

# Approximating $k$ -Edge Connected Spanning Subgraph via a Fast LP Solver

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# kECSS problem

$$\text{mincut} \geq k$$

- A graph is *k-edge-connected* if it remains connected after removing  $k-1$  edges
- **Input:** An undirected graph  $G = (V, E)$  and a cost function  $c$  on edges ( $n := |V|, m := |E|$ )  
**Output:** A min-cost *k-edge-connected spanning* subgraph  $H = (V, E'), E' \subseteq E$
- **Example:**  $k = 1$  is easy (why?)

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- **Example:**  $k = 1$  is easy (why?)
- *APX-hard* for  $k > 1$  even on bounded degree graphs and binary cost function [Pritchard'10]
- Best known approximation is 2 [Khuller and Vishkin, STOC'92]
- A special case of survivable network design problem (SNDP) [Jain'01]

# History

- m-edge n-vertex graph G
- ignore polylog factor

	Approx.	Time	Remark
<b>Frederickson Jaja'81</b>	3	$n^2$	for $k = 2$ (2-ECSS)
<b>Khuller Vishkin'94</b>	2	$nmk$	
<b>Gabow Goemans Williamson'98</b>	$2k-1$	$n^2$	
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<b>This work</b>	$2 + \epsilon$	$O(m \cdot \epsilon^{-2})$	<b>Only output the estimate</b>
<b>This work</b>	$2 + \epsilon$	$O(\epsilon^{-2} \cdot (m + n^{1.5}k^2))$	

# Fast LP Solvers

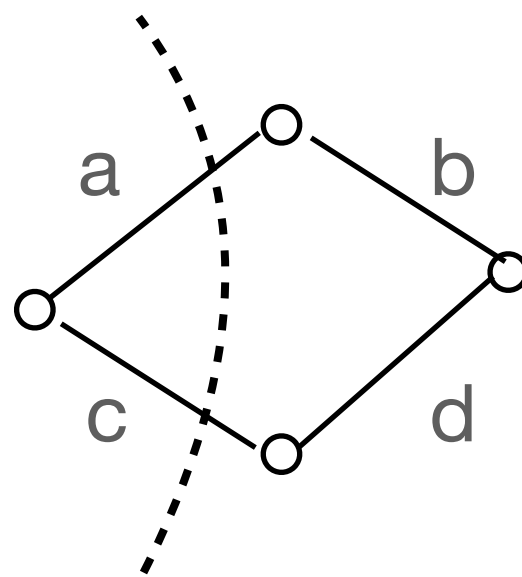
**kECSS LP:**  $\min \sum_{e \in E} c_e x_e$

For all cut  $C$ ,  $\sum_{x_e \in C} x_e \geq k$

$x \in [0,1]^E$

Set of edges

$C = \{a,b\}$



How fast can we solve the kECSS LP?

-  $\tilde{O}\left(\frac{mn}{\epsilon^2}\right)$  time [Fleischer'04]

# Fast LP Solvers

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$$\mathbf{kECSM LP:} \quad \min \sum_{e \in E} c_e x_e$$

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A similar LP (kECSM) can be solved fast!

**Theorem:** [Chekuri, Quanrad, FOCS'17]

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**Theorem:** (This work)

$$\text{kECSS LP can be solved in } \tilde{O}\left(\frac{m}{\varepsilon^2}\right) \text{ time}$$

Extend the techniques from [CQ, FOCS'17]  
to solve the kECSS LP



# Applications of the kECSS LP solver

- We can **estimate** the optimal integral solution within  $(2 + \epsilon)$  factor

(since the integrality gap of the kECSS LP is 2 [KV'94])

- $(2 + \epsilon)$  Integral solution to kECSS in time  $\tilde{O}\left(\frac{m}{\epsilon^2} + n^{1.5}k^2\epsilon^{-2}\right)$

- **Approach:**

(1) Solve kECSS LP  $m\epsilon^{-2}$

$$m' = \tilde{O}(k^2n\epsilon^{-2})$$

(2) Sparsify the LP solution by using the graph compression theorem from [Benzur Karger'15]

(3) run [Khuller Vishkin'94] algorithm on the support of the sparsified graph

$$\tilde{O}(m'\sqrt{n}) = \tilde{O}(k^2n^{1.5}\epsilon^{-2})$$

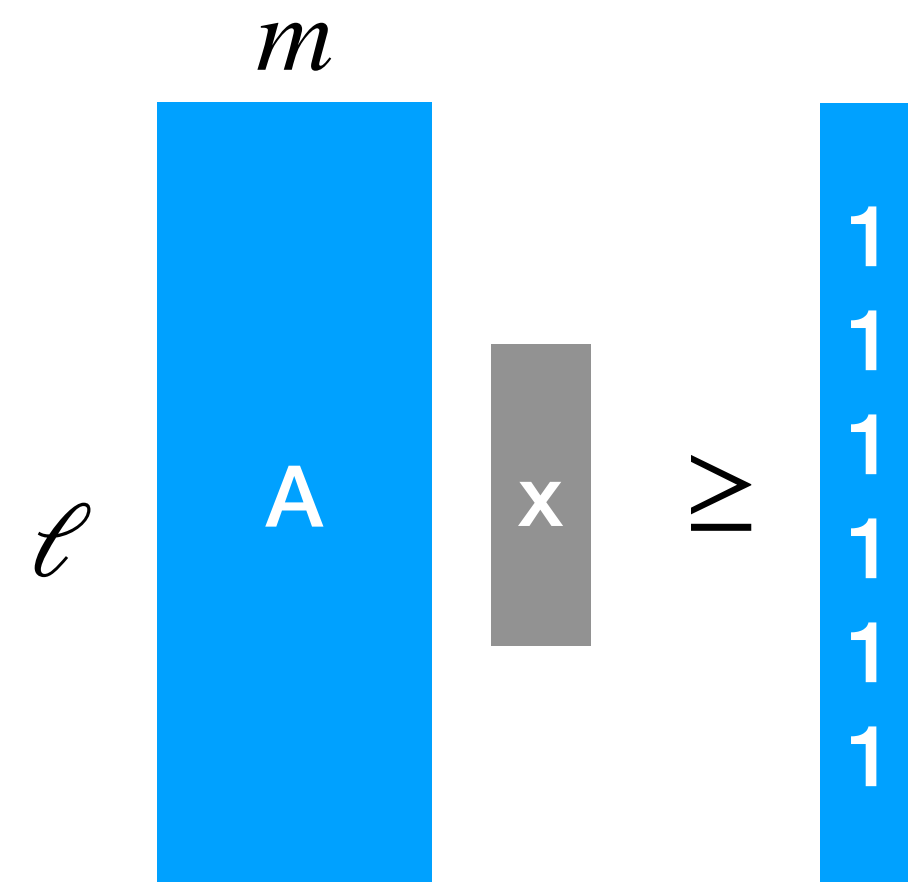
# Preliminaries: MWU framework

Covering LP:

$$\begin{aligned} \min c^T x \\ Ax \geq \vec{1} \\ x \geq 0 \end{aligned}$$

**MinRow Problem:** given  $w_t \in R_{\geq 0}^m$

$$\text{MinRow}(A, w_t) := \arg \min_{\text{row } i} \langle A_i, w_t \rangle$$



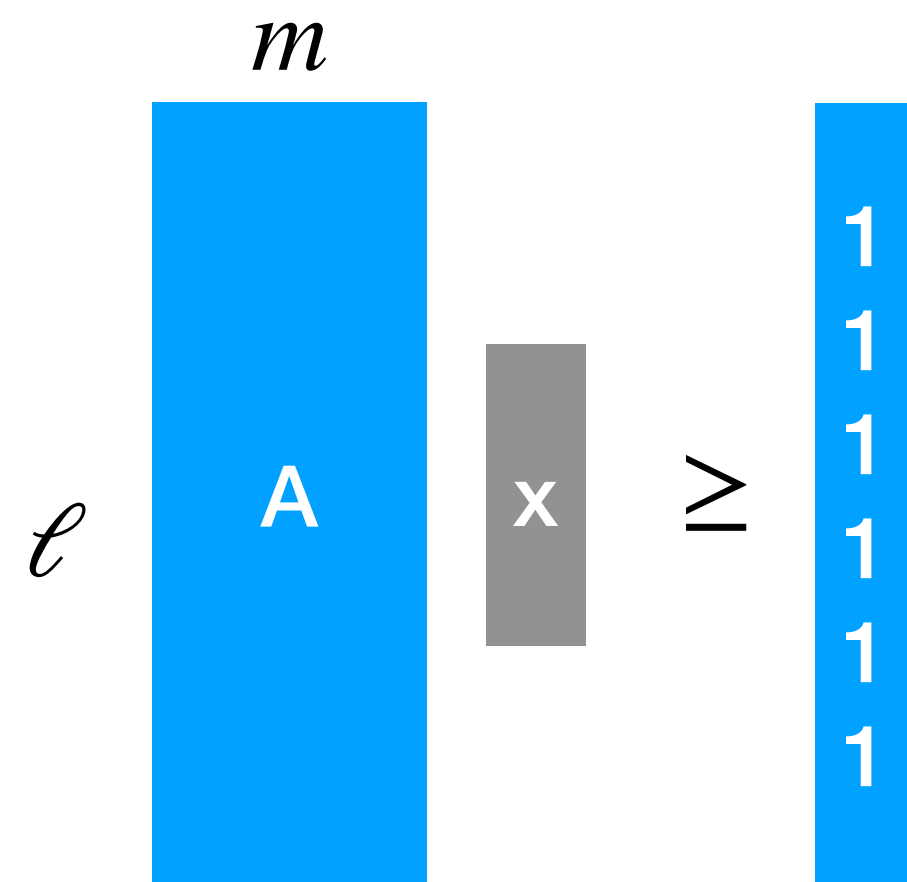
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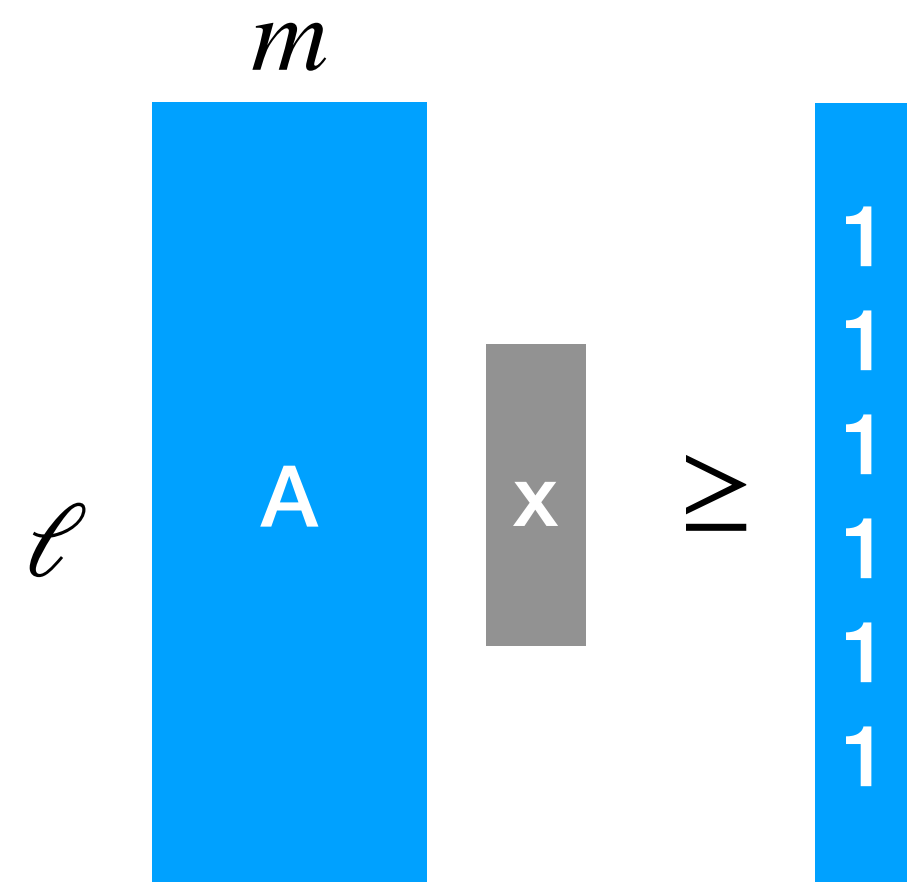
**Theorem: MWU (width-independent) [GK FOCS'98]**

We can obtain  $(1 + \epsilon)$ -approx solution to the covering LP by solving a sequence of Minrow problems for  $O\left(\frac{m \log m}{\epsilon^2}\right)$  iterations

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Omri's talk on

Accelerating the Multiplicative-Weights Framework  
(Workshop on Dynamic graphs and Algorithm Design)

For example,

$$\text{kECSM LP: } \min \sum_{e \in E} c_e x_e$$

For all cut C,  $\sum_{x_e \in C} x_e \geq k$

$$x \geq 0$$

=

$$\text{kECSM LP:}$$

$$\min c^T x$$

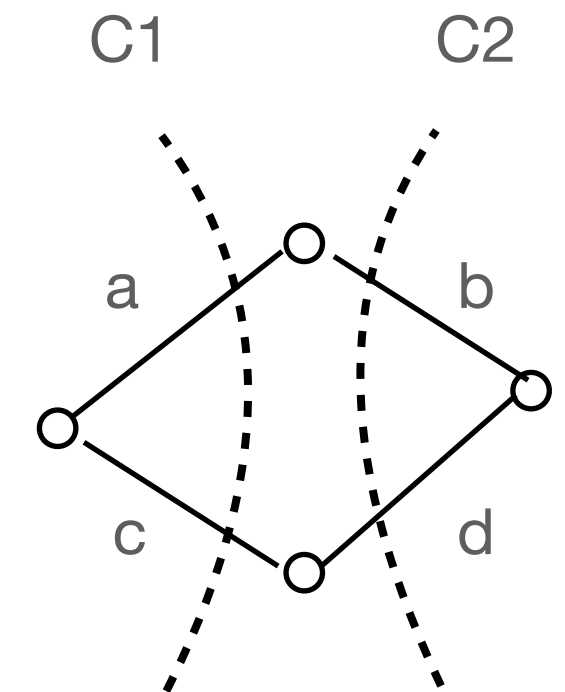
$$Ax \geq \vec{1} \cdot k$$

$$x \geq 0$$

$$A = \begin{matrix} & a & b & c & d \\ \text{C1} & \left[ \begin{array}{cccc} 1 & 0 & 1 & 0 \\ \text{C2} & 0 & 1 & 0 & 1 \\ \vdots & & & \dots & \\ \vdots & & & & \\ \vdots & & & & \end{array} \right. \end{matrix}$$

$$w : E \rightarrow \mathbb{R}_{\geq 0}$$

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(Global) mincut problem

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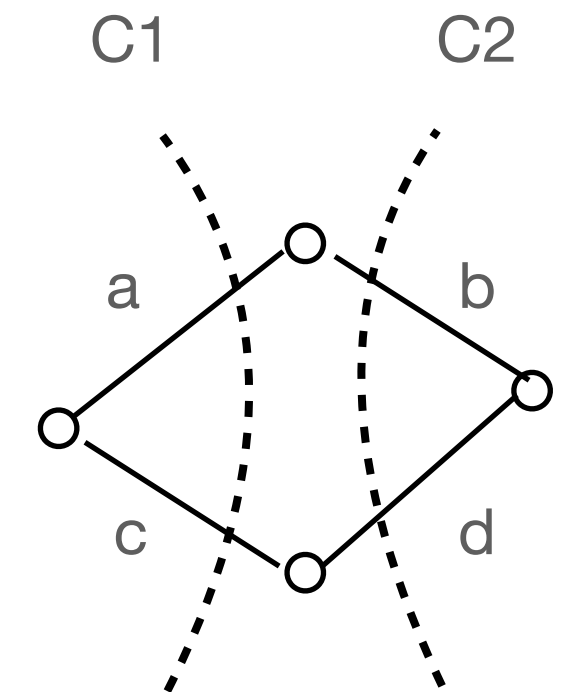
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		a	b	c	d	
A =	C1	1	0	1	0	]
	C2	0	1	0	1	
	⋮	...				
	⋮					
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$w : E \rightarrow \mathbb{R}_{\geq 0}$

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However,

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- To apply MWU algorithm, need a **pure** covering LP
- To get rid of the box-constraints, add extra inequalities **aka, knapsack cover inequality [CFLP'00]**

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For each cut  $C$ :

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For each  $F \subseteq C, |F| < k$ ,

$\sum_{e \in C \setminus F} x_e \geq k - |F|$

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**kECSS Pure:**  $\min \sum_{e \in E} c_e x_e$

For each  $F \subseteq C, |F| < k$ ,  $\sum_{e \in C \setminus F} x_e \geq k - |F|$  Same as  $\sum_{e \in C \setminus F} x_e / (k - |F|) \geq 1$

↑  
free-edge set

$x \geq 0$

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**kECSS Pure:**

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where  $A^{kc}$  is a (cut,free-edge)-matrix of  $G$

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$k=3$ ,  $C_1$

$A = \text{cut-incidence matrix}$

	$e_1$	$e_2$	$e_3$	$e_4$	$e_5$	...
$C_1$	1	1	1	0	0	

$\Rightarrow A^{kc}$

	$e_1$	$e_2$	$e_3$	$e_4$	$e_5$
$(C_1, \emptyset)$	$1/k$	$1/k$	$1/k$	0	0
$(C_1, \{e_1\})$	0	$1/(k-1)$	$1/(k-1)$	0	0
$(C_1, \{e_2\})$	$1/(k-1)$	0	$1/(k-1)$	0	0
$(C_1, \{e_3\})$	$1/(k-1)$	$1/(k-1)$	0	0	0
$(C_1, \{e_1, e_2\})$	0	0	$1/(k-2)$	0	0

$\text{MinRow}(A^{kc}, w) = \min_{\substack{C, F \subseteq C \\ |F| < k}} A_{(C,F)}^{kc} \cdot w = \min_{\substack{C, F \subseteq C \\ |F| < k}} \frac{w(C \setminus F)}{k - |F|}$

• where  $w(S) := \sum_{e \in S} w(e)$



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For each cut C:

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**kECSS Pure:**

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$$A'x \geq \vec{1}$$

$$x \geq 0$$

where  $A'$  is a (cut,free-edge)-matrix of G obtained by adding above inequalities

- **Fact:** These two LPs are equivalent
- $\text{MinRow}(A', w) = ?$

The Normalized  
Free Cut

$$\text{MinRow}(A^{kc}, w) := \min_{\text{row}(C,F)} \langle A_{(C,F)}^{kc}, w \rangle = \min_{C, F \subseteq C, |F| < k} \frac{w(C \setminus F)}{k - |F|}$$

Mincut

$$\text{MinRow}(A, w) := \min_C w(C)$$

- **Upshot:** removing the box constraint makes the **MinRow** problem more complex

The Normalized  
Mincut Problem

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“Free” up to k-1 edges

Let  $\lambda_i = \min_{C, F \subseteq C, |F|=i} w(C \setminus F) =$  Mincut with i edges being free

The **more** free,  
the **less** normalizing factor

$$\text{MinRow}(A^{kc}, w) := \min \left\{ \frac{\lambda_0}{k}, \frac{\lambda_1}{k-1}, \dots, \frac{\lambda_{k-1}}{1} \right\}$$

Brute-force?

The Normalized Mincut Problem

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---

Fast Algorithm ?

**Fact:** Computing  $\lambda_i =$  connectivity interdiction problem  
in time  $O(mn^4)$  [Zenklusen14]

**Thus:**  $\text{MinRow}(A^{kc}, w)$  in  $O(kmn^4) = O(m^2n^4)$  Time **Fastest known**  
(Based on cut enumeration)

Furthermore, we need dynamic algorithm for maintaining MinRow problems

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Main Technical  
Results

**Theorem:** (Static MinRow)

$\text{MinRow}(A^{kc}, w)$  can be approximated in  $\tilde{O}(m\epsilon^{-1})$  time

Reduction to the mincut problem

**Theorem:** (Dynamic MinRow)

$\text{MinRow}(A^{kc}, w)$  can be dynamically maintained  
under the weight  $w$  increases by MWU in  $\tilde{O}(m\epsilon^{-2})$  total time

Reduction to the dynamic mincut algorithm of [Chekuri, Quanrad, FOCS'17]

# Static Reduction

- **Input:** a weighted graph  $G = (V, E, w)$
- **Output:**  $(1 + \epsilon)$ -normalized min-cut in nearly linear time
- Denote  $\text{OPT} = \text{MINROW}(A^{kc}, w) = \min_{C, F \subseteq C, |F| < k} \frac{w(C \setminus F)}{k - |F|}$
- Let  $\rho := (1 + \epsilon)\text{OPT}$
- Truncated Weight:  $w_\rho(e) = \min\{w(e), \rho\}$

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- Let  $\rho := (1 + \epsilon)\text{OPT}$
- Truncated Weight:  $w_\rho(e) = \min\{w(e), \rho\}$

- **Lemma 1:** Let  $C$  be the minimum cut wrt.  $w_\rho$ . Then, there exists a set of free edges  $F \subseteq C, |F| < k$  such that  $\frac{w(C \setminus F)}{k - |F|} \leq (1 + \epsilon)\text{OPT}$
- **Theorem 2** [Karger, STOC'96]: minimum cut can be solved in nearly-linear time



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- **Input:** a weighted graph  $G = (V, E, w)$
- **Output:**  $(1 + \epsilon)$ -normalized min-cut in nearly linear time
- Denote  $\text{OPT} = \text{MINROW}(A^{kc}, w) = \min_{C, F \subseteq C, |F| < k} \frac{w(C \setminus F)}{k - |F|}$
- Let  $\rho := (1 + \epsilon)\text{OPT}$
- Truncated Weight:  $w_\rho(e) = \min\{w(e), \rho\}$

- **Lemma 1:** Let  $C$  be the minimum cut wrt.  $w_\rho$ . Then, there exists a set of free edges  $F \subseteq C, |F| < k$  such that  $\frac{w(C \setminus F)}{k - |F|} \leq (1 + \epsilon)\text{OPT}$
- **Theorem 2** [Karger, STOC'96]: minimum cut can be solved in nearly-linear time

## Algorithm:

1. Let  $C^*$  be the minimum cut wrt.  $w_\rho$
2. Find  $F^*$  of size less than  $k$  that minimizes  $\frac{w(C^* \setminus F^*)}{k - |F^*|}$
3. **Return**  $(C^*, F^*)$

- **Lemma 1:** Let  $C^*$  be the minimum cut wrt.  $w_\rho$ . Then, there exists a set of free edges  $F \subseteq C^*$ ,  $|F| < k$  such that  $\frac{w(C^* \setminus F)}{k - |F|} \leq (1 + \epsilon)\text{OPT}$
- **Proof:** (for any cut  $C$ )
  - **Claim 1:** If  $w_\rho(C) < k(1 + \epsilon)\text{OPT}$ , then, there exists a set  $F \subseteq C$ ,  $|F| < k$  such that  $\frac{w(C \setminus F)}{k - |F|} \leq (1 + \epsilon)\text{OPT}$
  - **Claim 2:**  $w_\rho(C^*) < k(1 + \epsilon)\text{OPT}$

- **Lemma 1:** Let  $C^*$  be the minimum cut wrt.  $w_\rho$ . Then, there exists a set of free edges  $F \subseteq C^*$ ,  $|F| < k$  such that 
$$\frac{w(C^* \setminus F)}{k - |F|} \leq (1 + \epsilon)\text{OPT}$$

- **Proof:** (for any cut  $C$ )

- **Claim 1:** If  $w_\rho(C) < k(1 + \epsilon)\text{OPT}$ , then, there exists a set

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- **Claim 2:**  $w_\rho(C^*) < k(1 + \epsilon)\text{OPT}$

- **Proof of Claim 2:** • Recall  $w_\rho(e) = \min\{w(e), \rho\}$

Let  $(D, F \subseteq D)$  be the minimum normalized cut

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$$w_\rho(D \setminus F) \leq w(D \setminus F) \stackrel{\text{def}}{=} (k - |F|)\text{OPT} < (1 + \epsilon)(k - |F|)\text{OPT}$$

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$$w_\rho(F) \leq \rho|F| = (1 + \epsilon)|F|\text{OPT}$$

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$$w_\rho(F) \leq \rho|F| = (1 + \epsilon)|F|\text{OPT}$$

Therefore,  $w_\rho(D) < (1 + \epsilon)k\text{OPT}$

$$w_\rho(C^*) \leq w_\rho(D) < (1 + \epsilon)k\text{OPT} \quad QED$$

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$$w(e) \geq (1 + \epsilon)\text{OPT}$$

Let  $F$  be the set of heavy edges in  $C$



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$$w(C \setminus F) = w_\rho(C \setminus F)$$

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So,  $|F| < k$  (o.w.  $w_\rho(C) \geq (1 + \epsilon)k\text{OPT}$ )

$$\begin{aligned} w(C \setminus F) &= w_\rho(C \setminus F) = w_\rho(C) - |F|\rho \\ &\leq (k - |F|)(1 + \epsilon)\text{OPT} \end{aligned}$$

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$$\text{Therefore, } \frac{w(C \setminus F)}{k - |F|} \leq (1 + \epsilon)\text{OPT} \quad \text{QED}$$

# Dynamic Reduction

**Theorem:** (Dynamic MinRow)

MinRow( $A^{kc}, w$ ) can be dynamically maintained  
under the weight  $w$  increases by MWU in  $\tilde{O}\left(\frac{m}{\epsilon^2}\right)$  total time

**Review MWU  
Framework**  
[GK'98]

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**Review MWU Framework**  
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**Initialize**  $w : E \rightarrow \mathbb{R}_{\geq 0}$

**Repeat** for  $O(\epsilon^{-2} \cdot m \log m)$  iterations

- Compute  $(C, F) = (1 + \epsilon)$ - approximate  $\text{MinRow}(A^{kc}, w) = \min_{C, F \subseteq C, |F| < k} \frac{w(C \setminus F)}{k - |F|}$
- For each  $e \in C \setminus F$ ,  $w(e) \leftarrow w(e)(1 + \frac{c_{\min}}{c_e})$

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Assume free for this talk



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**Issue 1:** Need to update  $\rho$  every time

**Issue 2:** Given  $C$ , how to identify its best free set quickly?

**To handle issue 1:** batch OPT into a range of the powers of  $(1 + \epsilon)^i$

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**Epoch-based  
MWU Framework**  
[Fleischer'00]

**Initialize**  $w : E \rightarrow \mathbb{R}_{\geq 0}$

$\lambda \leftarrow \text{MinRow}(A^{kc}, w)$

**Repeat** for  $O(\epsilon^{-2} \log m)$  **epochs**

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- Compute  $(C, F) =$  with normalized weight in  $[\lambda, (1 + \epsilon)\lambda)$
- Update weights  $w$  and repeat **until**  $\text{MinRow}(A^{kc}, w) \geq (1 + \epsilon)\lambda$

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Same threshold

$\lambda \leftarrow (1 + \epsilon)\lambda$   
start a new epoch

## Review MWU Framework

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## Epoch-based MWU Framework

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- Update weights  $w$  and repeat **until**  $\text{MinRow}(A^{kc}, w) \geq (1 + \epsilon)\lambda$

**Goal:** Implement each epoch in time  $\tilde{O}(m + K_i)$  where  $K_i = \# \text{ cuts}$

## Epoch-based MWU Framework

Repeat for  $O(\epsilon^{-2} \log m)$  epochs

- Compute  $(C, F) =$  with normalized weight in  $[\lambda, (1 + \epsilon)\lambda]$
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**Therefore:**  $\sum_{\text{each epoch } i} \tilde{O}(m + K_i) = \tilde{O}(m\epsilon^{-2})$  as  $\sum_i K_i \leq$  # iterations in the MWU  $= O(\epsilon^{-2} m \log m)$

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**Therefore:**  $\sum_{\text{each epoch } i} \tilde{O}(m + K_i) = \tilde{O}(m\epsilon^{-2})$  as  $\sum_i K_i \leq \# \text{ iterations in the MWU} = O(\epsilon^{-2} m \log m)$

**Theorem:** (Dynamic MinRow) During an epoch,  
 $\text{MinRow}(A^{kc}, w)$  can be dynamically maintained  
under the weight  $w$  increases by MWU in  $\tilde{O}(m)$  total time

**For simplicity,** assume #of edges is bounded  $|C| = \tilde{O}(1)$

(we use the data structure from **[CQ'17]** to handle the **general** case)



## Epoch-based MWU Framework

Repeat for  $O(\epsilon^{-2} \log m)$  epochs

- Compute  $(C, F) =$  with normalized weight in  $[\lambda, (1 + \epsilon)\lambda]$
- Update weights  $w$  and repeat **until**  $\text{MinRow}(A^{kc}, w) \geq (1 + \epsilon)\lambda$

**Goal:** Implement each epoch in time  $\tilde{O}(m + K_i)$  where  $K_i = \# \text{ cuts}$

**Issue 2:** Given  $C$ , how to identify its best free set quickly?

**Answer:** Thresholding automatically hints the free set!

**Range Mapping Theorem:**

Fix  $\rho = (1 + \epsilon)\lambda$      $\text{OPT}_w := \text{MinRow}(A^{kc}, w)$

$w_\rho(e) := \min\{w(e), \rho\}$

1. If  $\text{OPT}_w \in [\lambda, (1 + \epsilon)\lambda]$  then minimum cut w.r.t.  $w_\rho \in [\frac{k\rho}{1 + \epsilon}, k\rho)$

2. If a cut  $C$  having  $w_\rho(C) \leq k\rho$  then  $\frac{w(C \setminus F^*)}{k - |F^*|} < (1 + \epsilon)\lambda$

$F^* := \{e \in C : w(e) \geq \rho\}$

**Range Mapping  
Theorem:**

Fix  $\rho = (1 + \epsilon)\lambda$

$\text{OPT}_w := \text{MinRow}(A^{kc}, w)$

$w_\rho(e) := \min\{w(e), \rho\}$

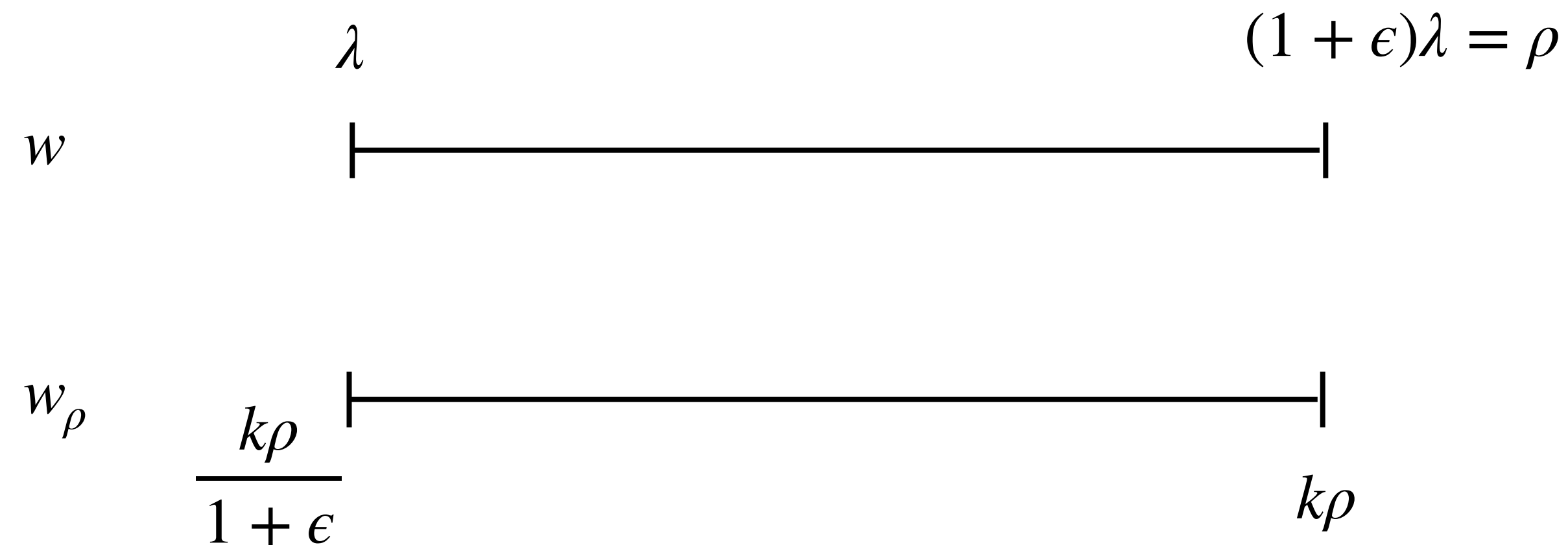
1. If  $\text{OPT}_w \in [\lambda, (1 + \epsilon)\lambda)$  then minimum cut w.r.t.  $w_\rho \in [\frac{k\rho}{1 + \epsilon}, k\rho)$
2. If a cut  $C$  having  $w_\rho(C) \leq k\rho$  then  $\frac{w(C \setminus F^*)}{k - |F^*|} < (1 + \epsilon)\lambda$

**Algorithm:**

**Initialize**  $w_\rho$

**Run** the dynamic mincut algorithm from [CQ'17] in  $w_\rho$

- List mincut in  $[\frac{k\rho}{1 + \epsilon}, k\rho)$
- Update weights and repeat until mincut  $> k\rho$



**Range Mapping  
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Fix  $\rho = (1 + \epsilon)\lambda$

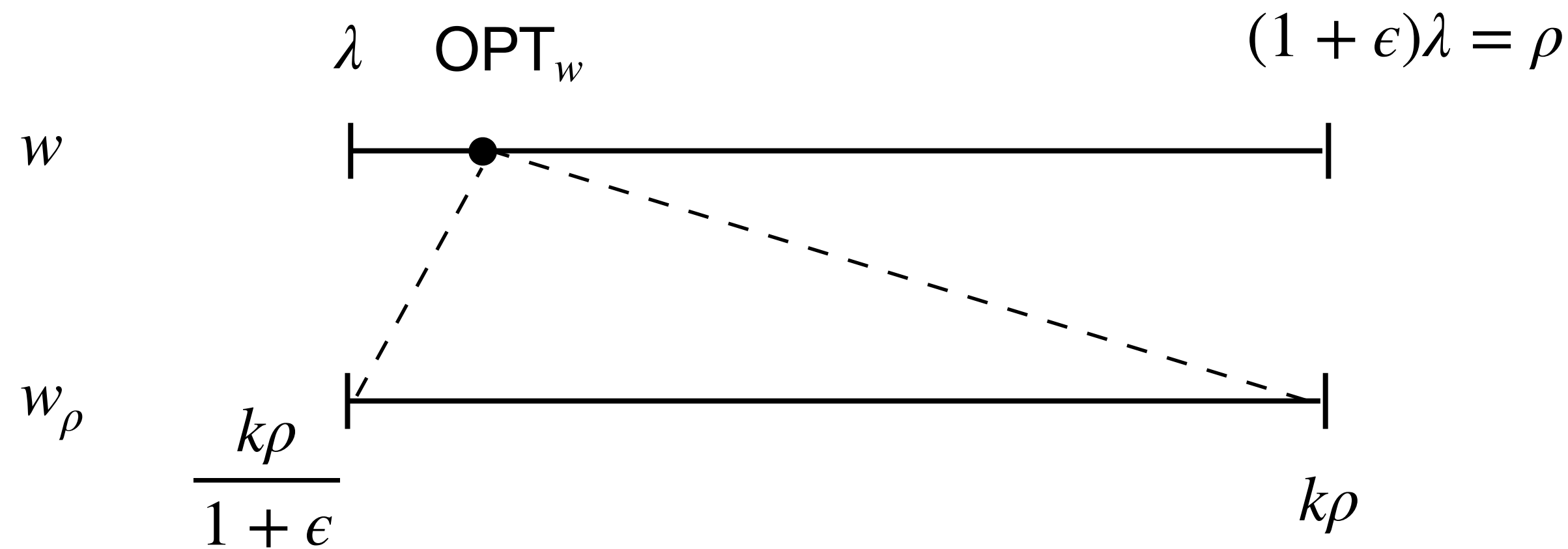
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2. If a cut C having  $w_\rho(C) \leq k\rho$  then  $\frac{w(C \setminus F^*)}{k - |F^*|} < (1 + \epsilon)\lambda$

**Range Mapping  
(1)**



**Algorithm:**

**Initialize**  $w_\rho$

**Run** the dynamic mincut algorithm from [CQ'17] in  $w_\rho$

- List mincut in  $[\frac{k\rho}{1 + \epsilon}, k\rho)$
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**Range Mapping  
Theorem:**

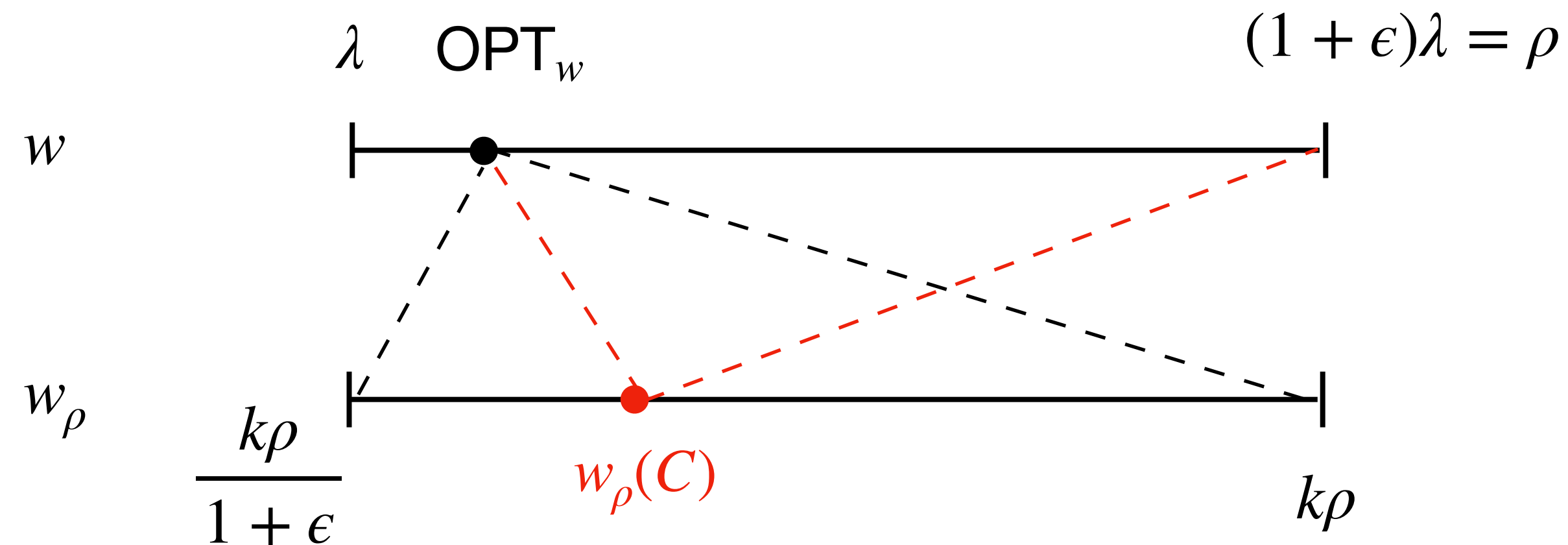
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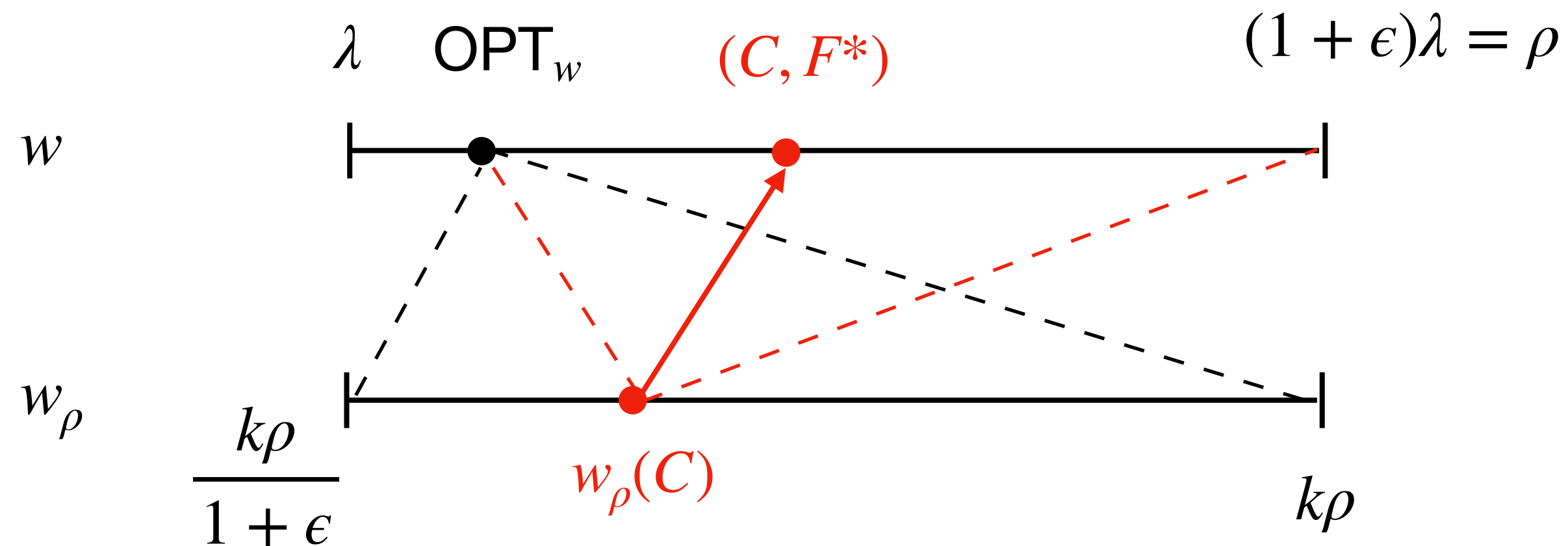
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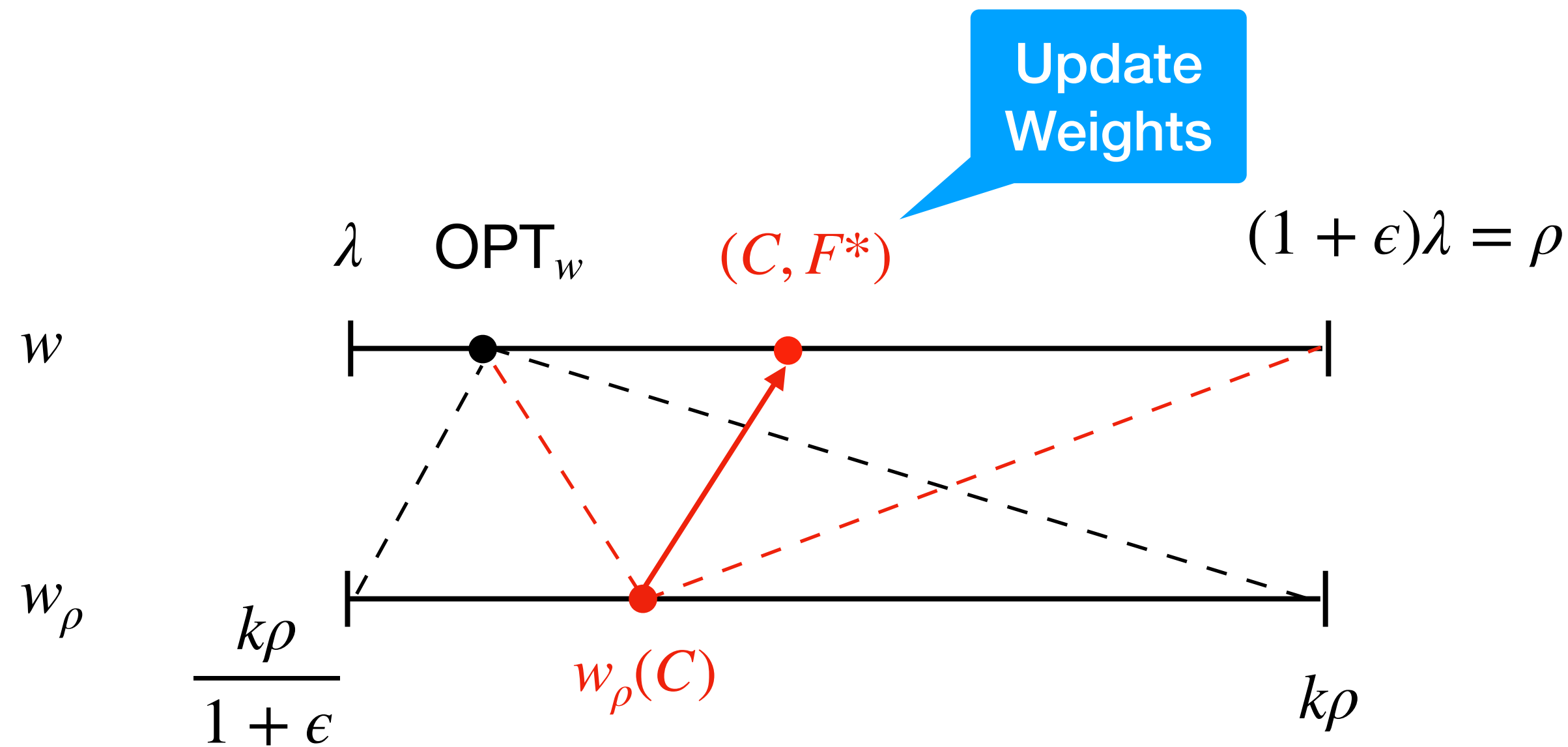
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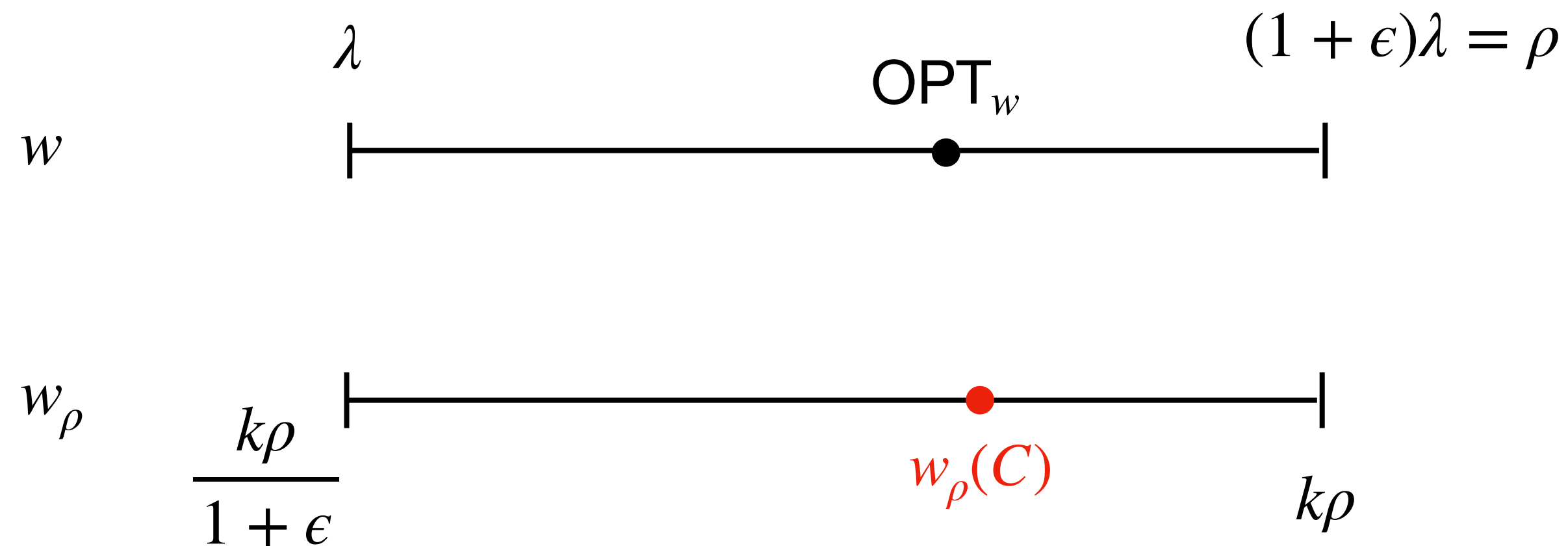
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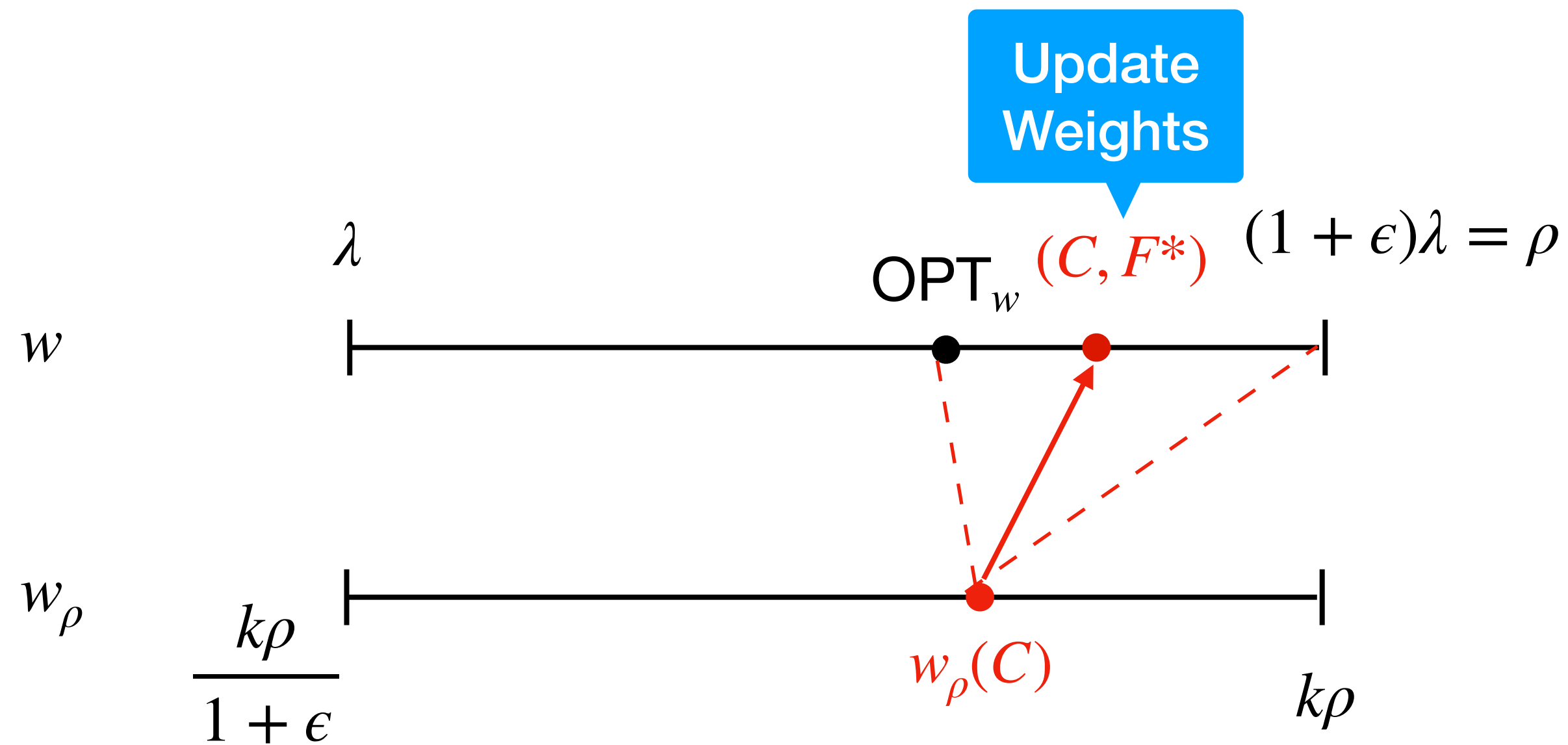
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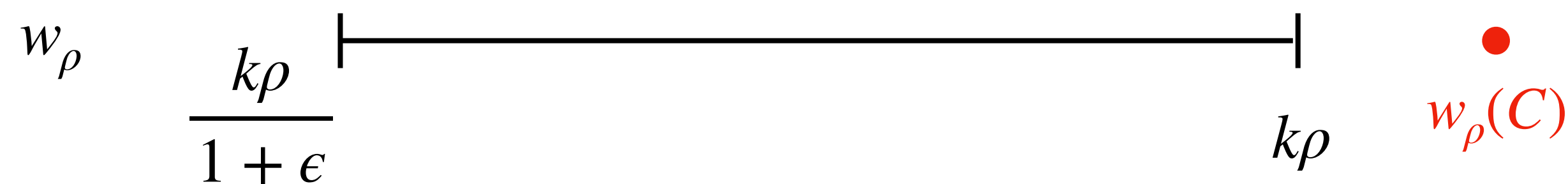
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End of the epoch

**Possible to Implement in time**  $\tilde{O}(m + K_i)$   $K_i = \# \text{ cuts}$

# Open Problems

- Theory of **Fast Approximation** Algorithms
  - **Fast rounding** algorithms? Nearly linear time for 2ECSS?
  - **Fast LP Solvers** for a broader class e.g., SNDP?
  - Can we solve LP with **high-accuracy** in nearly linear time?
    - Iterative rounding algorithm needs high-accuracy solvers