

# A $(1 + \epsilon)$ -Approximation for Ultrametric Embedding in Subquadratic Time

## Ultrametrics

**Ultrametric:** *metric + ultrametric inequality.*

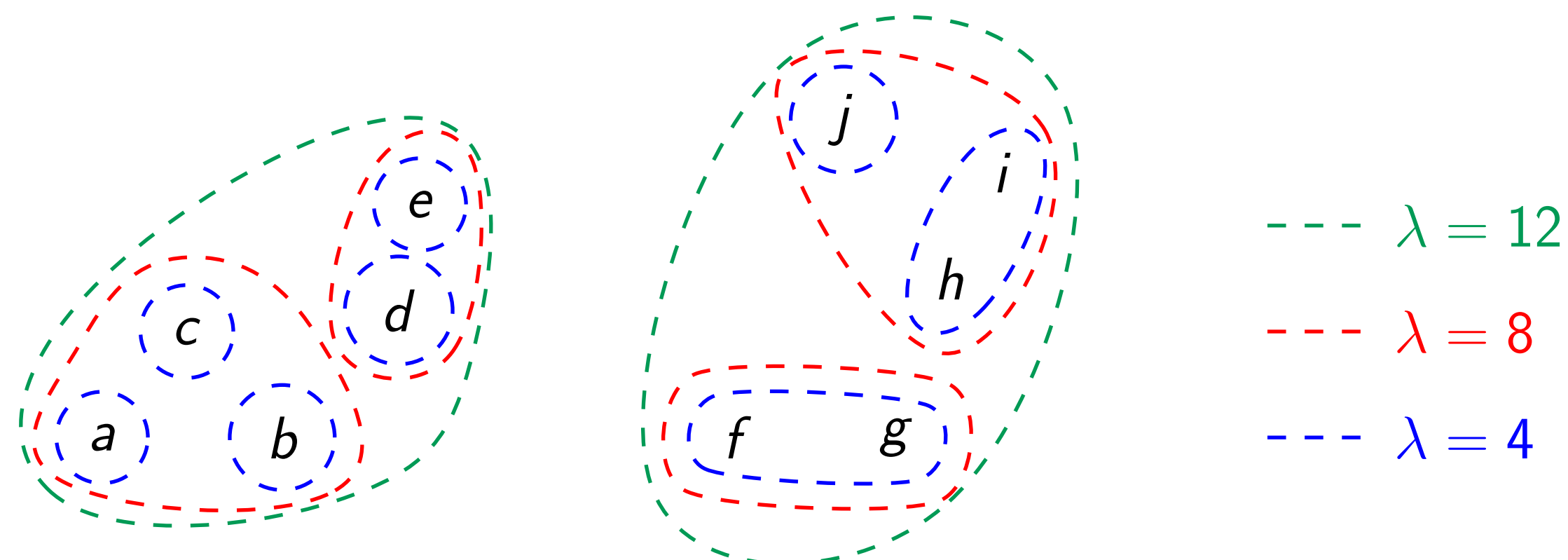
$$\forall x, y, z, \Delta(x, y) \geq 0 \quad \Delta(x, y) = 0 \iff x = y$$

$$\Delta(x, y) = \Delta(y, x) \quad \Delta(x, y) \leq \Delta(x, z) + \Delta(z, y)$$

Ultrametric:  $\Delta(x, y) \leq \max(\Delta(x, z), \Delta(z, y))$

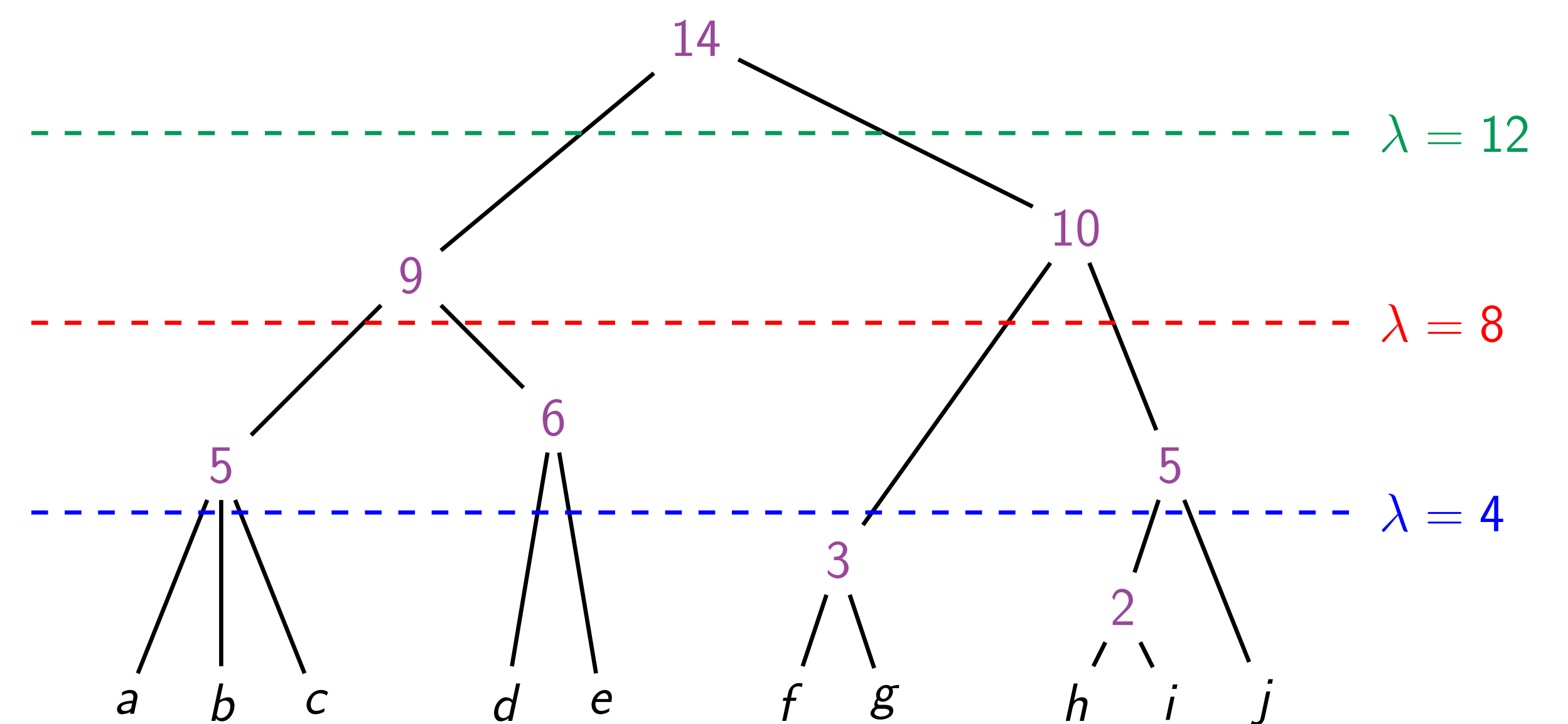
## Ultrametrics and Hierarchical Clustering

**Ultrametrics:** Mathematical formalization of Hierarchical Clustering



## Ultrametrics as Trees

$(X, \Delta)$  is an ultrametric space  $\iff \exists$  tree  $T = \underbrace{N}_{\text{nodes}} \cup \underbrace{X}_{\text{leaves}}$  with weights  $w$   
s.t.  $\forall u \in T, w(u) \leq w(\text{parent}(u))$   
 $\forall x \in X, w(x) = 0$



Mapping:  $\Delta(x, y) = w(\text{LCA}(x, y))$

## Ultrametric Embedding

**Goal:** Given a metric space  $(X, d)$ , find the ultrametric  $\Delta$  that **agrees** the most with  $d$ .

Minimize the **distortion**  $\alpha$ :

$$\forall x, y, \Delta(x, y) \leq d(x, y) \leq \alpha \cdot \Delta(x, y).$$

**Theorem:** In the **Euclidean** case, for any  $c > 1$ , we can compute a  $c$ -approximation of the best ultrametric embedding in time  $\mathcal{O}(n^{1+1/c})$ .

$$\forall x, y, \Delta(x, y) \leq \ell_2(x, y) \leq c \cdot \alpha \cdot \Delta(x, y).$$

## Algorithm for Ultrametric Embedding

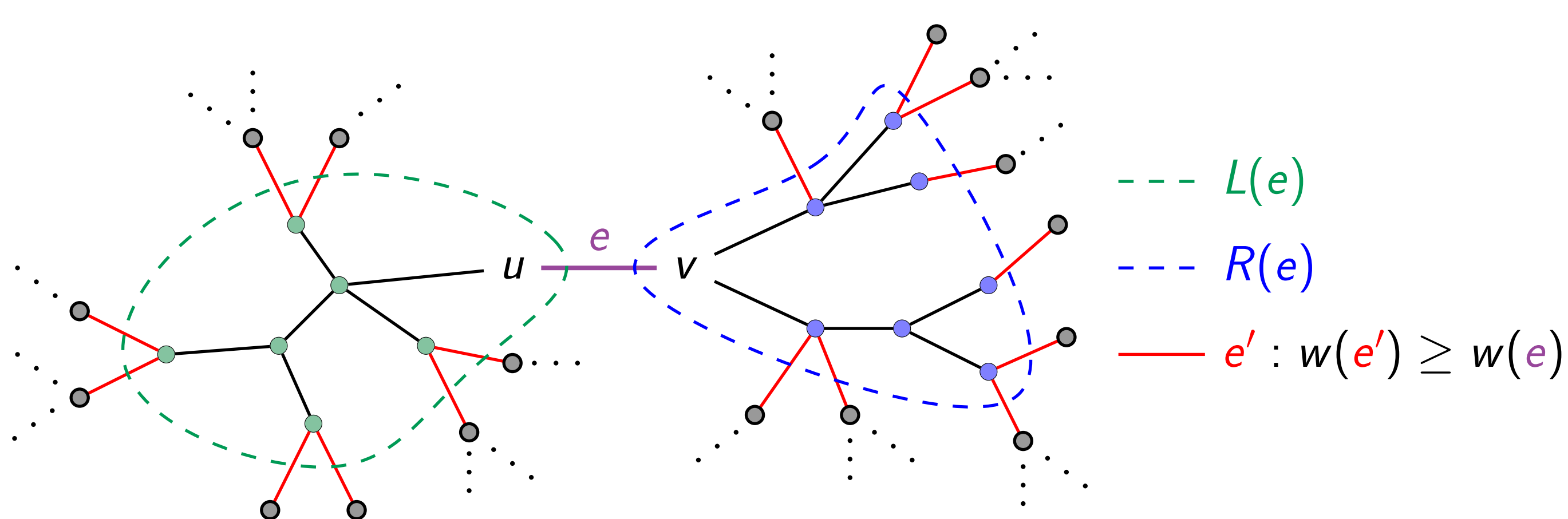
$\mathcal{O}(n^2)$ -time algorithm of Farach, Kannan and Warnow [?]:

1. Compute **minimum spanning tree**  $T$  of  $(X, d)$
2. Compute the **cut weights**  $CW$  of  $T$
3. Compute a cartesian tree  $CT$  of  $(T, CW) \rightarrow \Delta$

Approximation algorithm:

1. Compute a  $\gamma$ -**Kruskal Tree**  $T$  of  $(X, d)$  in  $\mathcal{O}(n^{1+1/\gamma^2})$
2. Compute the  $\alpha$ -**approximate cut weights**  $ACW$  of  $T$  in  $\mathcal{O}(n^{1+1/\alpha^2})$
3. Compute a cartesian tree  $CT$  of  $(T, ACW) \rightarrow \Delta$ ,  $\alpha \cdot \gamma$  approx  
 $\rightarrow$  for  $\alpha = \gamma = \sqrt{c}$ ,  $c$ -approx. in  $\mathcal{O}(n^{1+1/c})$

## Cut weights



$$CW(e) = \max_{x \in L(e), y \in R(e)} d(x, y)$$

$\alpha$ -**Approx. cut weights:**

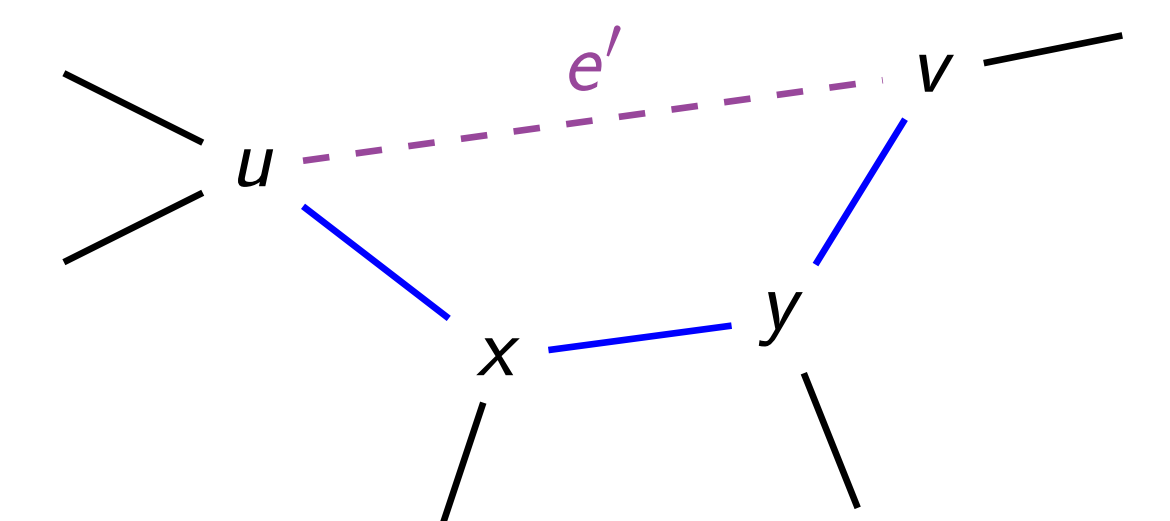
$$\forall e, ACW(e) \leq CW(e) \leq \alpha \cdot ACW(e)$$

## $\gamma$ -Kruskal Trees: Locally Approximate Minimum Spanning Trees

$\forall e$  on  $u$ - $v$  path,  
MST:  $w(e') \geq w(e)$

$$\gamma\text{-KT: } w(e') \geq \frac{1}{\gamma} w(e)$$

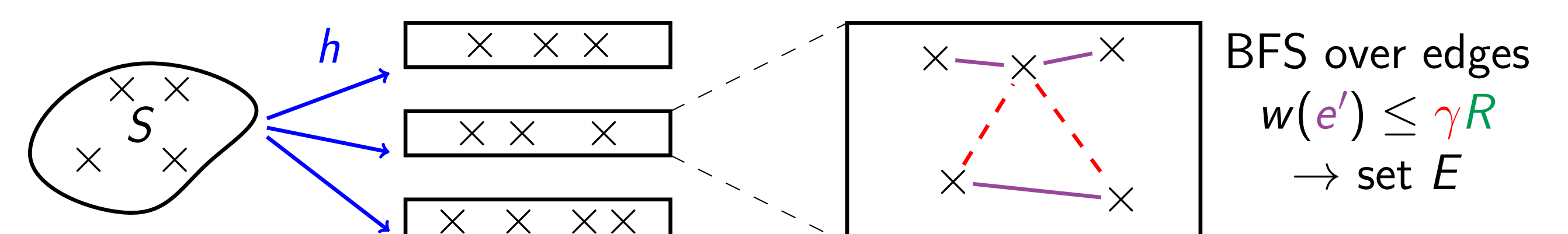
$\rightarrow$  Cannot take MST + long edge.



## $\gamma$ -Kruskal Trees via Locality Sensitive Hashing

**Locality Sensitive Hashing:** hash function  $h$

1. if  $d(u, v) \leq R$ , then  $h(u) = h(v)$  w.h.p.,
2. if  $d(u, v) \geq \gamma R$ , then  $h(u) \neq h(v)$  w.h.p.,



**Prop:** Takes  $\mathcal{O}(n^{1+1/\gamma^2})$  time.

**Prop:** if  $w(uv) \leq R$ , then path with edges  $w(e') \leq \gamma R$  between  $u$  and  $v$  in  $E$ .

**Algorithm for  $\gamma$ -KT:**

- ▶ Repeat for  $R = d_{\min}, 2d_{\min}, 4d_{\min}, \dots, d_{\max}$
- ▶ take MST of union of all  $E$ 's.

## Approximate Cut Weights via Approximate Farthest Neighbor

$$CW(e) = \max_{x \in L(e), y \in R(e)} d(x, y) = \max_{x \in L(e)} d(x, \text{Farthest}_{y \in R(e)}(x))$$

$$ACW(e) = \max_{x \in L(e)} d(x, \text{ApproxFarthest}_{y \in R(e)}(x))$$

$\rightarrow$  take smallest of  $L(e), R(e)$ :  $\mathcal{O}(n \log n)$  queries in total.

**Theorem:** Dynamic data structure for  $\alpha$ -AFN queries in time  $\mathcal{O}(n^{1/\alpha^2})$ .

$\rightarrow$   $\alpha$ -AFN: point  $p \in S$  s.t.  $d(x, p) \geq d(x, y)/\alpha, \forall y \in S$ .

**Technique:**

- ▶ Project all points on  $\mathcal{O}(n^{1/\alpha^2})$  random lines,
- ▶ Keep  $\mathcal{O}(n^{1/\alpha^2})$  farthest points on each line,
- ▶ Return farthest point among those.

## References