## CSE 421

# Dynamic Programming 

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## Sequence Alignment

Given two strings $x_{1}, \ldots, x_{m}$ and $y_{1}, \ldots, y_{n}$ find an alignment with minimum number of mismatch and gaps.

An alignment is a set of ordered pairs $\left(x_{i_{1}}, y_{j_{1}}\right),\left(x_{i_{2}}, y_{j_{2}}\right), \ldots$ such that $i_{1}<i_{2}<\cdots$ and $j_{1}<j_{2}<\cdots$

Example: ctaccg vs. tacAtg.
Sol: We aligned
$\mathrm{x}_{2}-\mathrm{y}_{1}, \mathrm{x}_{3}-\mathrm{y}_{2}, \mathrm{x}_{4}-\mathrm{y}_{3}, \mathrm{x}_{5}-\mathrm{y}_{4}, \mathrm{x}_{6}-\mathrm{y}_{6}$.
So, the cost is 3 .


## DP for Sequence Alignment

Let $O P T(i, j)$ be min cost of aligning $x_{1}, \ldots, x_{i}$ and $y_{1}, \ldots, y_{j}$

Case 1: OPT matches $x_{i}, y_{j}$

- Then, pay mis-match cost if $x_{i} \neq y_{j}+\min$ cost of aligning $x_{1}, \ldots, x_{i-1}$ and $y_{1}, \ldots, y_{j-1}$ i.e., $\operatorname{OPT}(i-1, j-1)$

Case 2: OPT leaves $x_{i}$ unmatched

- Then, pay gap cost for $x_{i}+O P T(i-1, j)$

Case 3: OPT leaves $y_{j}$ unmatched

- Then, pay gap cost for $y_{j}+O P T(i, j-1)$


## Bottom-up DP

```
Sequence-Alignment(m, n, }\mp@subsup{x}{1}{}\mp@subsup{\mathbf{x}}{2}{}\ldots..\mp@subsup{x}{m}{},\mp@subsup{y}{1}{}\mp@subsup{Y}{2}{}\ldots..\mp@subsup{y}{n}{\prime})
    for i = 0 to m
        M[0, i] = i
    for j = 0 to n
        M[j, 0] = j
    for i = 1 to m
        for j = 1 to n
        M[i, j] = min( ( }\mp@subsup{\textrm{x}}{\textrm{i}}{=}=\mp@subsup{y}{j}{}\mathrm{ ? 0:1) + M[i-1, j-1],
                        1 + M[i-1, j],
                        1 + M[i, j-1])
    return M[m, n]
}
```

Analysis: $\Theta(m n)$ time and space.
English words or sentences: m, $\mathrm{n} \leq 10, . ., 20$.
Computational biology: $m=n=100,000$. 10 billions ops OK, but 40GB array?

## Optimizing Memory

If we are not using strong induction in the DP, we just need to use the last (row) of computed values.
}

```


```

```
    for i = 0 to m
```

```
    for i = 0 to m
        M[0, i] = i
        M[0, i] = i
    for j = 0 to n
    for j = 0 to n
        M[j, 0] = j
        M[j, 0] = j
    for i = 1 to m
    for i = 1 to m
        for j = 1 to n
        for j = 1 to n
            M[i, j] = min( ( }\mp@subsup{x}{i}{}=\mp@subsup{y}{j}{\prime}\mathrm{ ? 0:1) + M[i-1, j-1],
            M[i, j] = min( ( }\mp@subsup{x}{i}{}=\mp@subsup{y}{j}{\prime}\mathrm{ ? 0:1) + M[i-1, j-1],
            l + M[i-1, j],
            l + M[i-1, j],
            l +M[i-1, j],
            l +M[i-1, j],
    return M[m, n]
```

    return M[m, n]
    ```


Just need \(i-1\), \(i\) rows
to compute M[i,j]

\section*{DP with \(O(m+n)\) memory}
- Keep an Old array containing values of the last row
- Fill out the new values in a New array
- Copy new to old at the end of the loop
```

Sequence-Alignment(m, n, m
for i = 0 to m
O[i] = i
for i = 1 to m
N[0]=i
M[i-1, j-1]
for j = 1 to n
N[j] = min( ( }\mp@subsup{x}{i}{}=\mp@subsup{y}{j}{\prime}\mathrm{ ? 0:1) + O[j-1],
1 +O[j], M[i-1, j]
1 + N[j-1]) }~M[i, j-1
for j = 1 to n
O[j]=N[j]
return N[n]
}

```

\section*{Lesson}

Advantage of a bottom-up DP:

It is much easier to optimize the space.

\section*{Longest Path in a DAG}

\section*{Longest Path in a DAG}

Goal: Given a DAG G, find the longest path.

Recall: A directed graph \(G\) is a DAG if it has no cycle.

This problem is NP-hard for general directed graphs:
- It has the Hamiltonian Path as a special case


\section*{DP for Longest Path in a DAG}

Q: What is the right ordering?
Remember, we have to use that G is a DAG, ideally in defining the ordering

We saw that every DAG has a topological sorting
So, let's use that as an ordering.


\section*{DP for Longest Path in a DAG}

Suppose we have labelled the vertices such that \((i, j)\) is a directed edge only if \(i<j\).


Let \(O P T(j)=\) length of the longest path ending at \(j\)
Suppose in the longest path ending at \(j\), last edge is \((i, j)\).
Then, none of the \(i+1, \ldots, j-1\) are in this path since topological ordering. Furthermore the path ending at i must be the longest path ending at i ,
\[
O P T(j)=O P T(i)+1 .
\]

\section*{DP for Longest Path in a DAG}

Suppose we have labelled the vertices such that \((i, j)\) is a directed edge only if \(i<j\).

Let \(O P T(j)=\) length of the longest path ending at \(j\)
\[
O P T(j)= \begin{cases}0 & \text { If } j \text { is a source } \\ 1+\max _{i:(i, j) \text { an edge }} O P T(i) & \text { o.w. }\end{cases}
\]

\section*{DP for Longest Path in a DAG}
```

Let G be a DAG given with a topological sorting: For all edges
(i,j) we have i<j.
Compute-OPT(j) {
if (in-degree(j)==0)
return 0
if (M[j]==empty)
M[j]=0;
for all edges (i,j)
M[j] = max(M[j],1+Compute-OPT(i))
return M[j]
}
Output max(M[1],..,M[n])

```

Running Time: \(O(n+m)\)
Memory: \(O(n)\)
Can we output the longest path?

\section*{Outputting the Longest Path}
```

Let G be a DAG given with a topological sorting: For all edges
(i,j) we have i<j.
Initialize Parent[j]=-1 for all j.
Compute-OPT (j) {
if (in-degree(j)==0)
return 0
if (M[j]==empty)
M[j]=0;
for all edges (i,j)
if (M[j] < 1+Compute-orT(i)) we used to compute OPT(j)
M[j]=1+Compute-OrT(i)
Parent[j]=i
return M[j]
}
Let M[k] be the maximum of M[1],...,M[n]
While (Parent[k]!=-1)
Print k
k=Parent[k]

```

\section*{Longest Increasing Subsequence}

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Given a sequence of numbers
Find the longest increasing subsequence
\(41,22,9,15,23,39,21,56,24,34,59,23,60,39,87,23,90\)
\(41,22,9,15,23,39,21,56,24,34,59,23,60,39,87,23,90\)

\section*{DP for LIS}

Let OPT(j) be the longest increasing subsequence ending at j .

Observation: Suppose the OPT(j) is the sequence
\[
x_{i_{1}}, x_{i_{2}}, \ldots, x_{i_{k}}, x_{j}
\]

Then, \(x_{i_{1}}, x_{i_{2}}, \ldots, x_{i_{k}}\) is the longest increasing subsequence ending at \(x_{i_{k}}\), i.e., \(O P T(j)=1+O P T\left(i_{k}\right)\)
\[
O P T(j)= \begin{cases}1 & \text { If } x_{j}<x_{i} \text { for all } i<j \\ 1+\max _{i: x_{i}<x_{j}} O P T(i) & \text { o.w. }\end{cases}
\]

Remark: This is a special case of Longest path in a DAG: Construct a graph \(1, \ldots \mathrm{n}\) where \((i, j)\) is an edge if \(i<j\) and \(x_{i}<x_{j}\).

\section*{Shortest Paths with Negative Edge Weights}

\section*{Shortest Paths with Neg Edge Weights}

Given a weighted directed graph \(G=(V, E)\) and a source vertex \(s\), where the weight of edge \((u, v)\) is \(c_{u, v}\)
Goal: Find the shortest path from \(s\) to all vertices of \(G\).


\section*{Impossibility on Graphs with Neg Cycles}

Observation: No solution exists if \(G\) has a negative cycle.

This is because we can minimize the length by going over the cycle again and again.

So, suppose G does not have a negative cycle.


\section*{DP for Shortest Path}

Def: Let \(\operatorname{OPT}(v, i)\) be the length of the shortest \(s-v\) path with at most \(i\) edges.
Let us characterize \(\operatorname{OPT}(v, i)\).

Case 1: \(O P T(v, i)\) path has less than \(i\) edges.
- Then, \(\operatorname{OPT}(v, i)=O P T(v, i-1)\).

Case 2: \(\operatorname{OPT}(v, i)\) path has exactly \(i\) edges.
- Let \(s, v_{1}, v_{2}, \ldots, v_{i-1}, v\) be the \(O P T(v, i)\) path with \(i\) edges.
- Then, \(s, v_{1}, \ldots, v_{i-1}\) must be the shortest \(s-v_{i-1}\) path with at most \(i\) - 1 edges. So,
\[
O P T(v, i)=O P T\left(v_{i-1}, i-1\right)+c_{v_{i-1}, v}
\]

\section*{DP for Shortest Path}

Def: Let \(\operatorname{OPT}(v, i)\) be the length of the shortest \(s-v\) path with at most \(i\) edges.
\(\operatorname{OPT}(v, i)=\left\{\begin{array}{lr}0 & \text { if } v=s \\ \infty & \text { if } v \neq s, i=0 \\ \min \left(\operatorname{OPT}(v, i-1), \min _{u:(u, v) \text { an edge }} \operatorname{OPT}(u, i-1)+c_{u, v}\right)\end{array}\right.\)

So, for every \(\mathrm{v}, \operatorname{OPT}(v, ?)\) is the shortest path from s to v .
But how long do we have to run?
Since G has no negative cycle, it has at most \(n-1\) edges. So, \(\operatorname{OPT}(v, n-1)\) is the answer.

\section*{Bellman Ford Algorithm}
```

for v=1 to n
if v}=\boldsymbol{S}\mathrm{ then
M[v,0]=\infty
M[s,0]=0.
for i=1 to n-1
for v=1 to n
M[v,i]=M[v,i-1]
for every edge (u,v)
M[v,i]=min(M[v,i], M[u,i-1]+cu,v)

```

Running Time: \(O(n m)\)
Can we test if G has negative cycles?

\section*{Bellman Ford Algorithm}
```

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for v=1 to n
M[v,i]=M[v,i-1]
for every edge (u,v)
M[v,i]=min(M[v,i], M[u,i-1]+cu,v)

```

Running Time: \(O(n m)\)
Can we test if G has negative cycles?
Yes, run for \(\mathrm{i}=1 \ldots 2 \mathrm{n}\) and see if the \(\mathrm{M}[\mathrm{v}, \mathrm{n}-1]\) is different from \(\mathrm{M}[\mathrm{v}, 2 \mathrm{n}]\)

\section*{DP Techniques Summary}

\section*{Recipe:}
- Follow the natural induction proof.
- Find out additional assumptions/variables/subproblems that you need to do the induction
- Strengthen the hypothesis and define w.r.t. new subproblems

Dynamic programming techniques.
- Whenever a problem is a special case of an NP-hard problem an ordering is important:
- Adding a new variable: knapsack.
- Dynamic programming over intervals: RNA secondary structure.

Top-down vs. bottom-up:
- Different people have different intuitions
- Bottom-up is useful to optimize the memory```

