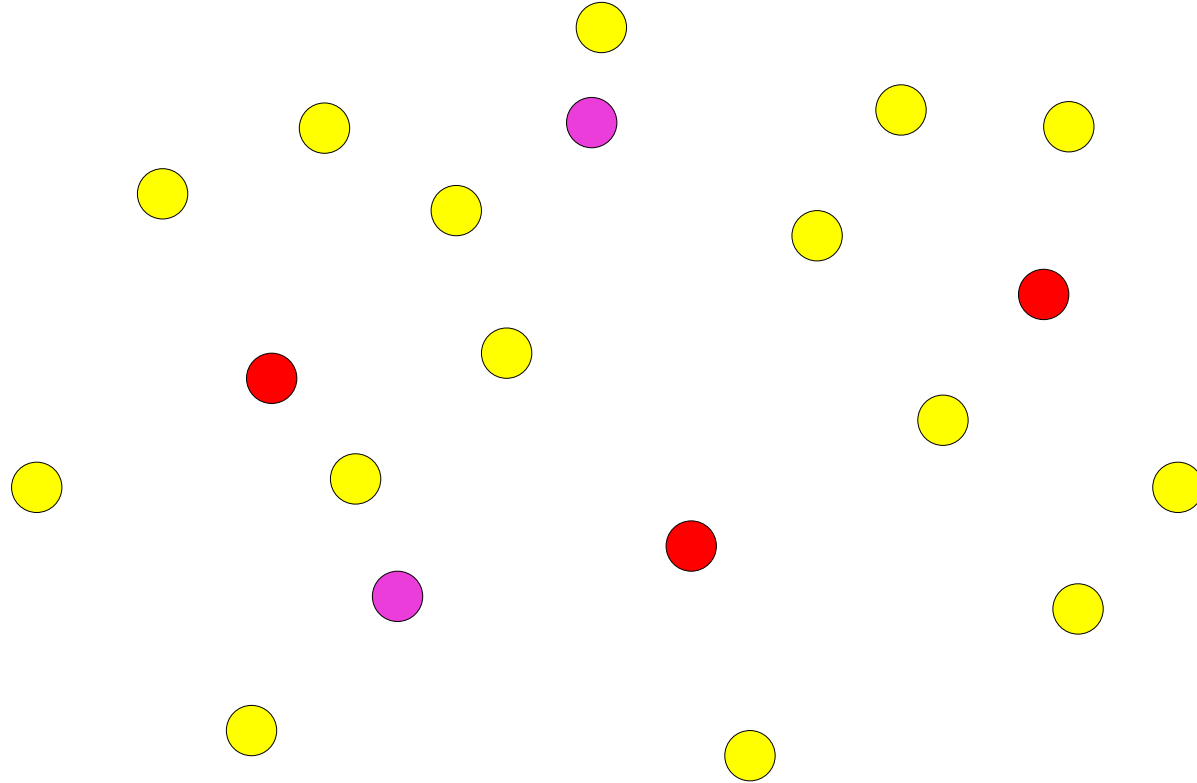
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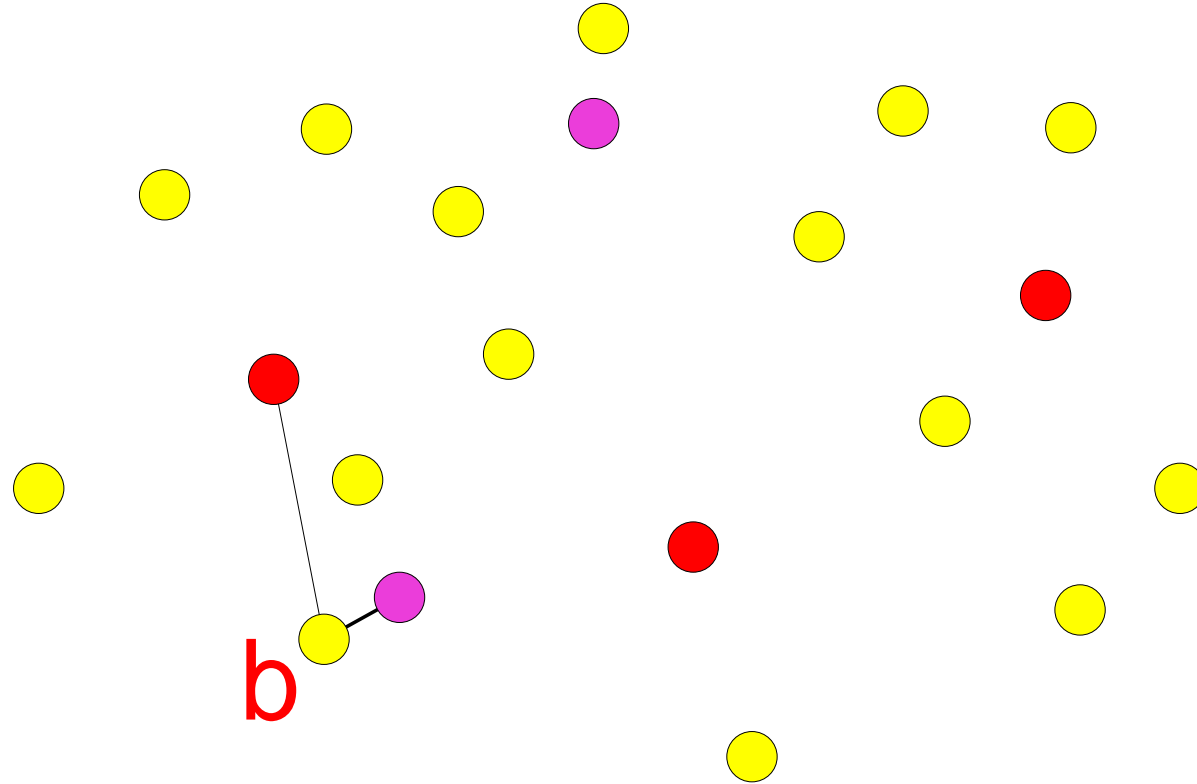


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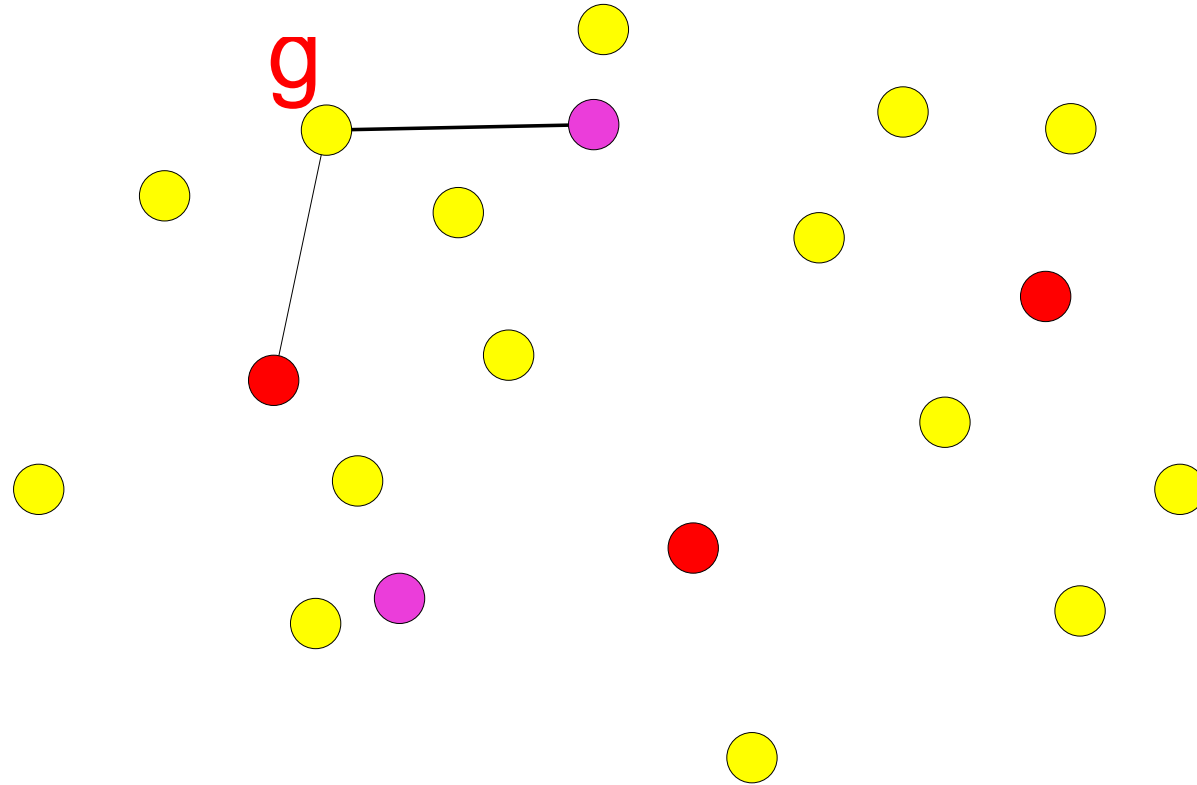
Consider Y_i that is constructed during the i^{th} iteration

A point $b \in P$ is bad for Y_i , if:



$$\text{dist}(b, Y_i) > 2 \cdot \text{dist}(b, Y^*)$$

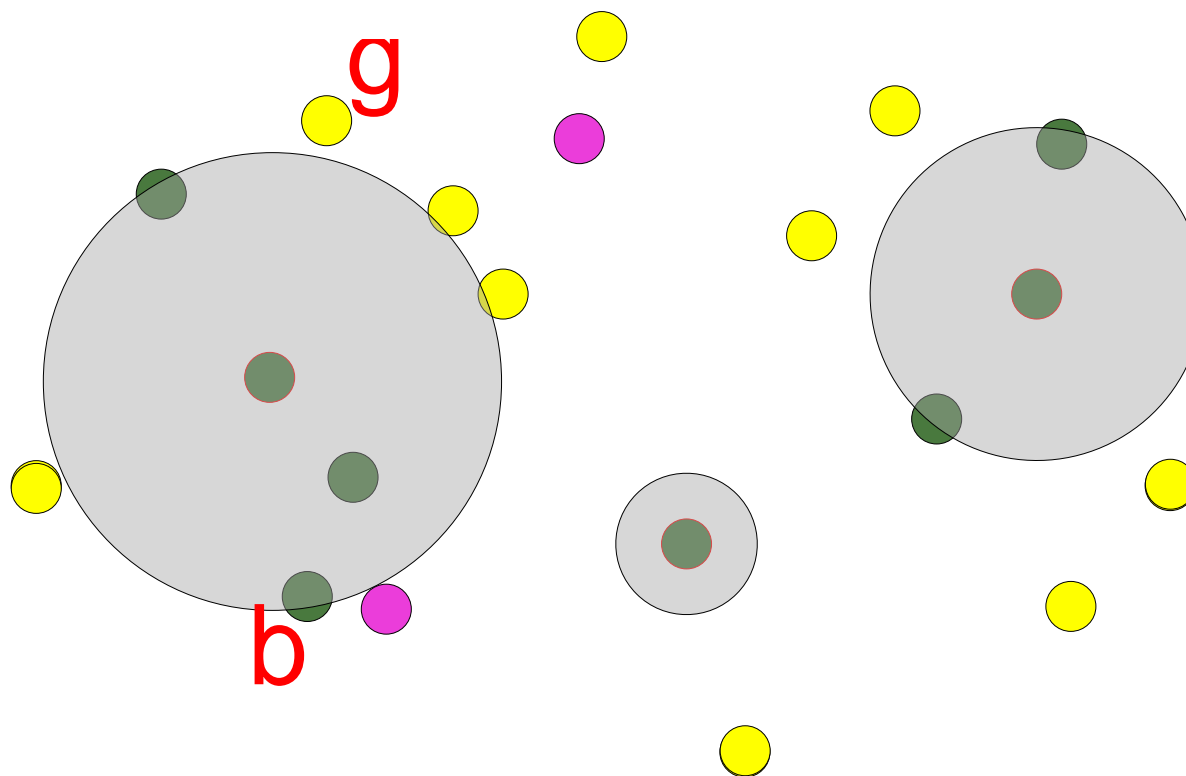
A point $g \in P$ is good for Y_i otherwise:



$$\text{dist}(g, Y_i) \leq 2 \cdot \text{dist}(b, Y^*)$$

Main Technical Theorem

We can map every bad point $b \in P_i$ to a distinct good point $g \in P_{i+1}$



$\text{dist}(b, Y) \leq \text{dist}(b, Y_i)$, because $Y_i \subseteq Y$.

Since $b \in P_i$ and $g \in P_{i+1}$:

$$\text{dist}(b, Y_i) \leq \text{dist}(g, Y_i)$$

Since g is good for Y_i :

$$\text{dist}(g, Y_i) \leq 2 \cdot \text{dist}(g, Y^*)$$

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Bi-Criteria for k -Median

$$\begin{aligned}\sum_{p \in P} \text{dist}(p, Y) &= \sum_g \text{dist}(g, Y) + \sum_b \text{dist}(b, Y) \\ &\leq \sum_g 2 \cdot \text{dist}(g, Y^*) + \sum_g 2 \cdot \text{dist}(g, Y^*) \\ &\leq \sum_g 4 \cdot \text{dist}(g, Y^*)\end{aligned}$$

Proof of the Technical Theorem

- The number of bad points is at most:

$$|B| = \frac{|Y_i|}{8}$$

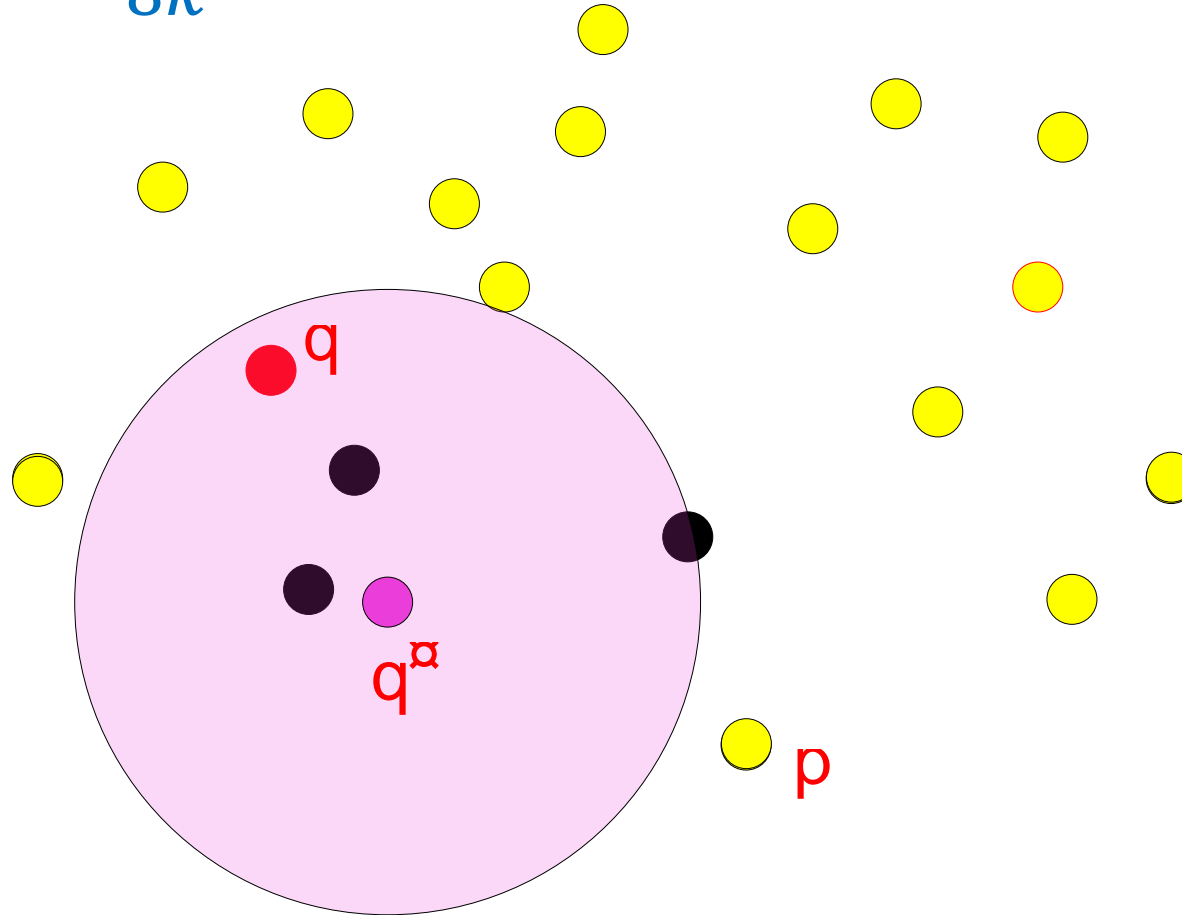
- $|Y_{i+1}| = \frac{|Y_i|}{2}$



The number of good points in Y_{i+1} is at most:

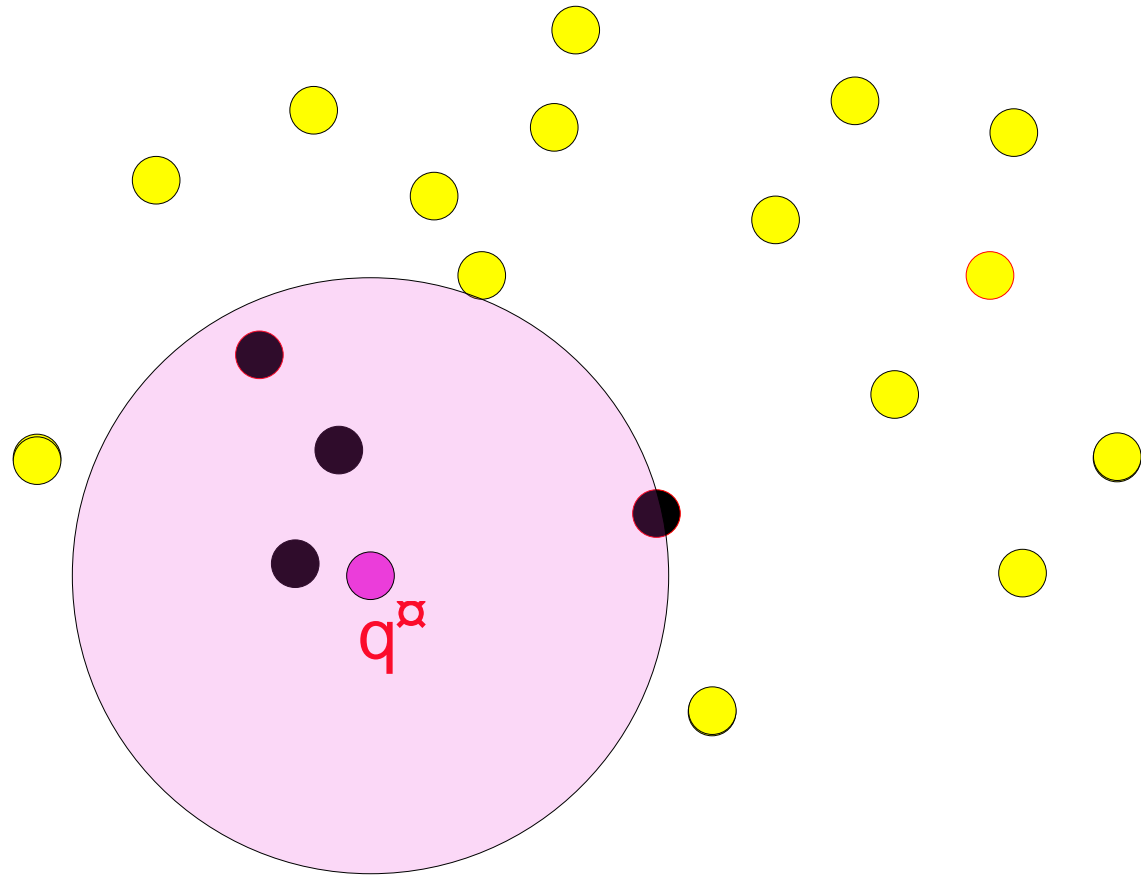
$$|Y_{i+1}| - |B| \geq \frac{|Y_i|}{2} - \frac{|Y_i|}{8} \geq |B|$$

Claim: Only $B_0 = \frac{|Y_i|}{8k}$ points are bad for $q \in Y_i$

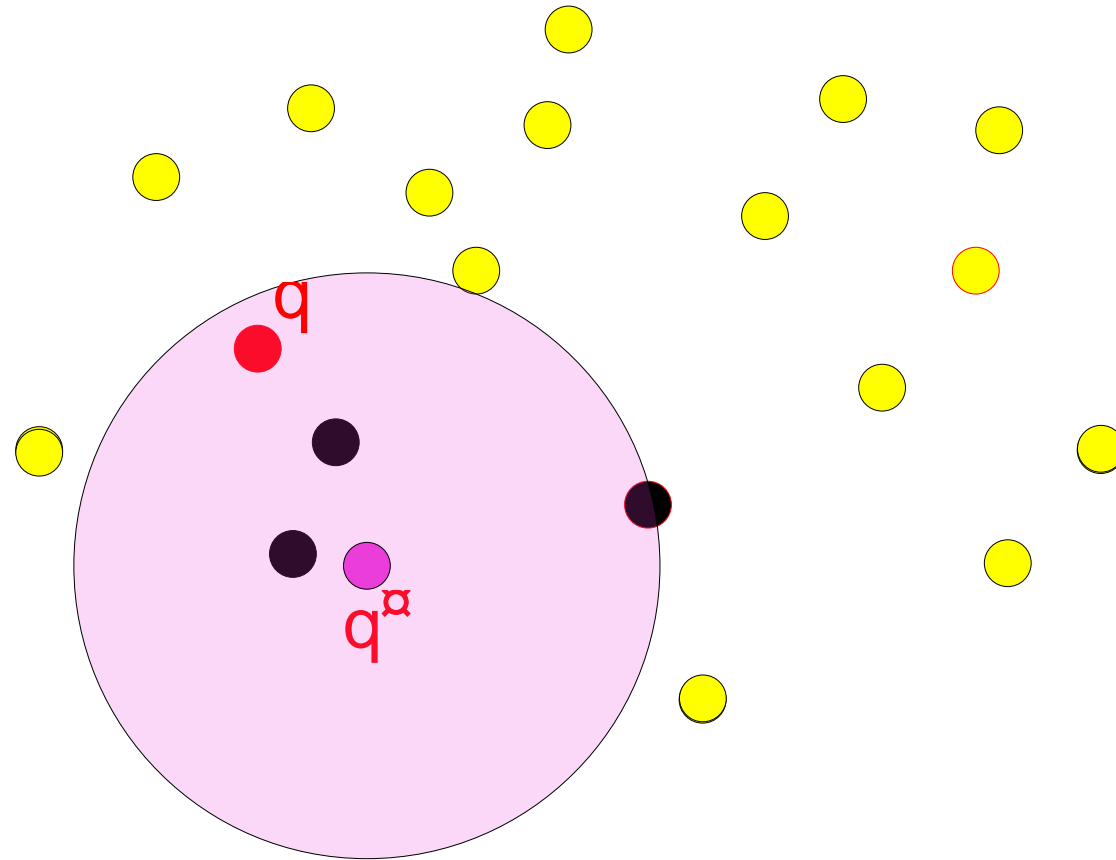


$$\text{dist}(p, q) \leq 2 \cdot \text{dist}(p, q^*)$$

B_0 : the $\frac{|Y_i|}{8k}$ closest points to q^*

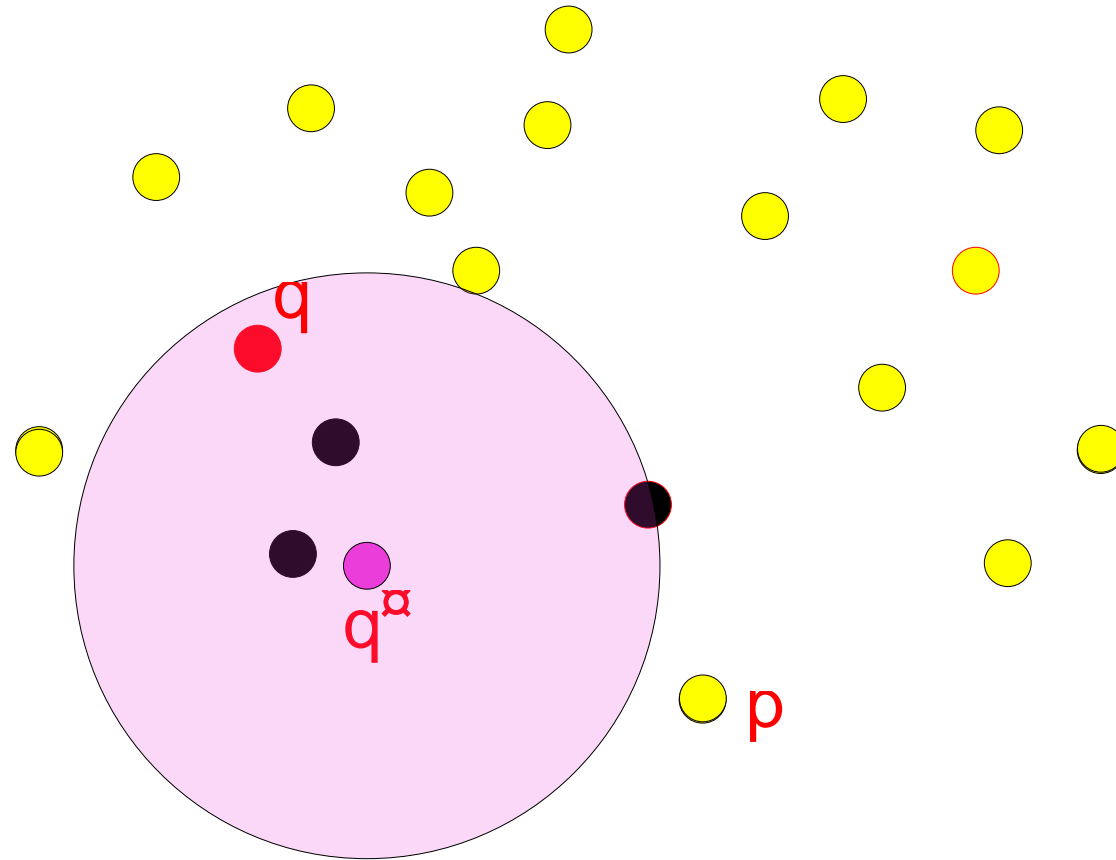


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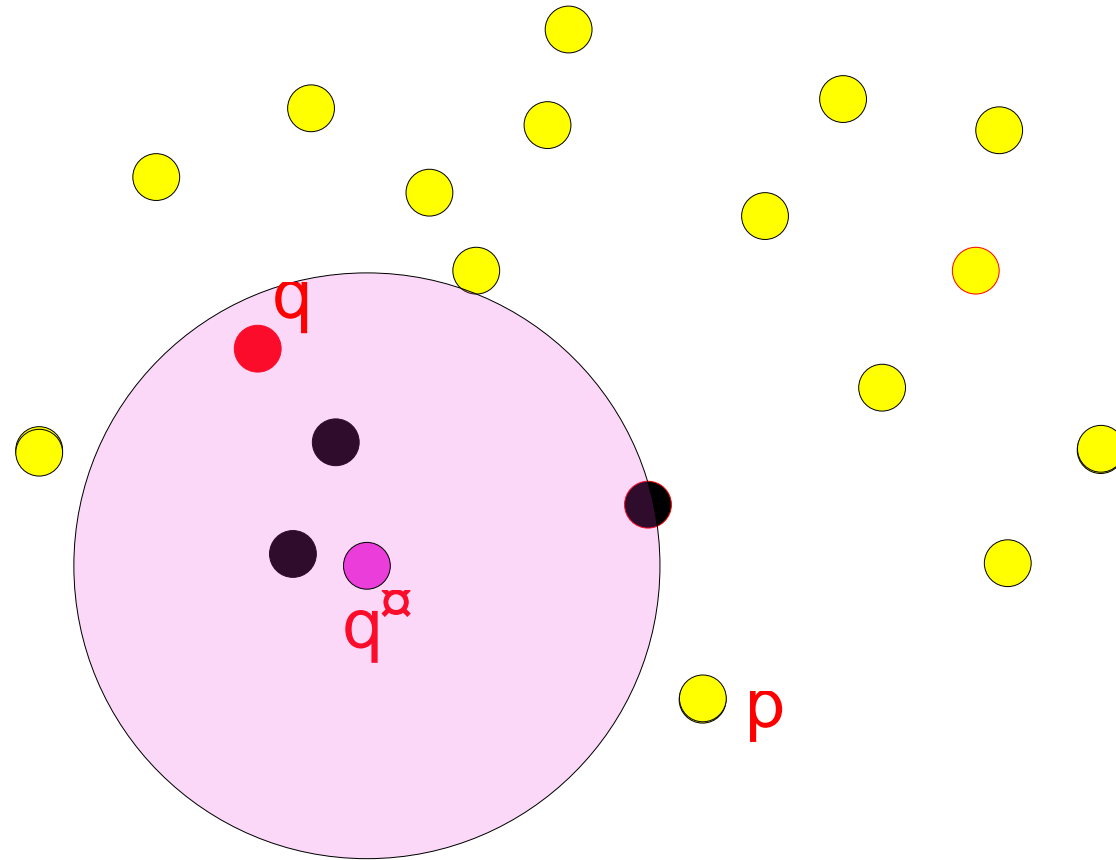
B_0 contains $q \in Y_i$ ($\frac{1}{8k} - net$)

For every yellow point $p \in P \setminus B_0$:



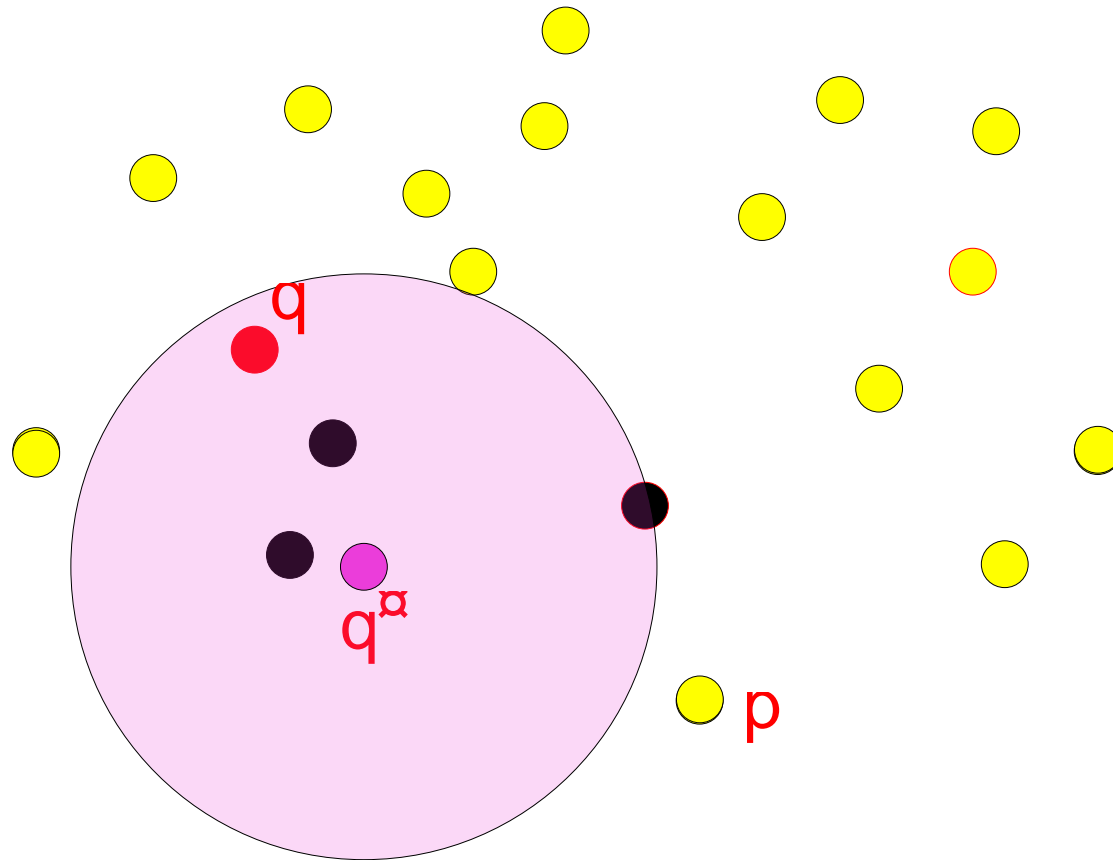
$$\begin{aligned} \text{dist}(p, q) &\leq \text{dist}(p, q^*) + \text{dist}(q^*, q) \\ &\leq 2 \cdot \text{dist}(p, q^*) \end{aligned}$$

All the yellow points are good for Y_i



$$\text{dist}(p, q) \leq 2 \cdot \text{dist}(p, q^*)$$

Only the black points B_0 are bad for Y_i



$$B_0 = \frac{|Y_i|}{8k}$$