## CSE 417: Algorithms and Computational Complexity

## 4: Dynamic Programming, I Fibonacci

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Lecture 4
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## A Possible Misunderstanding?

- We have looked at
\|l type of complexity analysis
worst-, best-, average-case
II types of function bounds
Insertion Sort:
$\Omega\left(\mathrm{n}^{2}\right)$ (worst case) $\mathrm{O}(\mathrm{n})$ (best case)
$\mathrm{O}, \Omega, \Theta$
These two considerations are independent of each other
\| one can do any type of function bound with any type of complexity analysis


## Some Algorithm Design <br> Techniques, I

|l General overall idea
\| Reduce solving a problem to a smaller problem or problems of the same type
\| Greedy algorithms
\| Used when one needs to build something a piece at a time
I Repeatedly make the greedy choice - the one that looks the best right away
e.g. closest pair in TSP search
\| Usually fast if they work (but often don't)

## Some Algorithm Design <br> Techniques, II

I. Divide \& Conquer

I Reduce problem to one or more sub-problems of the same type
I Typically, each sub-problem is at most a constant fraction of the size of the original problem e.g. Mergesort, Binary Search, Strassen's Algorithm, Quicksort (kind of)

## Some Algorithm Design <br> Techniques, III

- Dynamic Programming
\| Give a solution of a problem using smaller sub-problems, e.g. a recursive solution
\| Useful when the same sub-problems show up again and again in the solution


## A simple case: <br> Computing Fibonacci Numbers

- Recall $F_{n}=F_{n-1}+F_{n-2}$ and $F_{0}=0, F_{1}=1$
- Recursive algorithm:
\| Fibo(n)
if $\mathrm{n}=0$ then return(0)
else if $n=1$ then return $(1)$
else return(Fibo(n-1)+Fibo(n-2))


Fibonacci - Dynamic
Programming Version

```
|iboDP(n):
    F[0]\leftarrow0
    F[1]}\leftarrow
    for i=2 to n do
        F[i]=F[i-1]+F[i-1]
    endfor
    return(F[n])
FiboDP(n):
\(\mathrm{F}[0] \leftarrow 0\)
\(\mathrm{F}[1] \leftarrow 1\)
i=2 to n do
\(F[i]=F[i-1]+F[i-1]\)
return(F[n])
```


## Call tree - start



## Memo-ization (Caching)

- Remember all values from previous recursive calls

II Before recursive call, test to see if value has already been computed

Dynamic Programming
| Convert memo-ized algorithm from a recursive one to an iterative one

## Dynamic Programming

- Useful when

II same recursive sub-problems occur repeatedly
\| Can anticipate the parameters of these recursive calls
\| The solution to whole problem can be figured out with knowing the internal details of how the sub-problems are solved principle of optimality

## List partition problem

I. Given: a sequence of $n$ positive integers $\mathrm{s}_{1}, \ldots, \mathrm{~s}_{\mathrm{n}}$ and a positive integer k
I. Find: a partition of the list into up to $k$ blocks:
$\mathrm{s}_{1}, \ldots, \mathrm{~s}_{\mathrm{i}_{1}}\left|\mathrm{~s}_{\mathrm{i}_{1}+1} \ldots \mathrm{~s}_{\mathrm{i}_{2}}\right| \mathrm{s}_{\mathrm{i}_{2}+1} \ldots \mathrm{~s}_{\mathrm{i}_{\mathrm{k}-1}} \mid \mathrm{s}_{\mathrm{i}_{k-1}+1} \ldots \mathrm{~s}_{\mathrm{n}}$ so that the sum of the numbers in the largest block is as small as possible. i.e. find spots for up to $k$-1 dividers

## Greedy approach

- Ideal size would be $P=\quad \sum_{i=1}^{n} s_{i} / k$

II Greedy: walk along until what you have so far adds up to P then insert a divider
\| Problem: it may not exact (or correct)
100200400500900700600800600
| sum is 4800 so size must be at least 1600 .
| Greedy? Best?

