

# CS3383 Unit 3.2: Dynamic Programming Examples

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# Outline

## Dynamic Programming

Longest Increasing Subsequence

Edit Distance

Balloon Flight Planning

# Longest Increasing Subsequence problem

Input Integers  $a_1, a_2 \dots a_n$

Output

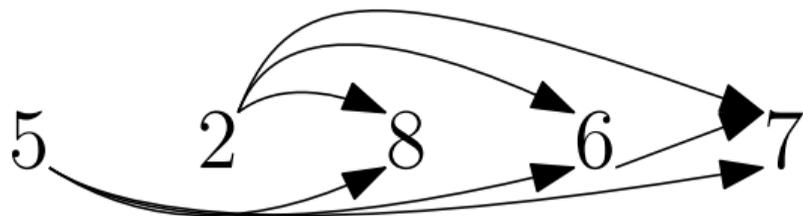
$$a_{i_1}, a_{i_2}, \dots, a_{i_k}$$

Such that

$$i_1 < i_2 < \dots < i_k$$

and

$$a_{i_1} < a_{i_2} < \dots < a_{i_k}$$

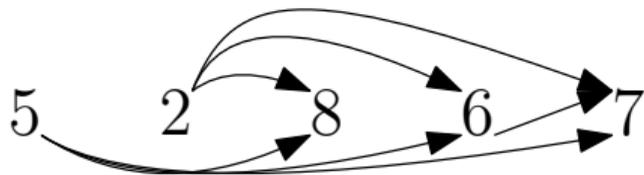


▶  $(a_i, a_j) \in E$  if  $i < j$  and  $a_i < a_j$ .

▶ DPV 6.2, JE 3.6

# Defining subproblems

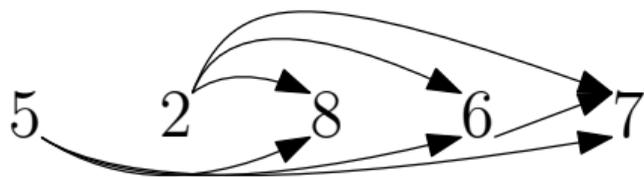
- ▶ Define  $F(i)$  as the length of longest sequence starting at position  $i$



- ▶ Topological sort is trivial

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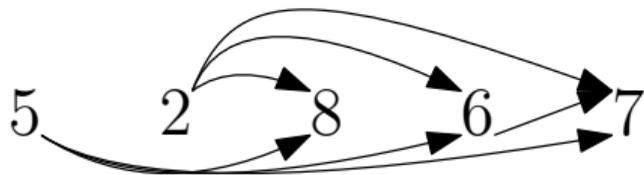
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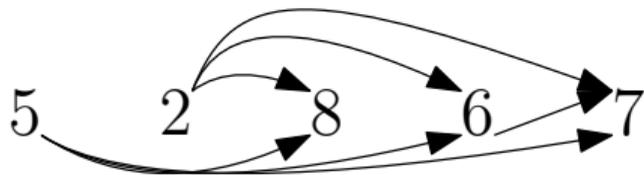


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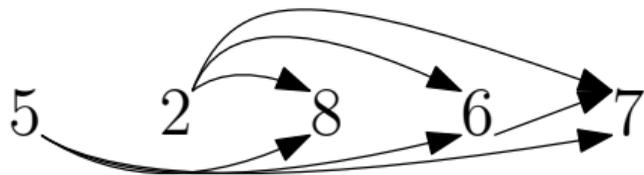
$$F(i) = 1 + \max\{F(j) \mid (i, j) \in E\}$$



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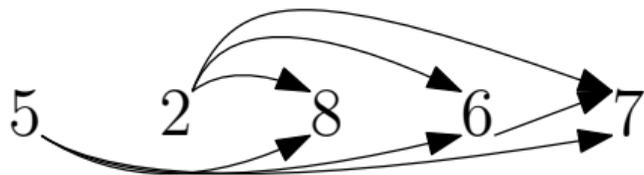
- ▶ Define  $F(i)$  as the length of longest sequence starting at position  $i$
- ▶ We could do  $n$  longest path in DAG queries.
- ▶ Thinking recursively:  
$$F(i) = 1 + \max\{F(j) \mid (i, j) \in E\}$$
- ▶ We could solve this reasonably fast e.g. by memoization.



- ▶ Topological sort is trivial

# Longest path in DAG, working backwards

- ▶ Define  $L[i]$  as the longest path *ending* at  $a_i$



For  $i = 1 \dots n$ :

$$L[i] = 1 + \max \{ L(j) \mid (j, i) \text{ in } E \}$$

- ▶ total cost is  $O(|E|)$ , *after* computing  $E$ .

# Improving memory use

- ▶ We can inline the definition of  $E$ .

```
def lis(A):  
    n = len(A)  
    L = [1 for j in range(n)]  
    for i in range(n):  
        for j in range(i):  
            if A[j] < A[i]:  
                L[i] = max(L[i], L[j]+1)  
    return max(L)
```

# Improving memory use

- ▶ We can inline the definition of  $E$ .
- ▶  $L(i) = 1 + \max\{L(j) \mid j < i \text{ and } a_j < a_i\}$

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# Edit (Levenshtein) Distance

- ▶ CLRS 14-5, DPV 6.3, JE3.7
- ▶ Minimum number of insertions, deletions, substitutions to transform one string into another.

Example: timberlake → fruitcake

- ▶ Using mostly insertions and deletions

```
i i i i   d d d d d s
_ _ _ _ T I M B E R L A K E
F R U I T _ _ _ _ C A K E
```

Total cost 10.

# Edit (Levenshtein) Distance

- ▶ CLRS 14-5, DPV 6.3, JE3.7
- ▶ Minimum number of insertions, deletions, substitutions to transform one string into another.

Example: timberlake → fruitcake

- ▶ Using more substitutions

```
s s s s s d s  
T I M B E R L A K E  
F R U I T _ C A K E
```

Total cost 7.

# Alignments (gap representation)

```
1 1 1 1 0 1 1 1 1 1 1 0 0 0
_ _ _ _ T I M B E R L A K E
F R U I T _ _ _ _ C A K E
```

- ▶ top line has letters from  $A$ , in order, or  $\_$
- ▶ bottom line has has letters from  $B$  or  $\_$
- ▶ cost per column is 0 or 1.

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1	1	1	1	0	1	1	1	1	1	1	0	0	0	
-	-	-	-		T	I	M	B	E	R	L	A	K	E
F	R	U	I	T	-	-	-	-	-	C	A	K	E	

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## Theorem (Optimal substructure)

*Removing any column from an optimal alignment, yields an optimal alignment for the remaining substrings.*

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proof.

By contradiction



## Subproblems (prefixes)

- ▶ Define  $E[i, j]$  as the minimum edit cost for  $A[1 \dots i]$  and  $B[1 \dots j]$

$$E[i, j] = \begin{cases} E[i, j - 1] + 1 & \text{insertion} \\ E[i - 1, j] + 1 & \text{deletion} \\ E[i - 1, j - 1] + 1 & \text{substitution} \\ E[i - 1, j - 1] & \text{equality} \end{cases}$$

justification.

We know deleting a column removes an element from one or both strings; all edit operations cost 1. □

## order of subproblems

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- ▶ dependency of subproblems is *exactly* the same as LCS, so essentially the same DP algorithm works.
- ▶ or just memoize the recursion
- ▶ what are the base cases?

# Edit distance

```
def dist(x,y):
    n = len(x); m=len(y)
    E = [ [max(i,j) for j in range(m+1)]
           for i in range(n+1) ]
    for i in range(1,n+1):
        for j in range(1,m+1):
            diff = int(x[i-1] != y[j-1])
            E[i][j] = min(E[i-1][j-1]+diff,
                          E[i-1][j]+1,
                          E[i][j-1]+1)
    return E
```

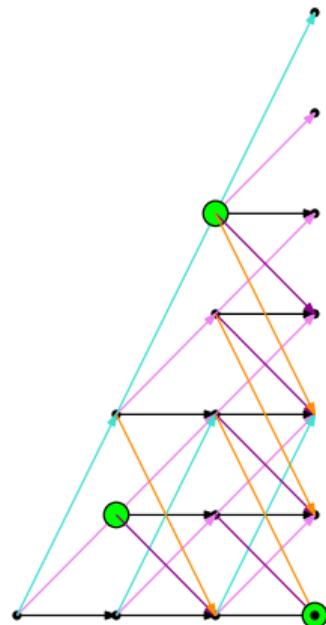
# Tracing back the edits

```
def trace(E,x,y,i,j):
    if (i<1):
        return "i" * j;
    elif (j<1):
        return "d" * i;
    elif x[i-1] == y[j-1]:
        return trace(E,x,y,i-1,j-1)+ "."
    elif E[i][j] == E[i-1][j-1] + 1:
        return trace(E,x,y,i-1,j-1)+ "s"
    elif E[i][j] == E[i-1][j]+1:
        return trace(E,x,y,i-1,j)+ "d"
    else:
        return trace(E,x,y,i,j-1)+ "i"
```



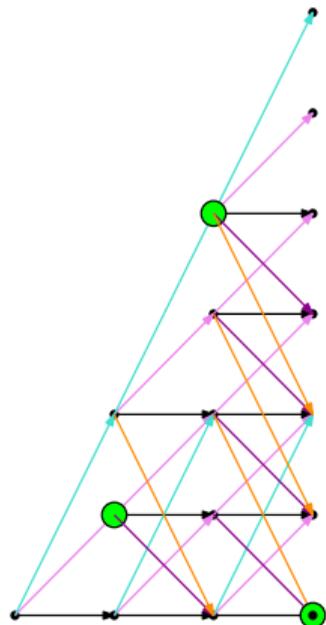
# Balloon Flight Planning

- ▶ Start at  $(0, 0)$
- ▶ At every time step, increase or decrease altitude up to  $k$  steps, and increase  $x$  by 1.



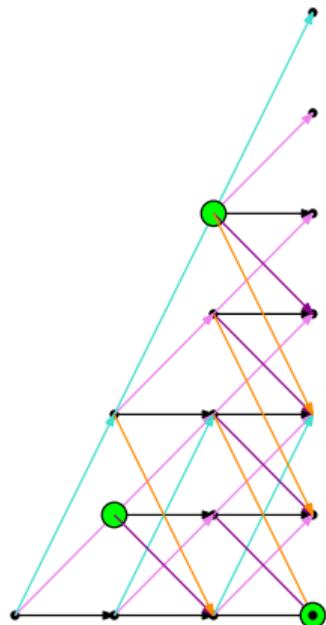
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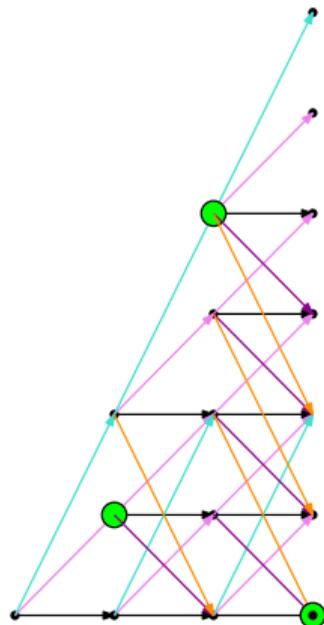
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- ▶ Maximize value of collected prizes



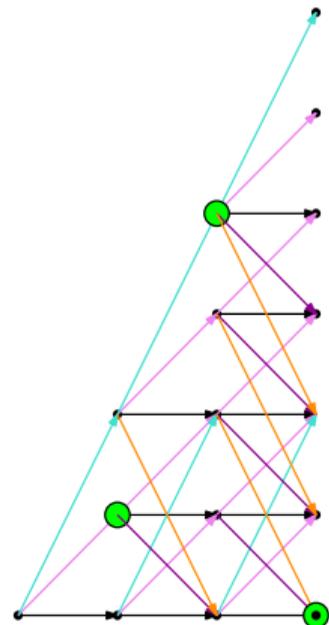
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- ▶ Maximize value of collected prizes
- ▶ We can discretize/simulate the problem as a graph search



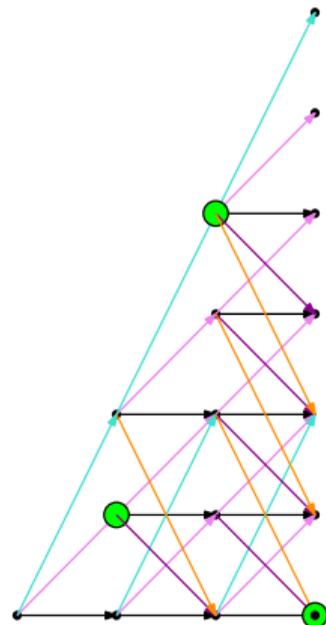
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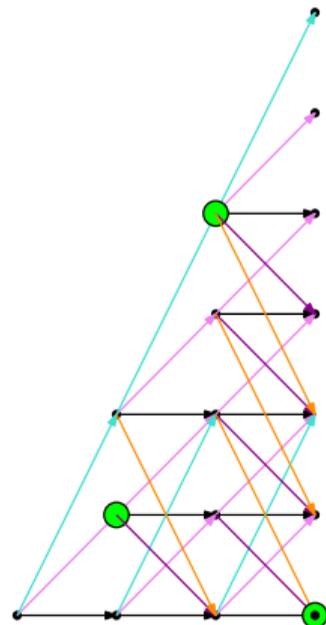
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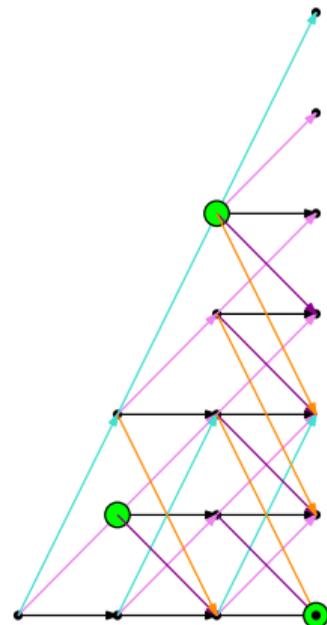
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- ▶ Worse, there could be a prize that high



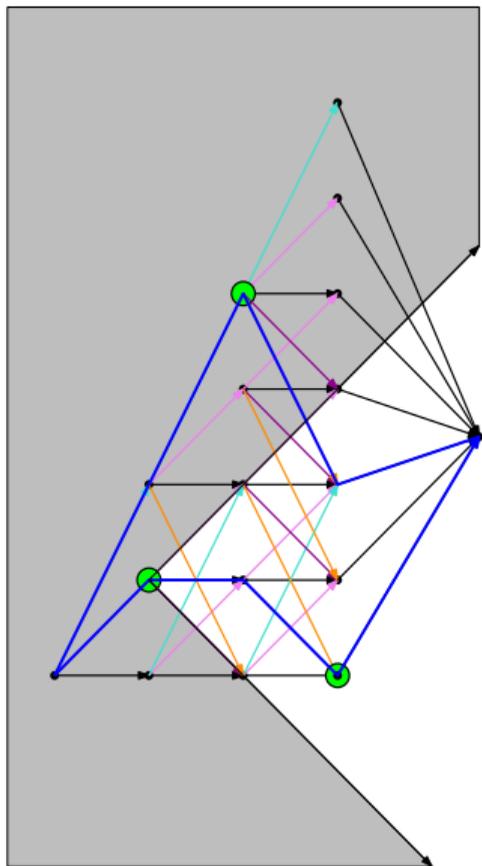


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- ▶ After  $n$  steps we could reach as high as  $kn$
- ▶ Worse, there could be a prize that high
- ▶ On the other hand the input (ignoring weights) is only  $O(n \log n + n \log k)$ .
- ▶ This means we have a bad dependence on  $k$ ; more about this later



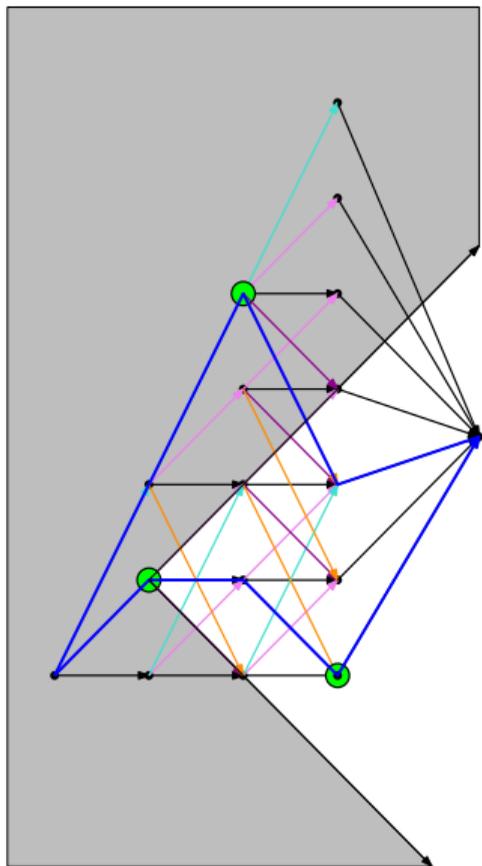
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## Lemma (Straightening Paths)

*There is a feasible path from  $p$  to  $q$  iff the segment  $[p, q]$  is feasible.*

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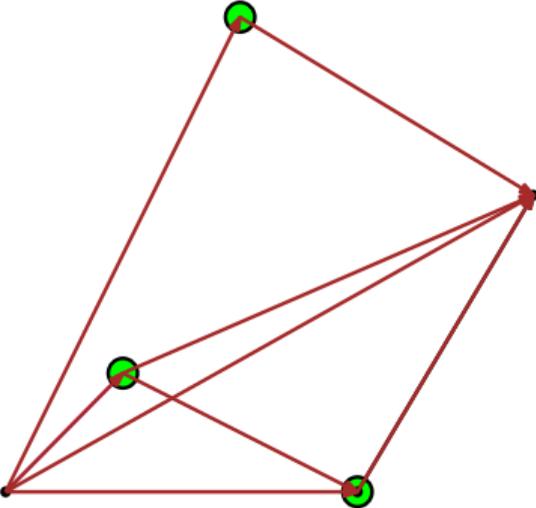
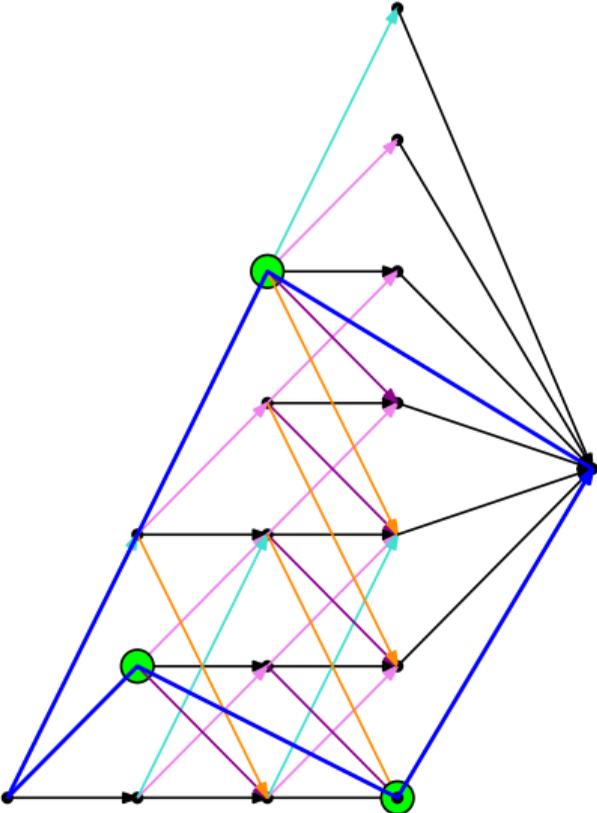
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## Proof sketch

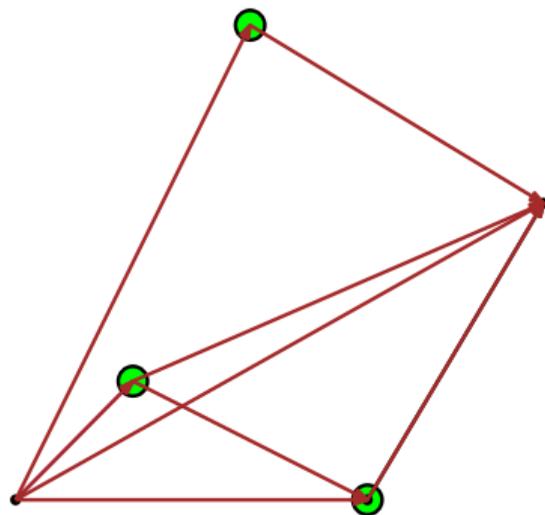
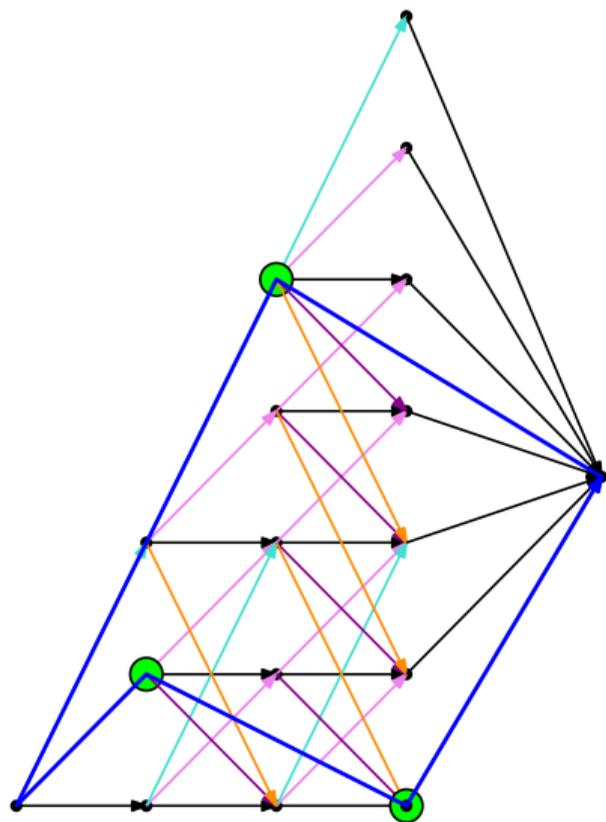
The path cannot escape the cone defined by the steepest possible segments.

There is always one step back towards start within cone. Apply induction.

# A new graph



# A new graph



Improved graph size

The new graph is  $O(p^2)$ ,  
where  $p \leq n$  is the  
number of prizes.