

# First Fit and Best Fit bin packing: A new analysis

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# A Brief Review of Bin Packing

## Bin packing

- Input: Sequence of **items**  $a_1, \dots, a_n \in [0, 1]$ .
- Output: Assign into **bins** of size 1.
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## Complexity results

- It is NP-hard to decide if  $OPT(I) = 2$ .  
Thus it is NP-hard to approximate with ratio  $< 3/2$ .
- There exists an asymptotic approximation scheme.  
I.e., in polynomial time we can pack the items into  $(1 + \varepsilon)OPT(I) + 1$  bins.

# Performance measures

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There exists a constant  $C$  such that for each instance  $I$ , the algorithm gives

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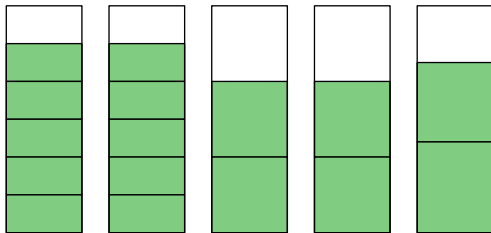
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## First Fit

Packs items one by one, always into the **first** bin where it fits.  
Opens a new bin only when necessary.

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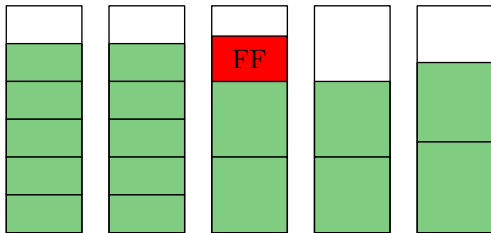
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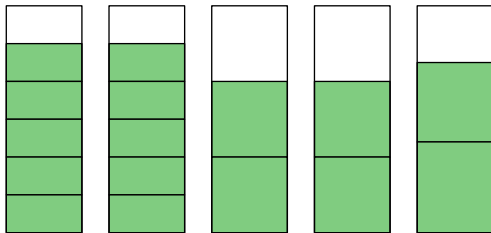
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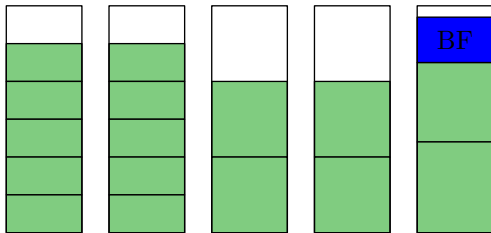
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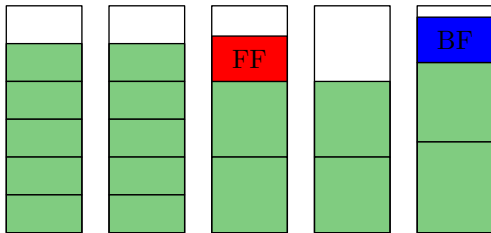
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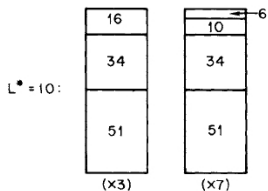
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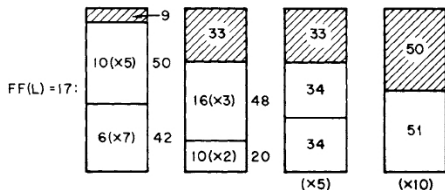
# Known Results

The asymptotic approximation ratio of both First Fit and Best Fit is equal to 1.7. More precisely,  $FF, BF \leq [1.7 \cdot OPT]$ .

Example with  $FF = BF = 17$  and  $OPT = 10$ :



Bin size is 101.



# Overview of this talk

- 1 An easy proof of the 1.7 asymptotic approximation ratio for First Fit.
- 2 An extension for Best Fit.
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## Main Technique

Classical technique: **Weight functions.**

Find a weight of items such that

- Each bin in OPT has weight  $\leq 1.7$ .
- Each bin in FF (BF) has weight  $\geq 1$  on average.

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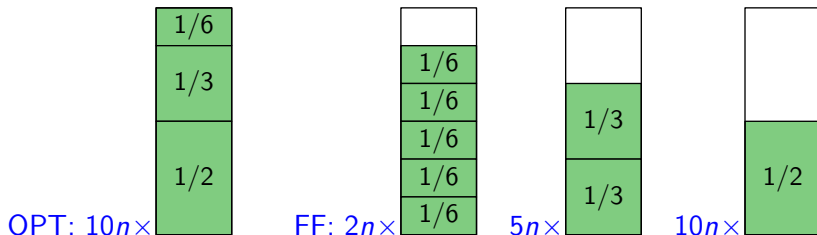
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Combine weight functions with **amortized analysis**.

# Idealized example for First Fit

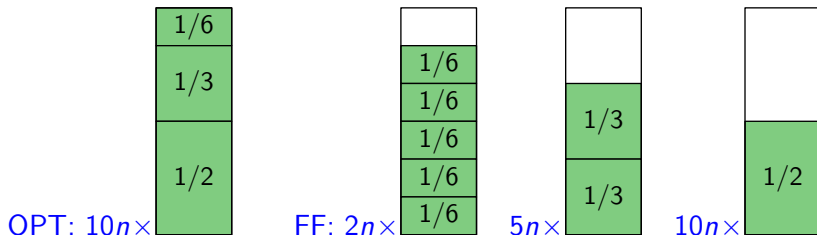
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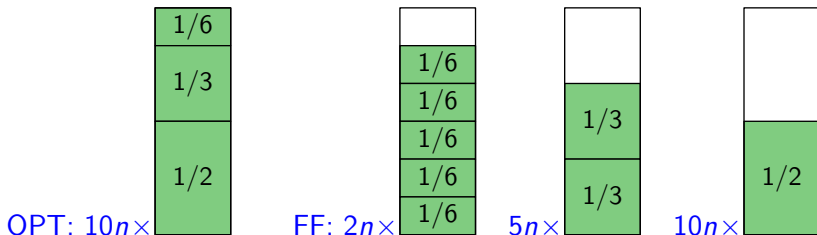


What should be the weights?



# Idealized example for First Fit

Assume that the algorithm cannot have bins of size exactly 1.



$$w(1/6) = 0.2 \quad w(1/3) = 0.5 \quad w(1/2) = 1$$

# The weight function

- Weight: **Scaled size** plus a **bonus**.

- $w(a) = \frac{6}{5}a + b(a)$

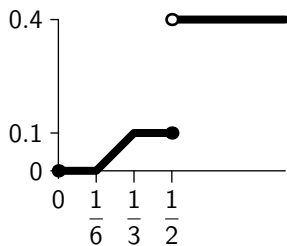
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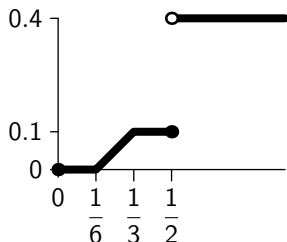
$$\begin{cases} 0 & \text{if } a \leq \frac{1}{6} \\ \frac{3}{5} \left( a - \frac{1}{6} \right) & \text{if } a \in \left[ \frac{1}{6}, \frac{1}{3} \right] \\ 0.1 & \text{if } a \in \left[ \frac{1}{3}, \frac{1}{2} \right] \\ 0.4 & \text{if } a > \frac{1}{2} \end{cases}$$



# Offline bins

Each bin (a set of items of size  $\leq 1$ ) contains **bonus items**:

- either no item of size  $> 1/2$  and at most 5 items with bonus at most 0.1 each (actually the total is  $< 0.3$ ),
- or one item of size  $> 1/2$  and at most 2 items with bonus at most 0.1 total.



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- Thus the **total bonus** is at most **0.5**;
- the **total scaled size** is at most **1.2**;
- the **total weight** is at most **1.7**.

# First Fit bins

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- There is at most one bin of size  $\leq 1/2$ .
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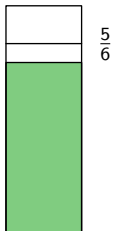
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- Bins with an item of size  $> 1/2$  have weight  $\geq 1$ .
- For the remaining bins with sizes in  $(2/3, 5/6)$  we use **amortization**.

We show that the scaled size of a bin plus the bonus of the **following** such bin is  $\geq 1$ .

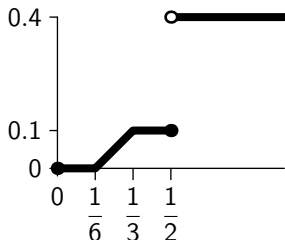
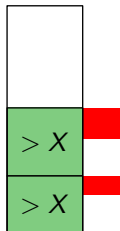
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## Theorem

**First Fit** has **asymptotic** approximation ratio **1.7**.

$$FF(I) \leq 1.7 \cdot OPT(I) + 3$$

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- The first item does not fit into any previous bin.
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- The first item does not fit into any previous bin.
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- We **close bins one by one**, paying **1** at each step.  
We always **close the largest bin**.
- The **bonus of one of the open bins** may be used to pay for the cost of closing **the previously closed bins**.

# Amortization for Best Fit

## The boss

One of the open bins is the **boss**.  
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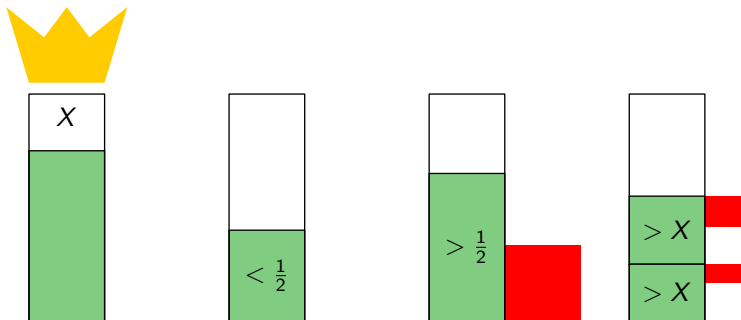
## When the boss is closed

- We choose the new boss and
- we use also **its bonus** to pay the cost.

# Choice of the new boss

The new boss is

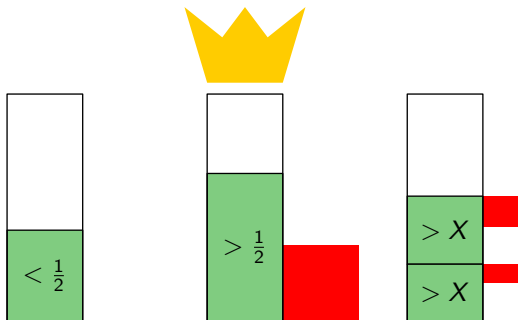
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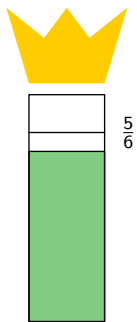
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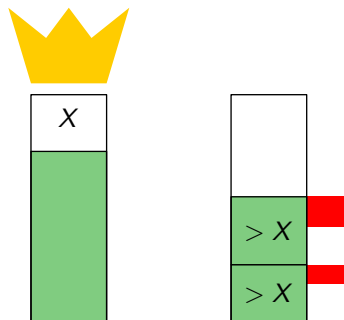


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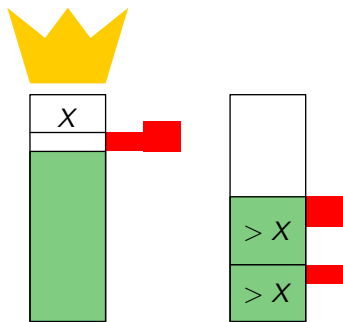
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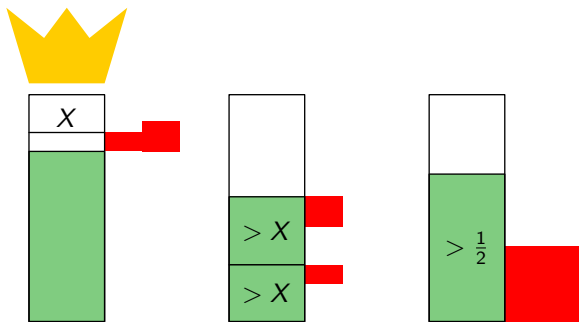
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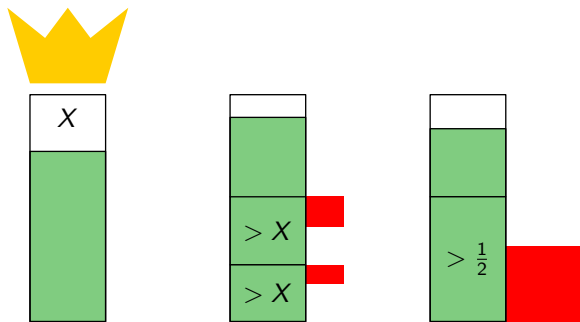
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- Or, even better, the new boss has an item of size  $> \frac{1}{2}$ .



# A regular bin is closed



- If a regular bin has enough to pay for the boss, then it has enough for itself.

# Results for Best Fit

At the end we have two bins left with total weight  $> 1.2$ . Thus

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## $k$ -bounded-space Best Fit

- The most full bin is closed when  $k$  bins are open and the next item does not fit into any of them.
- For  $k \geq 2$ ,  **$k$ -bounded-space Best Fit** has **asymptotic** approximation ratio  $1.7$ .

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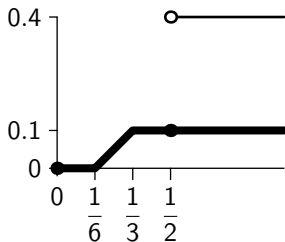
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(Actually, 1 bin may have an item  $\leq 1/2$ , needs to have a smaller bonus. Still average weight  $> 1$ .)
- **Common bins**: The rest. Bonus as before, but only 0.1 for items  $> 1/2$ . We need to prove that these  $C$  bins have **total weight**  $\geq C - 0.2$ .





# Common bins

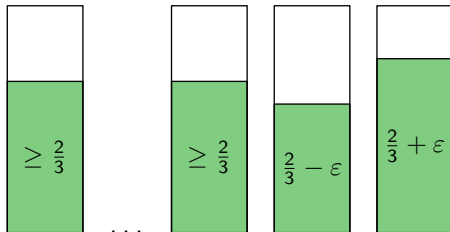
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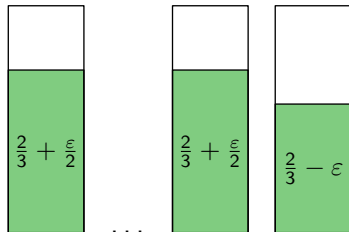
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- A bin of size  $< 2/3$ , but it is not the last common bin:  
Easy fix.
- The last common bin has size  $< 2/3$ : Harder, but works for large  $OPT$ . Some cases solved separately.



# Last 0.1

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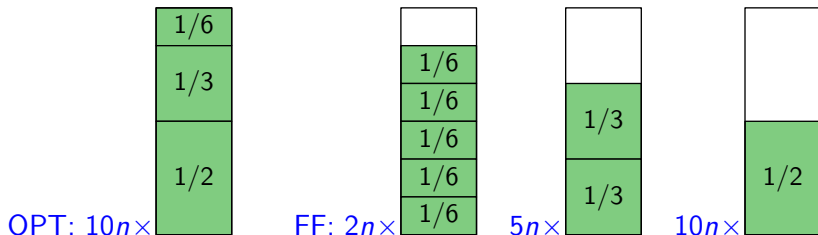
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  - the weight of this bin is at most 1.6 and thus  $w(I) \leq 1.7 \cdot OPT(I) - 0.1$ ;
  - the analysis for the common bins still holds, since the items with removed bonus are in a bin with two more items.

# Idealized example revisited

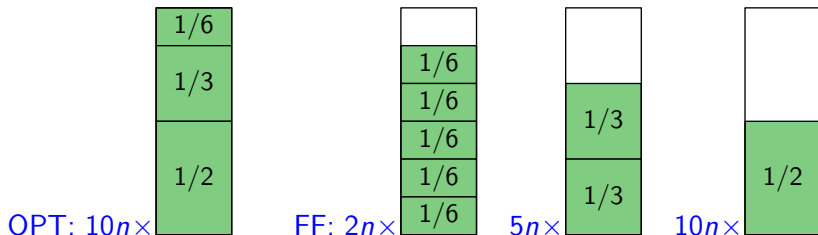
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We use this as a black box to get tight bounds.

# Lower bounds

Suppose that  $OPT = 10k + i$ ,  $i = 0, \dots, 9$ .

Then the lower and upper bounds for First Fit are:

$i =$	0	1	2	3	4	5	6	7	8	9
$FF \geq 17k +$	-1	1	3	4	6	8	10	11	13	15
$FF \leq \lfloor 17k + 1.7i \rfloor$ $= 17k +$	0	1	3	5	6	8	10	11	13	15

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We have shown

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- The **absolute** approximation ratio of **Best Fit**.
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- The **gap for First Fit** for  $OPT \equiv 0, 3 \pmod{10}$ .

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- The **absolute** approximation ratio of **Best Fit**.
- The **absolute** approximation ratio of **bounded space Best Fit**.
- The **gap for First Fit** for  $OPT \equiv 0, 3 \pmod{10}$ .
- General online algorithms.  
The best bounds are **1.54037** and **1.58889**.

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We have shown

$$FF \leq 1.7 \cdot OPT$$

Improves previous  $FF \leq 1.7 \cdot OPT + 0.7$  and  $FF \leq 1.7143 \cdot OPT$ .

## Open problems

- The **absolute** approximation ratio of **Best Fit**.
- The **absolute** approximation ratio of **bounded space Best Fit**.
- The **gap for First Fit** for  $OPT \equiv 0, 3 \pmod{10}$ .
- General online algorithms.  
The best bounds are [1.54037](#) and [1.58889](#).

# THANK YOU!