

# Online Algorithms

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Require immediate decisions to be made in real time.

Examples:

- decision making in financial market

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- Paging in virtual management system
- Routing in communication networks.

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## Comptitive Analysis

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## Competitive Ratio

$$CR(A) = \max_i \frac{A(i)}{Opt(i)}$$

Where

$A(i)$  = cost of algorithm  $A$  for input  $i$ .

$Opt(i)$  = the cost of the optimal offline algorithm for input  $i$ .

# Online Algorithms

## Ski Rental Problem

This is a rent/buy problem.

You are going skiing for an unknown number of days. Assume that renting skis costs 500 Taka per day and buying skis costs 1500 Taka. Every day you have to decide whether to continue renting skis for one more day or buy a pair of skis. If you know in advance how many days you will go skiing, you can decide your minimum cost. The question is what to do when you do not know in advance how many days you will ski.

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What is the best algorithm?

# Online Algorithms

## Problem Formulation

There is a number of days  $d$  (unknown to you) that you will ski. We are looking for an algorithm that minimizes the ratio between what you pay using the algorithm (that does not know  $d$ ) and what you would pay optimally if you knew  $d$  in advance. The problem is generally analyzed in the worst case, where the algorithm is fixed and then we look at the worst-case performance of the algorithm over all possible  $d$ .

What is the best algorithm?

# Online Algorithms

## Ski Rental

Input:  $1, 1, 1, 1, \dots$  (we do not know how many 1's)

Action: pay for single time or go for free drive



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Input:  $1, 1, 1, 1, \dots$  (we do not know how many 1's)

Action: pay for single time or go for free drive

## Algorithms

Algorithm 1: Always pay for one time.

Algorithm 2: free drive from the beginning

Algorithm 3: pay per time until two 1's and when the third 1 comes then free drive.

# Online Algorithms: Performance Measure

## Ski Rental: Optimal

$$Opt(1) = 500$$

$$Opt(11) = 1000$$

$$Opt(111) = 1500$$

$$Opt(111\dots) = 1500$$

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## Ski Rental: Algorithm 1

$$A_1(1) = 500, A_1(11) = 1000, A_1(111) = 1500, A_1(1111) = 2000$$

$$\frac{A_1(1)}{OPT(1)} = \frac{500}{500}, \frac{A_1(11)}{OPT(11)} = \frac{1000}{1000}, \frac{A_1(111)}{OPT(111)} = \frac{1500}{1500}, \frac{A_1(1111)}{OPT(1111)} = \frac{2000}{1500}$$

$$CR(A_1) = \frac{500 \times n}{1500} \Rightarrow \infty$$

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## Ski Rental: Algorithm 2

$$A_2(1) = 1500, A_2(11) = 1500, A_2(111) = 1500, A_2(1111\dots) = 1500$$

$$\frac{A_2(1)}{OPT(1)} = \frac{1500}{500}, \frac{A_2(11)}{OPT(11)} = \frac{1500}{1000}, \frac{A_2(111)}{OPT(111)} = \frac{1500}{1500}, \frac{A_2(1111\dots)}{OPT(1111\dots)} = \frac{1500}{1500}$$

$$CR(A_2) = \frac{1500}{500} = 3$$

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## Ski Rental: Optimal

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# Online Algorithms: Performance Measure

## Ski Rental: Optimal

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## Ski Rental: Algorithm 3

$$A_3(1) = 500, A_3(11) = 1000, A_3(111) = 2500, A_3(1111\dots) = 2500$$

$$\frac{A_3(1)}{OPT(1)} = \frac{500}{500}, \frac{A_3(11)}{OPT(11)} = \frac{1000}{1000}, \frac{A_3(111)}{OPT(111)} = \frac{2500}{1500}, \frac{A_3(1111)}{OPT(1111)} = \frac{2500}{1500}$$

$$CR(A_2) = \frac{2500}{1500} = 1.67$$



# Online Algorithms: Performance Measure

## Competitive Ratio

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# Online Algorithms: Performance Measure

## Competitive Ratio

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There are some problems for which we do not know the optimal solution.

How to compute competitive ratio?

# Online Algorithms

## Linear List Search

Given a set of items in a list where the cost of accessing an item is proportional to its distance from the head of the list, e.g. a Linked List, and a request sequence of accesses, the problem is to come up with a strategy of reordering the list so that the total cost of accesses is minimized.

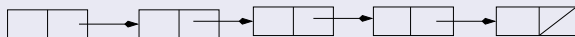


Figure: Linear Linked List.

# Online Algorithms

## Linear List Search

Input: Initial list  $l = (1, 2, 3, \dots, n)$  and sequence of requests  $i_1, i_2, \dots$

Action: Search item  $i_j$

Goal: minimize the total cost.

Strategy: move the access item forward.

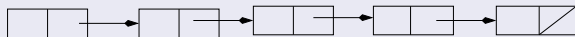


Figure: Linear Linked List.

Question: How many positions?

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Strategy: move the access item forward.

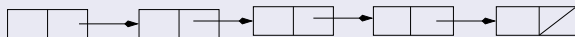


Figure: Linear Linked List.

Question: How many positions?

There are many possible choices: to the top, by 2 positions, to the middle ect.

If you move to the top, then in the worst case you never access that element.

# Online Algorithms

## Linear List Search

Strategy: move the access item forward by 2 position.



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Strategy: move the access item forward by 2 position.

“2 position is not good”

List:  $1, 2, 3 \dots n$

Requests:  $n, n, n \dots$  ( $n$  times)

Costs:  $n + (n - 2) + \dots = n^2$

Opt:  $n + 1 + 1 + \dots = 2n$

$CR = n$

$CR \Rightarrow \infty$  if  $n \Rightarrow \infty$

# Linear List Search

## Move To Front (MTF)

After accessing an item move it to the front of the list without changing the order of other items.

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## Theorem

*MTF has a CR of 2.0*

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*MTF has a CR of 2.0*

## Proof.

We do not know the optimal algorithm, but we need to compute CR.

We compare two algorithms: OPT (which we do not know) and MTF.

At the beginning:

OPT:  $1, 2, 3, \dots, n$

MFT:  $1, 2, 3, \dots, n$

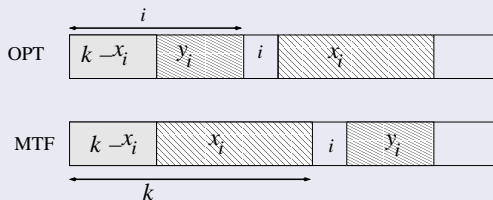




# Linear List Search

Proof.

At Step  $j$ :



The cost of MTF is  $k$ .

$x_i$ : number of items which are after  $i$  in OPT list and before  $i$  in MTF list

$y_i$ : number of items which are before  $i$  in OPT list and after  $i$  in MTF list

# Linear List Search

## Proof.

### Amortized Cost

$$T(j) = k + INV(j + 1) - INV(j)$$

$INV(j)$ : number of item pairs  $(a, b)$  such that the order of  $a$  and  $b$  is different between the OPT and the MTF lists at time  $j$ .

OPT:  $\dots a \dots b \dots$

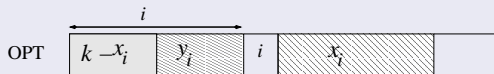
MTF:  $\dots b \dots a \dots$



# Linear List Search

Proof.

At Step  $j$ :



$$\begin{aligned}
 T(j) &= k + \overset{k}{(k - x_i + y_i - \alpha)} - (x_i + y_i) \\
 &= 2k - 2x_i - \alpha \\
 &\leq 2k - 2x_i \\
 &\leq 2i
 \end{aligned}$$



## Linear List Search

Proof.

$$T(1) = k_1 + INV(2) - INV(1)$$

$$T(2) = k_2 + INV(3) - INV(2)$$

$$\vdots$$

$$T(m) = k_m + INV(m+1) - INV(m)$$

$$T(1) + T(2) + \cdots + T(m) = k_1 + \cdots + k_m + INV(m+1) - INV(1)$$



# Linear List Search

Proof.

$$T(1) + T(2) + \dots + T(m) = k_1 + \dots + k_m + INV(m+1) - INV(1)$$

$$\begin{aligned} k_1 + k_2 + \dots + k_m &\leq T(1) + T(2) + \dots + T(m) - INV(m+1) \\ &\leq T(1) + T(2) + \dots + T(m) \\ &\leq 2OPT \end{aligned}$$

