

# Online Bin Packing with Advice

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- 1 The bin packing problem: offline and online
- 2 Advice complexity results for bin packing
- 3 Open problems

## Section 1

# The bin packing problem: offline and online

# Bin Packing Problem

**Input:** items of various sizes  $\in (0, 1]$

**Output:** packing of all items into unit size bins

**Goal:** use minimum number of bins

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**Applications:** storage, cutting stock...

# Offline Bin Packing Problem

The problem is NP-hard; Reduce from 2-PARTITION.

**First-Fit-Decreasing** has an approximation ratio of  $11/9 \approx 1.22$   
[Johnson, Demers, Ullman, Garey, Graham, 1974]

There is an asymptotic PTAS for the problem [de la Vega, Lueker, 1981]

# Online Bin Packing Problem

Request sequence is revealed in a sequential, online manner.

Examples:

- Next-Fit
- First-Fit
- Best-Fit
- Harmonic, Harmonic++

## First-Fit

- Find the first open bin with enough space, and place the item there
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## Next-Fit

- Put item in current open bin, if it fits
- Otherwise, close that bin and open a new current bin

# First-Fit vs. Next-Fit — Online

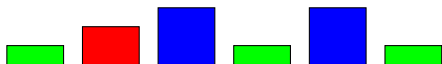


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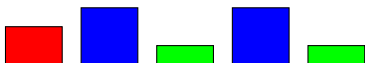


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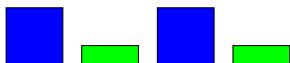


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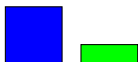


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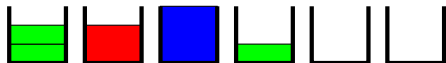


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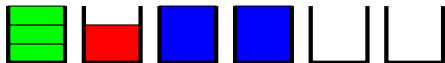


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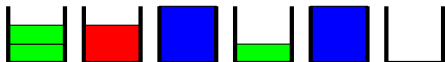


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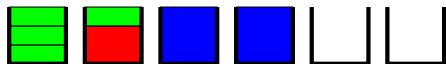
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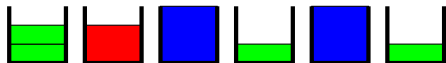
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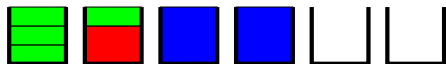


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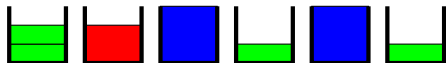


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# First-Fit vs. Next-Fit — Online



FIRST-FIT Result: 4



NEXT-FIT Result: 6

# Competitive Analysis

Compare the performance of an online algorithm,  $ALG$ , with an optimal **offline** algorithm,  $OPT$ :

- $OPT$  knows the whole sequence in the beginning.

**Competitive ratio** of  $ALG$  is the maximum ratio between the cost of  $ALG$  and  $OPT$  for serving the same sequence.

# Competitive Analysis

**Next-Fit** has competitive ratio 2  
[Johnson, 1974]

**Best-Fit** and **First-Fit** have competitive ratio 1.7  
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Best known online algorithm (**Harmonic++**) has competitive ratio 1.58889  
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Recall that offline **First-Fit-Decreasing** has approximation ratio  $\approx 1.22$ .

- A big gap between quality of online and offline solutions.
- What about an “almost online” algorithm?

## Section 2

# Advice complexity results for bin packing

# Advice Model for Online Bin Packing Problem

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- There are other advice models for bin packing
  - Original: [Dobrev, Královič, Markou, 2009]
  - Advice with request: [Fraigniaud, Korman, Rosén, 2011]

For a sequence of fixed length

- How many bits of advice are required (sufficient) to achieve an optimal solution?
- How many bits of advice are sufficient to outperform all online algorithms?
- How good can the competitive ratio be with advice of linear/sublinear size?

# Relevant Questions

For a sequence of fixed length

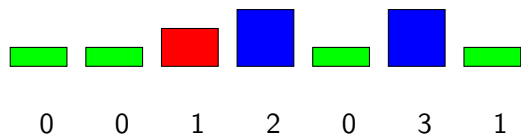
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- How many bits of advice are sufficient to outperform all online algorithms?
- How good can the competitive ratio be with advice of linear/sublinear size?

Is there useful advice one could reasonably get (without knowing  $\text{OPT}$ )?

# Optimal Solution with Advice

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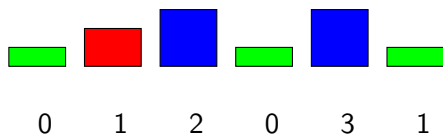
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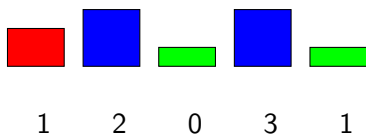




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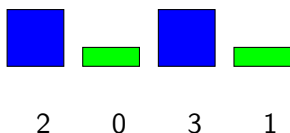
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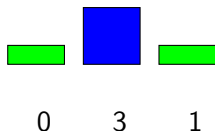
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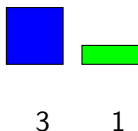
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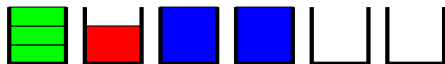
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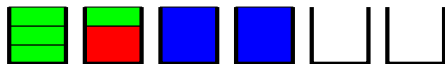
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## Comparison:

$n \lceil \log \mathbf{Opt}(\sigma) \rceil$  bits of advice are sufficient for optimality.

$(n - 2 \mathbf{Opt}(\sigma)) \log \mathbf{Opt}(\sigma)$  bits of advice are required to guarantee optimality.



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Apply **First-Fit** for the other items.

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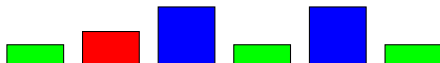
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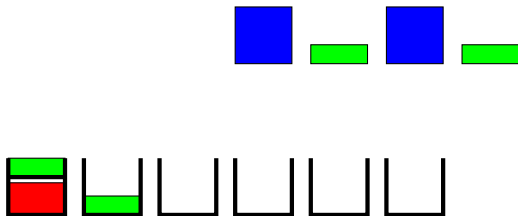
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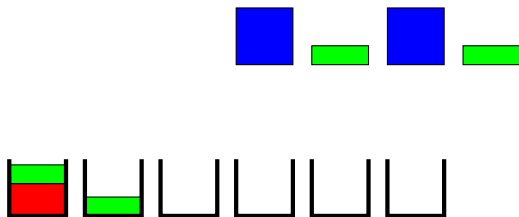
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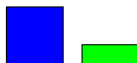
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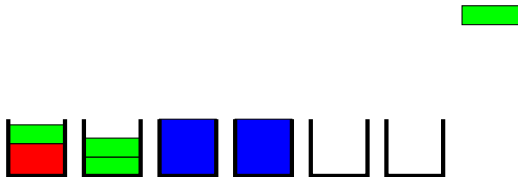
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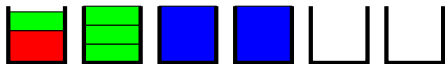
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Advice depends on  $\text{OPT}$ 's packing.



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A linear amount of advice is required to achieve a competitive ratio better than  $9/8$ .

Get a trade-off — better ratio requires more advice

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**Reduction order:**

Binary string guessing problem  $\longrightarrow$  Binary separation problem

Binary separation problem  $\longrightarrow$  Bin packing problem

# Binary String Guessing Problem

Binary string guessing problem (with known history): 2-SGKH

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## Theorem

*On inputs of length  $n$ , any deterministic algorithm for 2-SGKH that is guaranteed to guess correctly on more than  $\alpha n$  bits, for  $1/2 \leq \alpha < 1$ , needs to read at least  $(1 + (1 - \alpha) \log(1 - \alpha) + \alpha \log(\alpha))n$  bits of advice.*

Note: If we assume the number,  $n_0$ , of 0s is given, we need at least  $(1 + (1 - \alpha) \log(1 - \alpha) + \alpha \log(\alpha))n - e(n_0)$  bits of advice, where  $e(n_0) = \lceil \log(n_0 + 1) \rceil + 2 \lceil \log(\lceil \log(n_0 + 1) \rceil + 1) \rceil + 1$  (self-delimiting code).

# Binary Separation Problem

## Binary separation problem:

- For a sequence of  $n_1 + n_2$  items decide whether an item belongs to the  $n_1$  smaller items or  $n_2$  larger items.



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- Don't have to choose the exact middle value.

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Give **large items**,  $L$  and **small items**,  $S$ :

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For each **small item** of size  $\frac{1}{2} - \epsilon_i$ ,

give an item of size  $\frac{1}{2} + \epsilon_i$  — **matching items,  $M$** .



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Give **large items,  $L$**  and **small items,  $S$** :

- OPT places **large items** with **begin items**.
- OPT places **small items**, one per bin.
- ALG much choose.

For each **small item** of size  $\frac{1}{2} - \epsilon_i$ ,

give an item of size  $\frac{1}{2} + \epsilon_i$  — **matching items,  $M$** .

OPT packs **matching items** with **small items**, using  $n_1 + n_2$  bins.

# Reduction from Binary separation to Bin packing

Large item + matching item  $> 1$ .

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A large item may not be with a begin item because

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At most 2 fit in a bin together.

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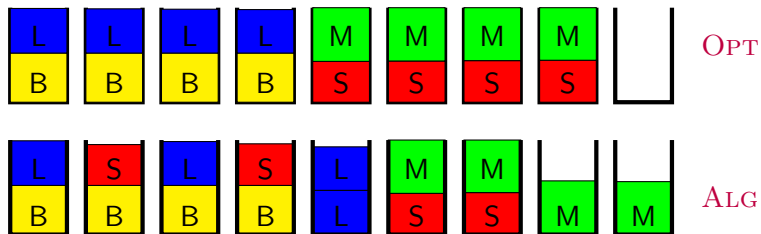
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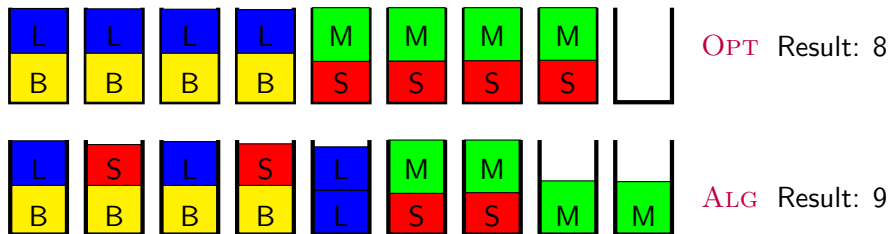
4 errors in binary separation  $\Rightarrow \geq 1$  more bin

# Reduction from Binary separation to Bin packing





# Reduction from Binary separation to Bin packing



## Theorem

*On inputs of length  $n$ , to achieve a competitive ratio of  $c$  ( $1 < c < 9/8$ ), an online algorithm must get at least*

*$(1 + (4c - 4) \log(4c - 4) + (5 - 4c) \log(5 - 4c))n - e(n)$  bits of advice.*

Recall that  $e(n) = \lceil \log(n + 1) \rceil + 2 \lceil \log(\lceil \log(n + 1) \rceil + 1) \rceil + 1$ .

[Renault, Rosén, van Stee, 2013] For a fixed competitive ratio, there exists an online algorithm which only needs linear advice:

They present an algorithm for online bin packing which is

$(1 + 3\delta)$ -competitive (or asymptotically  $(1 + 2\delta)$ -competitive), using

$s = \frac{1}{\delta} \log \frac{2}{\delta^2} + \log \frac{2}{\delta^2} + 3$  bits of advice per request.

## Section 3

# Open problems

- Linear advice is needed to be  $c$ -competitive,  $c < 9/8$ .  
Linear advice is sufficient for any fixed  $c$ . There is a huge gap, though.
- $(2 + o(1))n$  advice is sufficient to be  $4/3 + \epsilon$ -competitive.  
Can one get a better ratio with so few bits?
- $O(\log n)$  advice is sufficient to be  $3/2$ -competitive.  
How many bits are required to break the 1.54 lower bound?

Thank you for your attention.

# Reduction from 2-SGKH to Binary separation

```
1: small = 0; large = 1
2: repeat
3:   mid = (large - small) / 2
4:   class_guess = SeparationAlgorithm.ClassifyThis(mid)
5:   if class_guess = "large" then
6:     bit_guess = 0
7:   else
8:     bit_guess = 1
9:   actual_bit = Guess(bit_guess) {The actual value is received after
   guessing (2-SGKH).}
10:  if actual_bit = 0 then
11:    large = mid {We let "large" be the correct decision.}
12:  else
13:    small = mid {We let "small" be the correct decision.}
14: until end of sequence
```