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DYNAMIC PROGRAMMING

- *introduction*
- *Fibonacci numbers*
- *interview problems*
- *shortest paths in DAGs*
- *seam carving*

Algorithms

Robert Sedgewick | Kevin Wayne

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Dynamic Programming

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Dynamic programming

Algorithm design paradigm.

- Break up a problem into a series of overlapping subproblems.
- Build up solutions to larger and larger subproblems.

  (caching solutions to subproblems for later reuse)

THE THEORY OF DYNAMIC PROGRAMMING

RICHARD BELLMAN

1. **Introduction.** Before turning to a discussion of some representative problems which will permit us to exhibit various mathematical features of the theory, let us present a brief survey of the fundamental concepts, hopes, and aspirations of dynamic programming.

To begin with, the theory was created to treat the mathematical problems arising from the study of various multi-stage decision processes, which may roughly be described in the following way: We have a physical system whose state at any time t is determined by a set of quantities which we call state parameters, or state variables. At certain times, which may be prescribed in advance, or which may be determined by the process itself, we are called upon to make decisions which will affect the state of the system. These decisions are equivalent to transformations of the state variables, the choice of a decision being identical with the choice of a transformation. The outcome of the preceding decisions is to be used to guide the choice of future ones, with the purpose of the whole process that of maximizing some function of the parameters describing the final state.

Examples of processes fitting this loose description are furnished by virtually every phase of modern life, from the planning of industrial production lines to the scheduling of patients at a medical clinic; from the determination of long-term investment programs for universities to the determination of a replacement policy for machinery in factories; from the programming of training policies for skilled and unskilled labor to the choice of optimal purchasing and inventory policies for department stores and military establishments.

Richard Bellman, *46

Application areas.

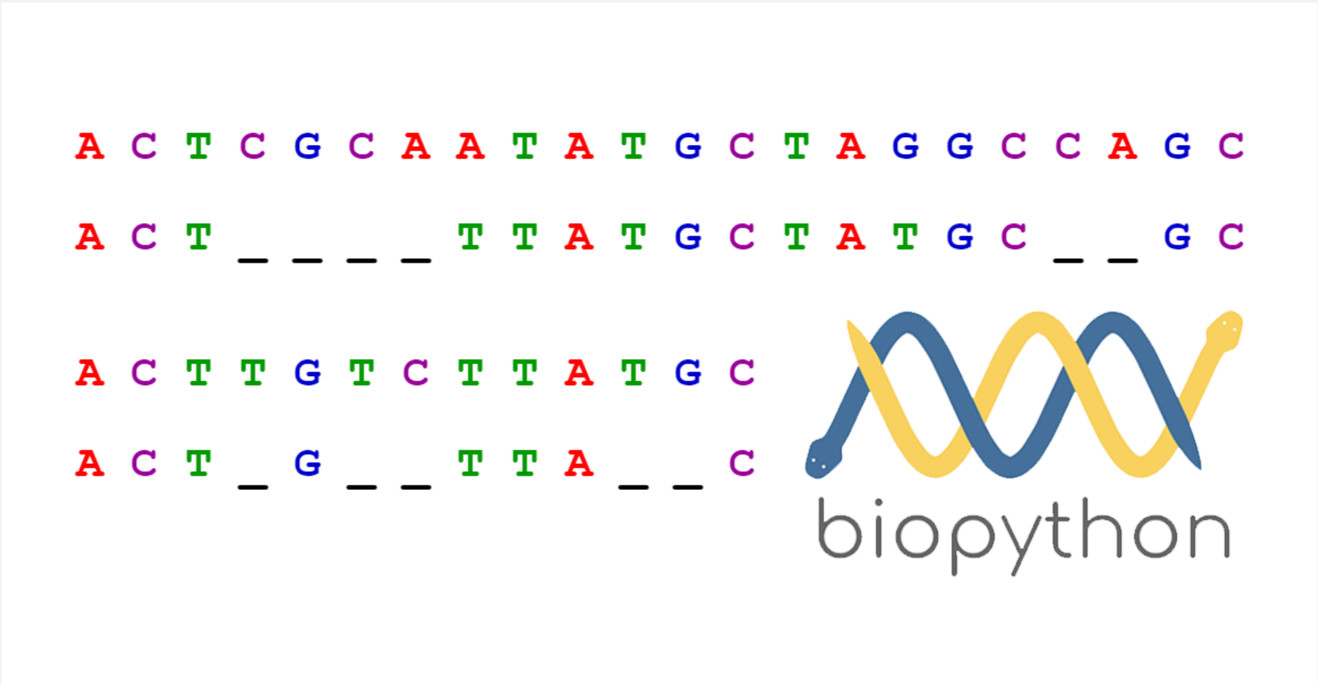
- Operations research: multistage decision processes, control theory, optimization, ...
- Computer science: AI, compilers, systems, graphics, databases, robotics, theory, ...
- Economics.
- Bioinformatics.
- Information theory.
- Tech job interviews.

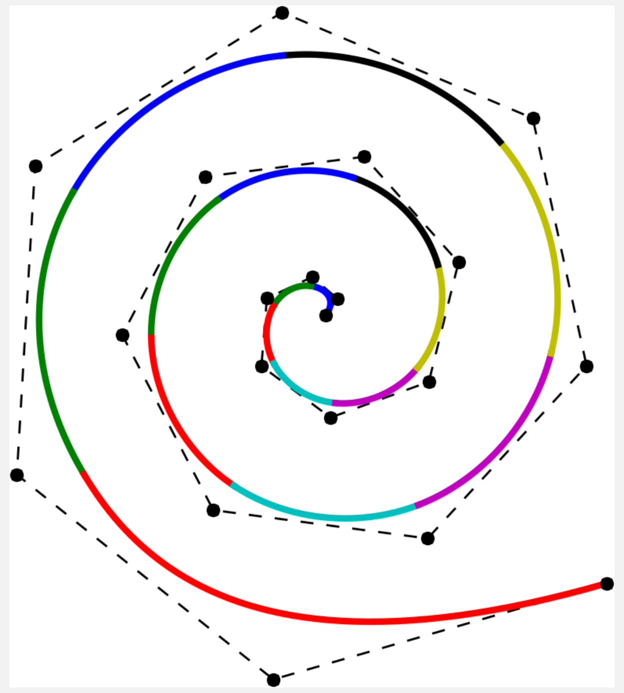
Bottom line. Powerful technique; broadly applicable.

Dynamic programming algorithms

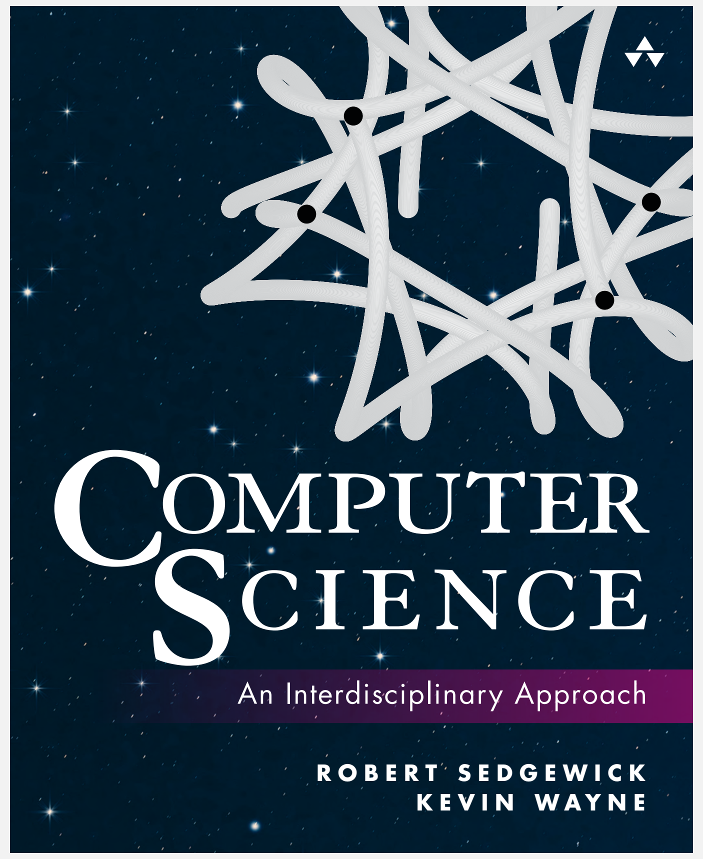
Some famous examples.

- System R algorithm for optimal join order in relational databases.
- Needleman–Wunsch/Smith–Waterman for sequence alignment.
- Cocke–Kasami–Younger for parsing context-free grammars.
- Bellman–Ford–Moore for shortest path.
- De Boor for evaluating spline curves.
- Viterbi for hidden Markov models.
- Unix diff for comparing two files.
- Avidan–Shamir for seam carving. ← see Assignment 6
- **NP**-complete graph problems on trees (vertex color, vertex cover, independent set, ...).
- ...





Dynamic programming books



pp. 284–289

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Dynamic Programming

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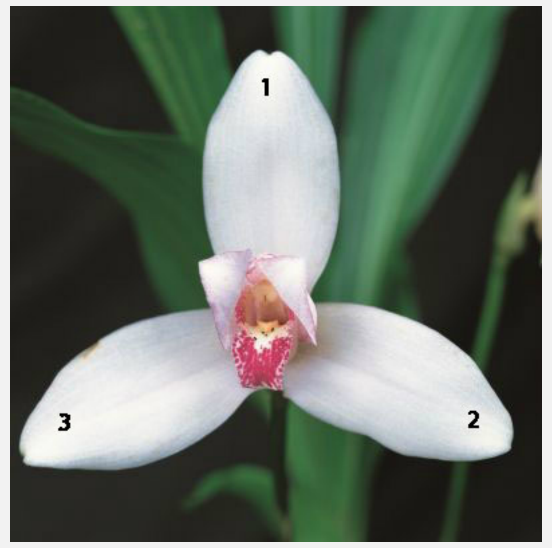
Fibonacci numbers

Fibonacci numbers. $0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, \ \ldots$

$$F_i = \begin{cases} 0 & \text{if } \ i = 0 \\ 1 & \text{if } \ i = 1 \\ F_{i-1} + F_{i-2} & \text{if } \ i > 1 \end{cases}$$

Leonardo Fibonacci



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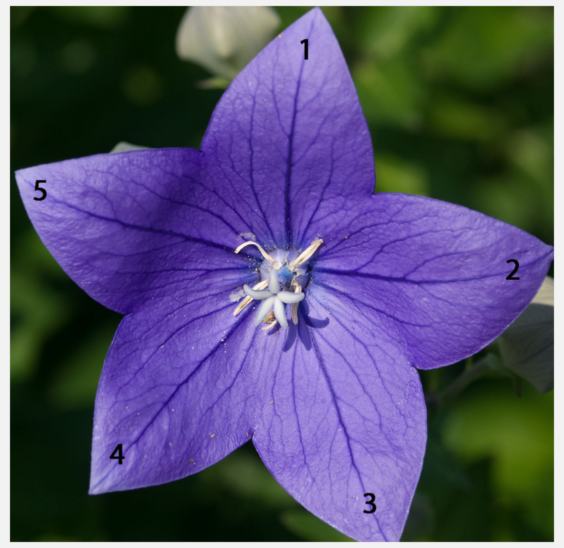
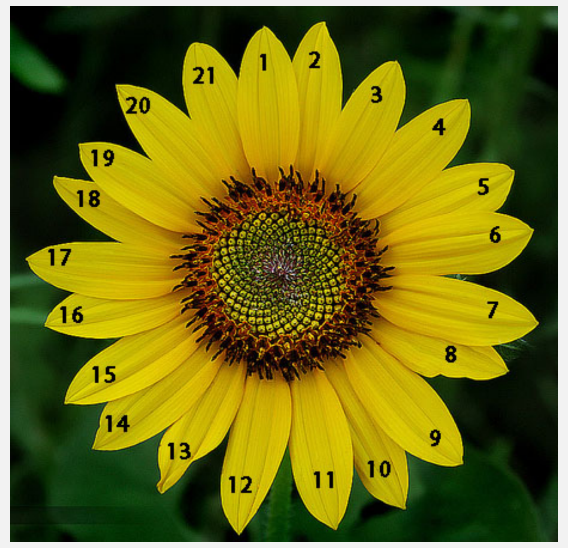


5

8

13



21

34

55

89

Fibonacci numbers: naïve recursive approach

Fibonacci numbers. $0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, \ \ldots$

$$F_i = \begin{cases} 0 & \text{if } \ i = 0 \\ 1 & \text{if } \ i = 1 \\ F_{i-1} + F_{i-2} & \text{if } \ i > 1 \end{cases}$$

Goal. Given n, compute F_n.

Naïve recursive approach:

```
public static long fib(int i)
{
   if (i == 0) return 0;
   if (i == 1) return 1;
   return fib(i-1) + fib(i-2);
}
```

How long to compute fib(80) using the naïve recursive algorithm?

- **A.** Less than 1 second.
- **B.** About 1 minute.
- **C.** More than 1 hour.
- **D.** Overflows a 64-bit `long` integer.

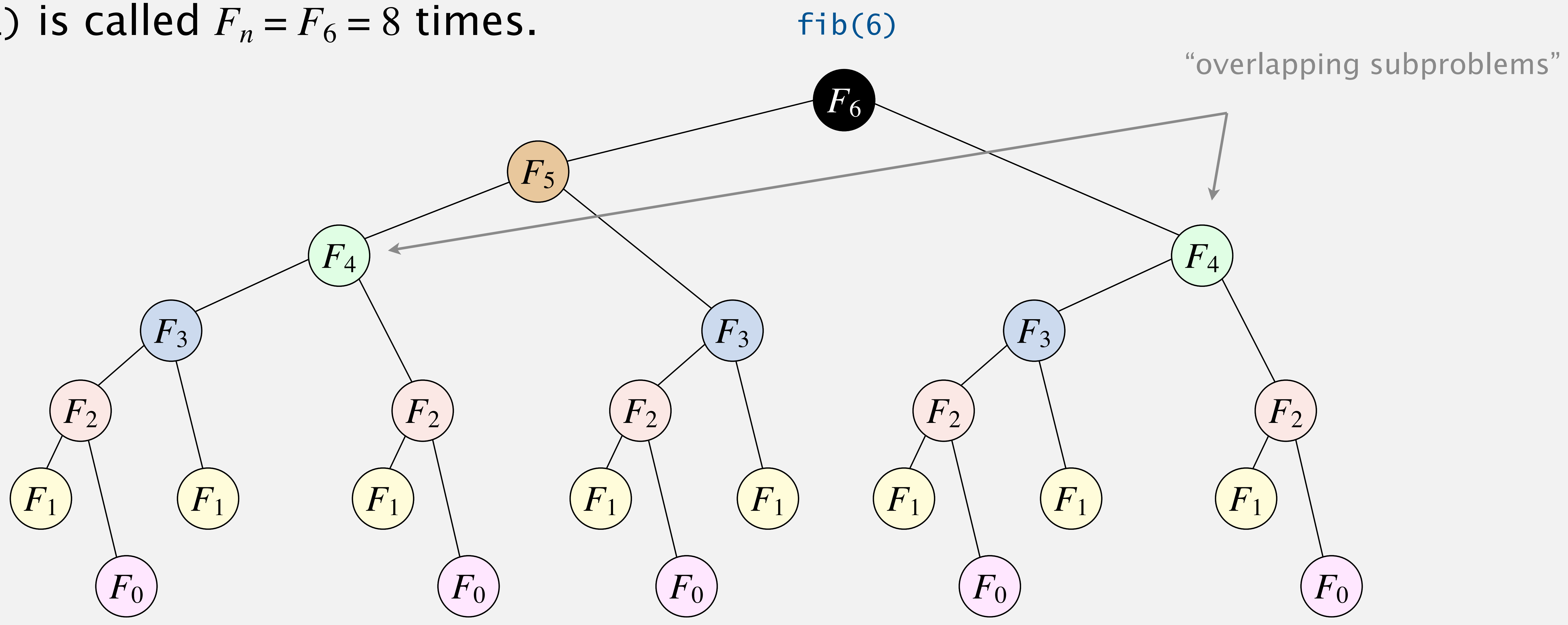
Fibonacci numbers: recursion tree and exponential growth

Exponential waste. Same overlapping subproblems are solved repeatedly.

Ex. To compute `fib(6)`:

- `fib(5)` is called 1 time.
- `fib(4)` is called 2 times.
- `fib(3)` is called 3 times.
- `fib(2)` is called 5 times.
- `fib(1)` is called $F_n = F_6 = 8$ times.

$$F_n \sim \phi^n, \quad \phi = \frac{1+\sqrt{5}}{2} \approx 1.618$$



running time = # subproblems × cost per subproblem

Fibonacci numbers: top-down dynamic programming

Memoization.

- Maintain an array (or symbol table) to remember all computed values.
- If value to compute is known, just return it;
  otherwise, compute it; remember it; and return it.

```
public static long fib(int i)
{
   if (i == 0) return 0;
   if (i == 1) return 1;
   if (f[i] == 0) f[i] = fib(i-1) + fib(i-2);
   return f[i];
}
```

assume global long array f[], initialized to 0 (unknown)

Impact. Solves each subproblem F_i only once; $\Theta(n)$ time to compute F_n.

Fibonacci numbers: bottom-up dynamic programming

Bottom-up dynamic programming.

- Build computation from the "bottom up."
- Solve small subproblems and save solutions.
- Use those solutions to solve larger subproblems.

```
public static long fib(int n)
{
   long[] f = new long[n+1];
   f[0] = 0;
   f[1] = 1;
   for (int i = 2; i <= n; i++)
       f[i] = f[i-1] + f[i-2];
   return f[n];
}
```

smaller subproblems

Impact. Solves each subproblem F_i only once; $\Theta(n)$ time to compute F_n; no recursion.

Fibonacci numbers: further improvements

Performance improvements.

- Save space by saving only two most recent Fibonacci numbers.

```
public static long fib(int n) {
   int f = 0, g = 1;
   for (int i = 0; i < n; i++) {
      g = f + g;
      f = g - f;
   }
   return f;
}
```

f and g are consecutive Fibonacci numbers

- Exploit additional properties of problem:

$$F_n = \left\lfloor \frac{\phi^n}{\sqrt{5}} \right\rceil, \quad \phi = \frac{1+\sqrt{5}}{2}$$

$$\begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}^n = \begin{pmatrix} F_{n+1} & F_n \\ F_n & F_{n-1} \end{pmatrix}^n$$

Dynamic programming recap

Dynamic programming.

- Divide a complex problem into a number of simpler overlapping subproblems.

  [define $n + 1$ subproblems, where subproblem i is computing the i^{th} Fibonacci number]

- Define a recurrence relation to solve larger subproblems from smaller subproblems.

  [easy to solve subproblem i if we know solutions to subproblems $i - 1$ and $i - 2$]

$$F_i = \begin{cases} 0 & \text{if } \ i = 0 \\ 1 & \text{if } \ i = 1 \\ F_{i-1} + F_{i-2} & \text{if } \ i > 1 \end{cases}$$

- Store solutions to each of these subproblems, solving each subproblem only once.

  [use an array, storing subproblem i in `f[i]`]

- Use stored solutions to solve the original problem.

  [subproblem n is original problem]

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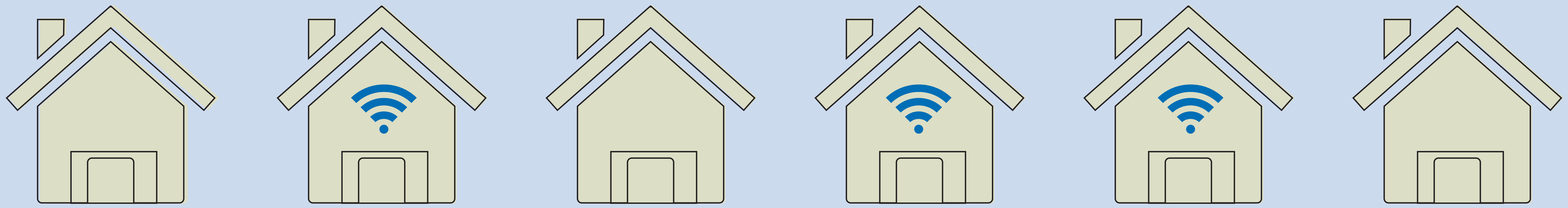
Dynamic Programming

Router installation problem

Goal. Install WiFi routers in a row of n houses so that:

- Minimize total cost, where $cost(i)$ = cost to install a router at house i.
- Requirement: no two consecutive houses without a router.



i	1	2	3	4	5	6
$cost(i)$	1	$\boxed{4}$	12	$\boxed{8}$	$\boxed{9}$	11

cost to install router at house i
(4 + 8 + 9 = 21)

Router installation problem: dynamic programming formulation

Goal. Install WiFi routers in a row of n houses so that:

- Minimize total cost, where $cost(i)$ = cost to install a router at house i.
- Requirement: no two consecutive houses without a router.

Subproblems.

- $yes(i)$ = min cost to install router at houses $1, \ldots, i$ with router at i.
- $no(i)$ = min cost to install router at houses $1, \ldots, i$ with no router at i.
- Optimal cost = $\min \{ yes(n), \ no(n) \}$.

Dynamic programming recurrence.

- $yes(0) = no(0) = 0$
- $yes(i) = cost(i) + \min \{ yes(i-1), \ no(i-1) \}$
- $no(i) = yes(i-1)$

"optimal substructure"
(optimal solution can be constructed from optimal solutions to smaller subproblems)

Router installation: naïve recursive implementation

A mutually recursive implementation.

```
private int yes(int i)
{
   if (i == 0) return 0;
   return cost[i] + Math.min(yes(i-1), no(i-1));
}

private int no(int i)
{
   if (i == 0) return 0;
   return yes(i-1);
}

public int minCost()
{
   return Math.min(yes(n), no(n));
}
```

$$yes(i) = cost(i) + \min \{ yes(i-1), no(i-1) \}$$

$$no(i) = yes(i-1)$$

Dynamic programming: quiz 2

What is running time of the naïve recursive algorithm as a function of n?

A. $\Theta(n)$

B. $\Theta(n^2)$

C. $\Theta(c^n)$ for some $c > 1$.

D. $\Theta(n!)$

Dynamic programming aphorism

> *" Those who cannot remember the past are condemned to repeat it. "*
>
> **— *Dynamic Programming***
>
> *(Jorge Agustín Nicolás Ruiz de Santayana y Borrás)*

Router installation: bottom-up implementation

Bottom-up DP implementation.

```
int[] yes = new int[n+1];
int[] no  = new int[n+1];

for (int i = 1; i <= n; i++)
{
   yes[i] = cost[i] + Math.min(yes[i-1], no[i-1]);
   no[i]  = yes[i-1];
}

return Math.min(yes[n], no[n]);
```

$$yes(i) \;=\; cost(i) \;+\; \min\,\{\, yes(i-1),\; no(i-1) \,\}$$
$$no(i) \;=\; yes(i-1)$$

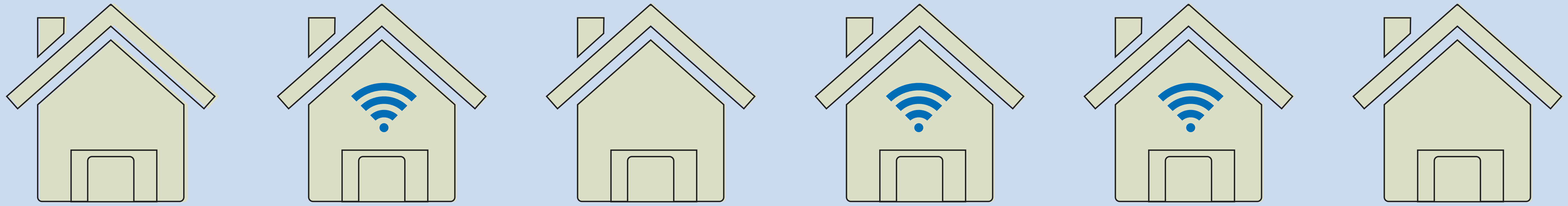
Proposition. Takes $\Theta(n)$ time and uses $\Theta(n)$ extra space.

Remark. Could eliminate the no[] array by substituting identity no[k] = yes[k-1].

ROUTER INSTALLATION: RECONSTRUCTING THE SOLUTION (BACKTRACE)

So far: we've computed the value of the optimal solution.

Still need: the solution itself (where to install routers).



i	0	1	2	3	4	5	6
$yes(i)$	0	1	4	13	12	21	23
$no(i)$	0	0	1	4	13	12	21

yes(i) = cost to install routers at houses 1, 2, …, i with router at house i

no(i) = cost to install routers at houses 1, 2, …, i with router not at house i

Coin changing

Problem. Given n coin denominations $\{ d_1, d_2, \ldots, d_n \}$ and a target value V, find the fewest coins needed to make change for V (or report impossible).

vending machine
(out of nickels)

Ex. Coin denominations = $\{1, 10, 25, 100\}$, $V = 130$.

Greedy (8 coins). $131¢ = 100 + 25 + 1 + 1 + 1 + 1 + 1 + 1$.

Optimal (5 coins). $131¢ = 100 + 10 + 10 + 10 + 1$.

8 coins
(131¢)

5 coins
(131¢)

Remark. Greedy algorithm is optimal for U.S. coin denominations $\{1, 5, 10, 25, 100\}$.

COIN CHANGING: DYNAMIC PROGRAMMING FORMULATION

Problem. Given n coin denominations $\{ d_1, d_2, \ldots, d_n \}$ and a target value V, find the fewest coins needed to make change for V (or report impossible).

Subproblems. $OPT(v)$ = fewest coins needed to make change for amount v.

Optimal value. $OPT(V)$.

Multiway choice. To compute $OPT(v)$,

- Select a coin of denomination $d_i \le v$ for some i.
- Use fewest coins to make change for $v - d_i$.

take best

optimal substructure

Dynamic programming recurrence.

$$OPT(v) = \begin{cases} 0 & \text{if } v = 0 \\ \min\limits_{i \,:\, d_i \le v} \{ 1 + OPT(v - d_i) \} & \text{if } v > 0 \end{cases}$$

Dynamic programming: quiz 3

In which order to compute OPT(v) in bottom-up DP ?

A. Increasing i.

B. Decreasing i.

C. Either A or B.

D. Neither A nor B.

```
for (int v = 1; v <= V; v++)
   opt[v] = ...
```

```
for (int v = V; v >= 1; v--)
   opt[v] = ...
```

$$OPT(v) = \begin{cases} 0 & \text{if } v = 0 \\ \min\limits_{i \,:\, d_i \le v} \{\, 1 + OPT(v - d_i) \,\} & \text{if } v > 0 \end{cases}$$

Coin changing: bottom-up implementation

Bottom-up DP implementation.

```
int[] opt = new int[V+1];
opt[0] = 0;

for (int v = 1; v <= V; v++)
{
   // opt[v] = min_i { 1 + opt[v - d[i]] }
   opt[v] = INFINITY;
   for (int i = 1; i <= n; i++)
      if (d[i] <= v)
         opt[v] = Math.min(opt[v], 1 + opt[v - d[i]]);
}
```

$$OPT(v) = \begin{cases} 0 & \text{if } v = 0 \\ \min\limits_{i \,:\, d_i \le v} \{\, 1 + OPT(v - d_i) \,\} & \text{if } v > 0 \end{cases}$$

Proposition. DP algorithm takes $\Theta(n\ V)$ time and uses $\Theta(V)$ extra space.

Note. Not polynomial in input size; underlying problem is **NP**-complete.

n, $\log V$

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Dynamic Programming

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- *shortest paths in DAGs*
- seam carving

Shortest paths in directed acyclic graphs: dynamic programming formulation

Problem. Given a DAG with positive edge weights, find shortest path from s to t.

Subproblems. $distTo(v)$ = length of shortest $s \rightsquigarrow v$ path.

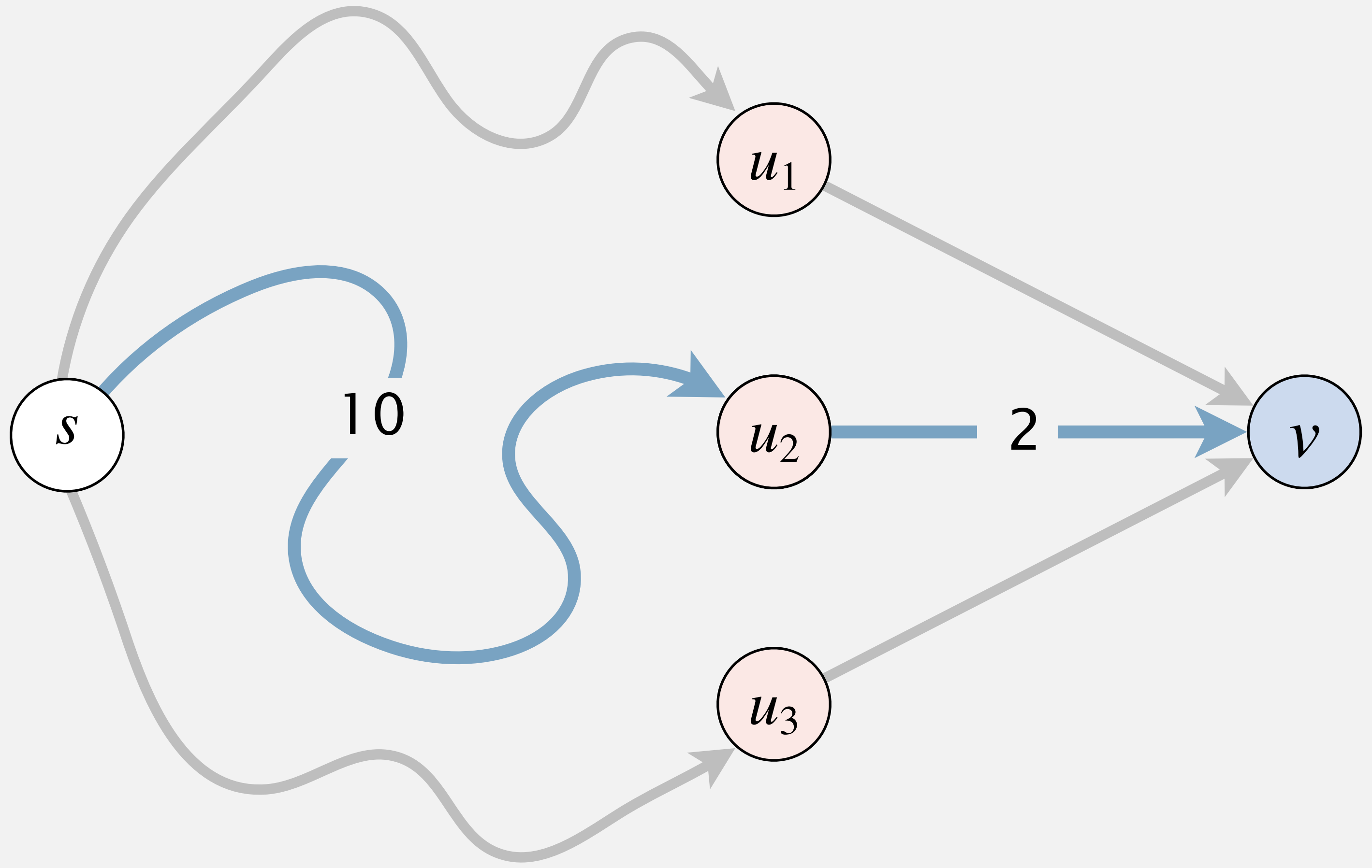
Goal. $distTo(t)$.

Multiway choice. To compute $distTo(v)$:

- Select an edge $e = u \rightarrow v$ entering v.
- Combine with shortest $s \rightsquigarrow u$ path.

take best

optimal substructure



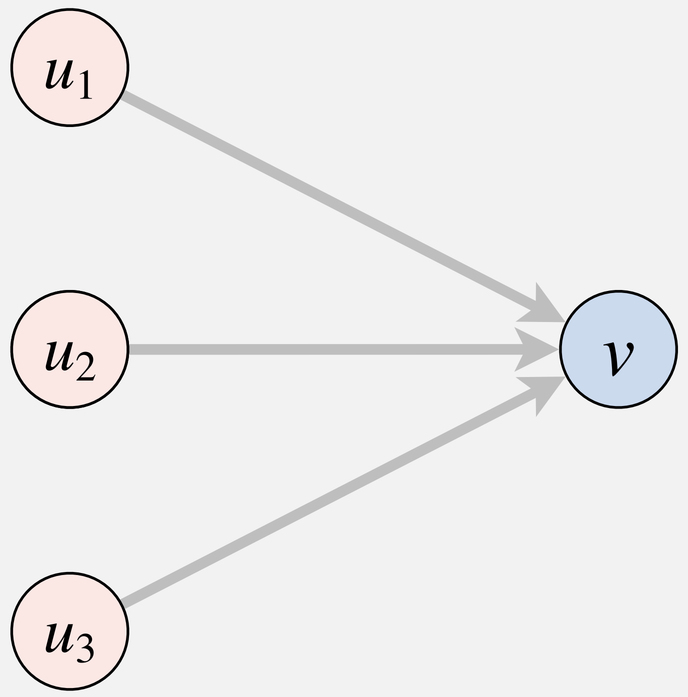
Dynamic programming recurrence.

$$distTo(v) = \begin{cases} 0 & \text{if } v = s \\ \min\limits_{e = u \to v} \{ distTo(u) + weight(e) \} & \text{if } v \neq s \end{cases}$$

Shortest paths in directed acyclic graphs: bottom-up solution

Bottom-up DP algorithm. Takes $\Theta(E + V)$ time with two tricks:

- Solve subproblems in topological order. ← ensures that "small" subproblems are solved before "large" ones
- Form reverse digraph G^R (to support iterating over edges incident to vertex v).

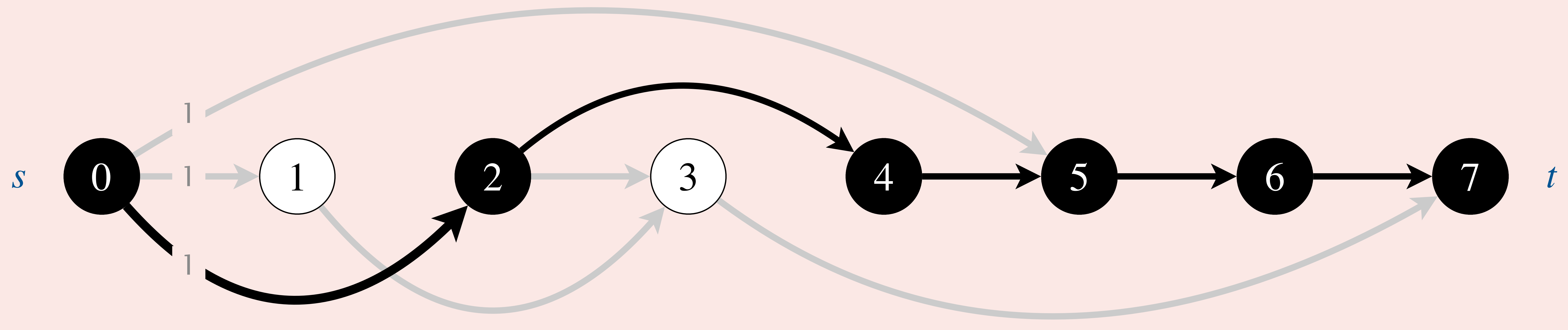


Equivalent (but simpler) computation. Relax vertices in topological order.

```
Topological topological = new Topological(G);
for (int v : topological.order())
   for (DirectedEdge e : G.adj(v))
      relax(e);
```

Remark. Can find the shortest paths themselves by maintaining edgeTo[] array.

Given a DAG, how to find longest path from s to t in $\Theta(E+V)$ time?



longest path from s to t in a DAG (all edge weights = 1)

A. Negate edge weights; use DP algorithm to find shortest path.

B. Replace *min* with *max* in DP recurrence.

C. Either A or B.

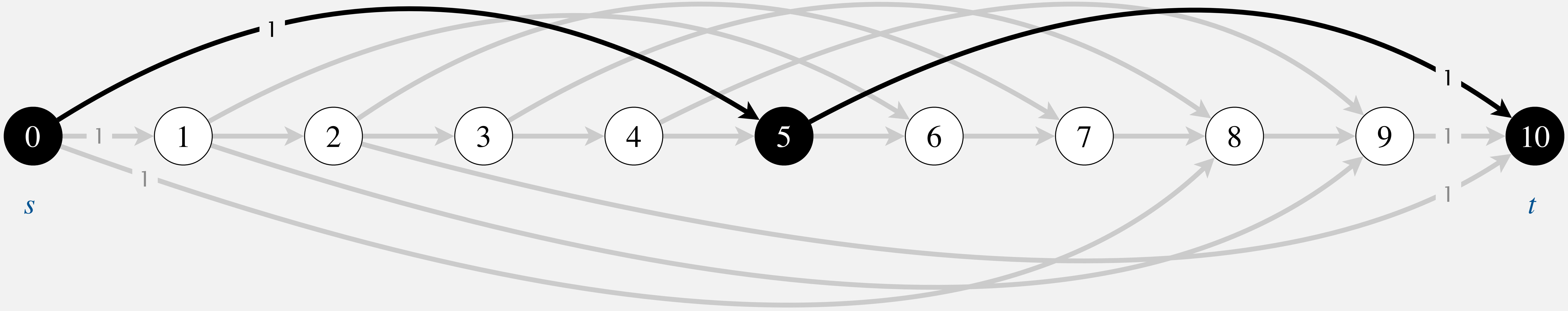
D. No poly-time algorithm is known (**NP**-complete).

Shortest paths in DAGs and dynamic programming

DP subproblem dependency digraph.

- Vertex v for each subproblem v.
- Edge $v \to w$, if subproblem v must be solved before subproblem w.
- Digraph must be a DAG. Why?

Ex 1. Modeling the coin changing problem as a shortest path problem in a DAG.



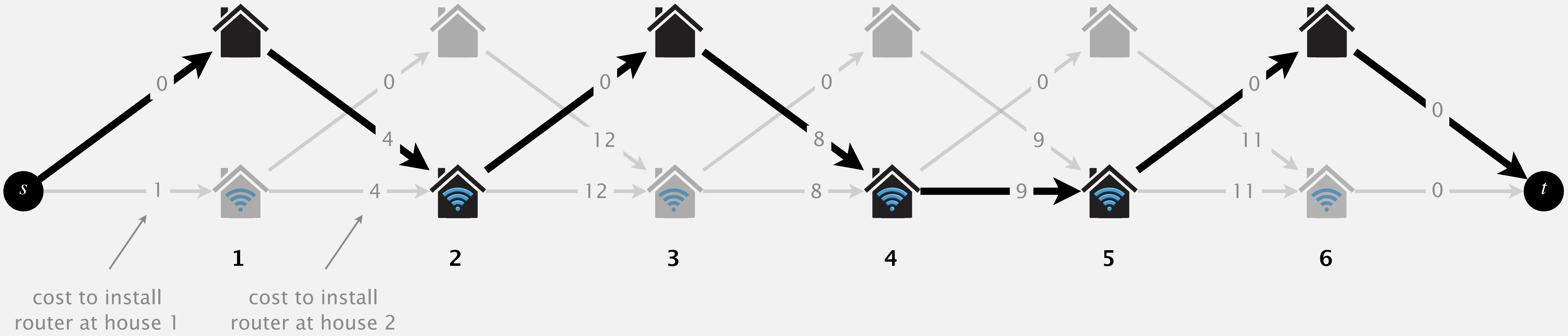
V = 10; coin denominations = { 1, 5, 8 }

Shortest paths in DAGs and dynamic programming

DP subproblem dependency digraph.

- Vertex v for each subproblem v.
- Edge $v \to w$, if subproblem v must be solved before subproblem w.
- Digraph must be a DAG. Why?

Ex 2. Modeling the router installation problem as a shortest path problem in a DAG.



4.4 Shortest Paths

- *introduction*
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- *shortest paths in DAGs*
- ***seam carving***

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Content-aware resizing

Seam carving. [Avidan–Shamir] Resize an image without distortion for display on cell phones and web browsers.

https://www.youtube.com/watch?v=vIFCV2spKtg

Content-aware resizing

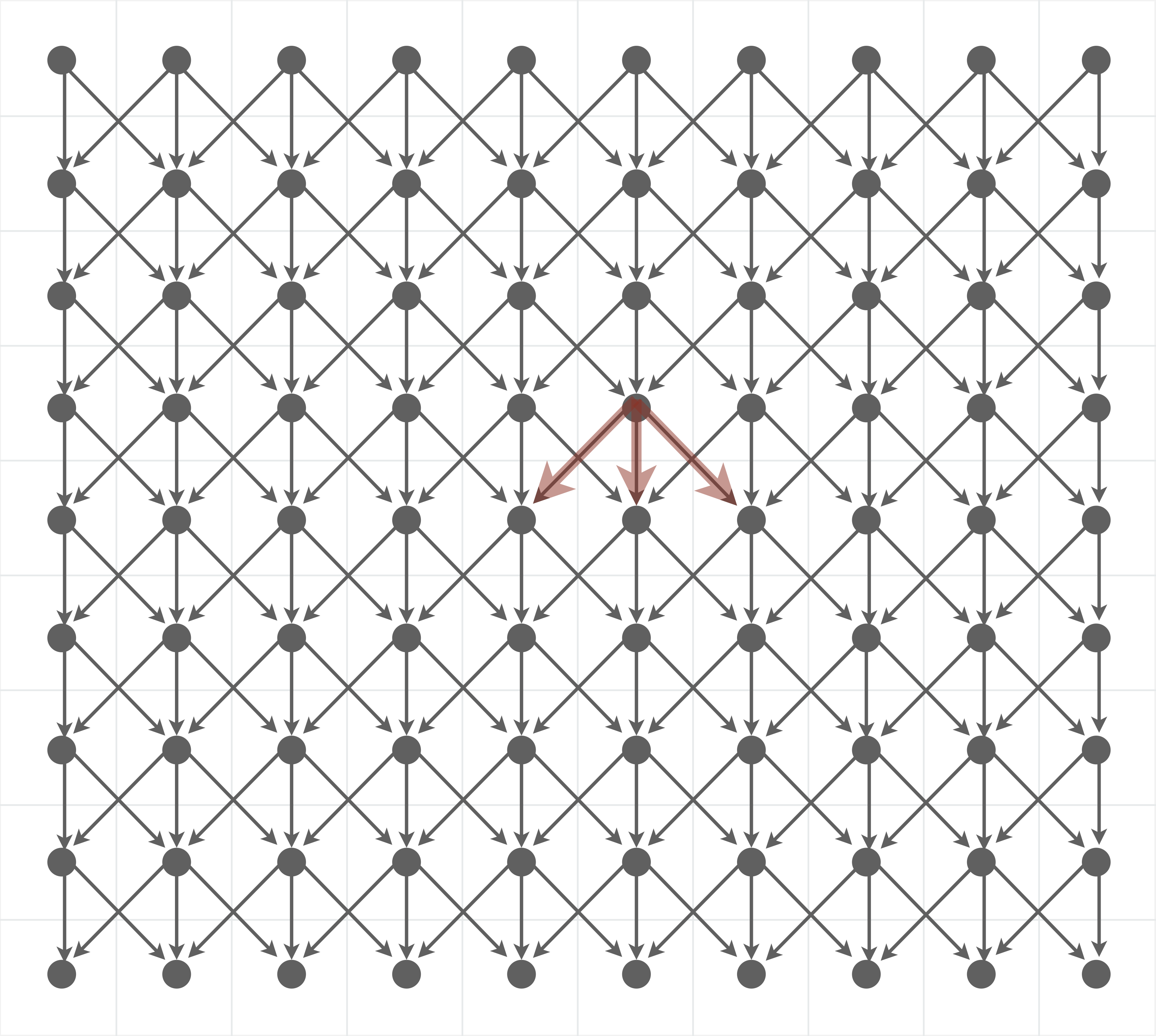
Seam carving. [Avidan–Shamir] Resize an image without distortion for display on cell phones and web browsers.

In the wild. Photoshop, ImageMagick, GIMP, ...

Content-aware resizing

To find vertical seam in a picture:

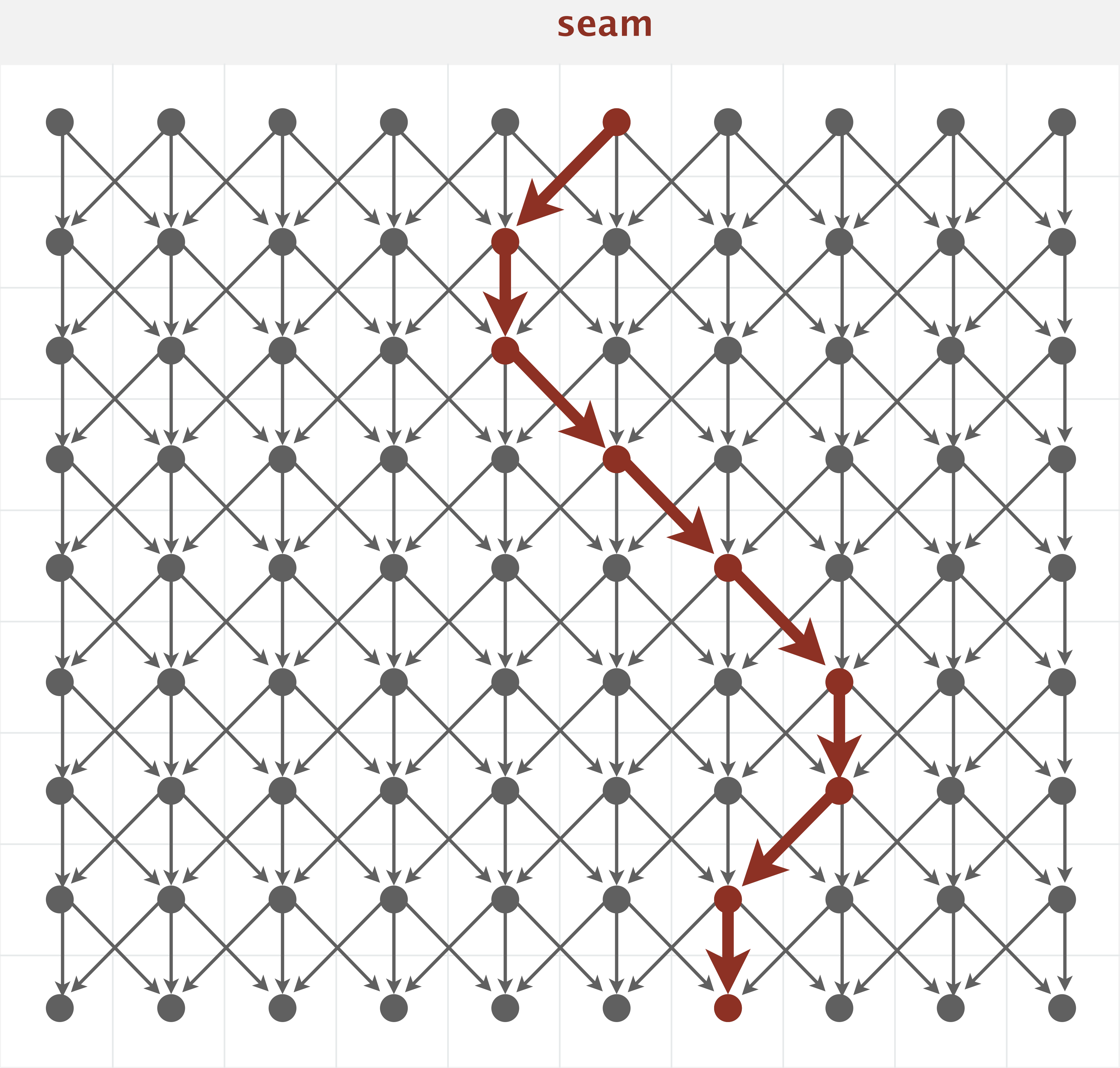
- Grid graph: vertex = pixel; edge = from pixel to 3 downward neighbors.
- Weight of pixel = "energy function" of 8 neighboring pixels.



Content-aware resizing

To find vertical seam in a picture:

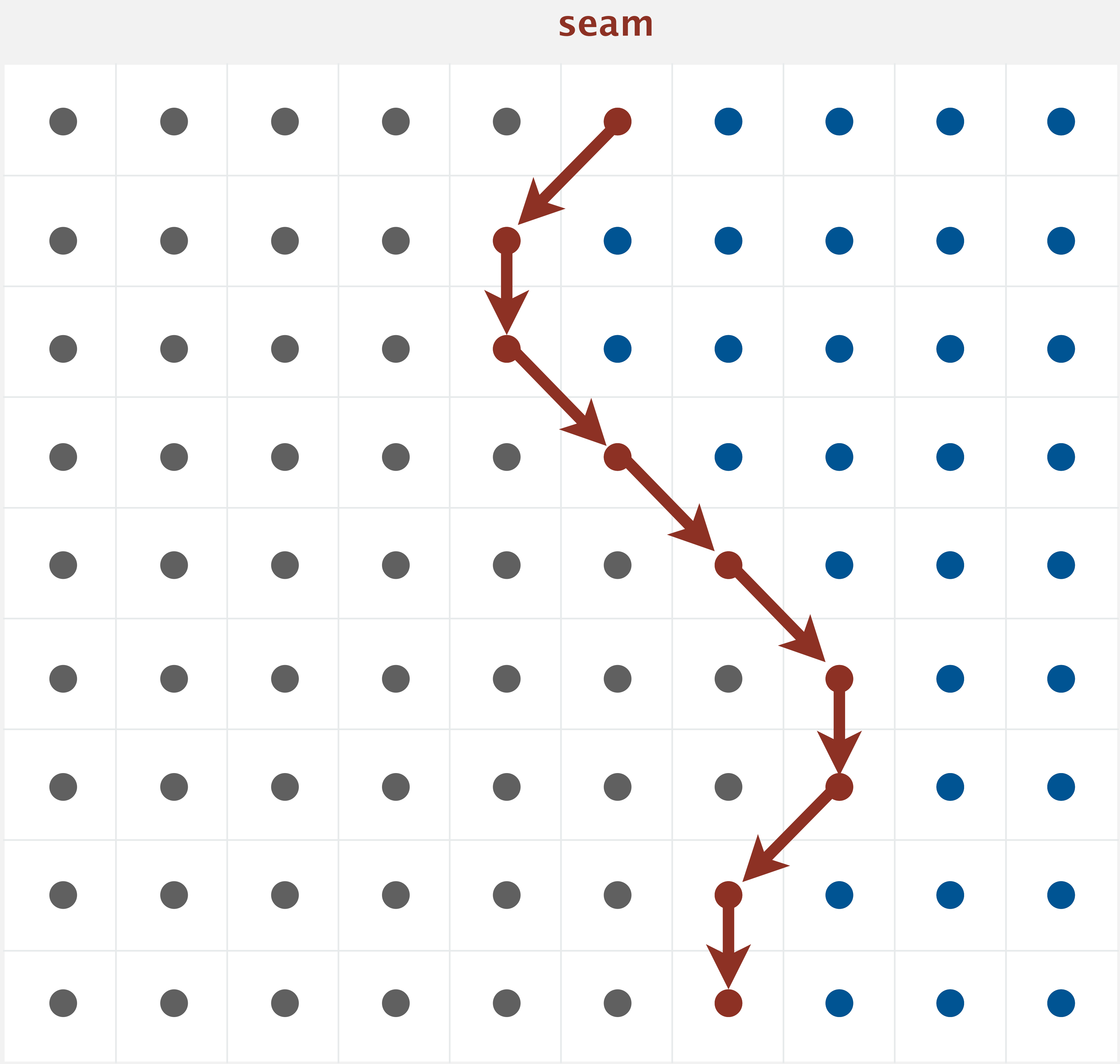
- Grid graph: vertex = pixel; edge = from pixel to 3 downward neighbors.
- Weight of pixel = "energy function" of 8 neighboring pixels.
- Seam = shortest path (sum of vertex weights) from top to bottom.



Content-aware resizing

To remove vertical seam in a picture:

- Delete pixels on seam (one in each row).

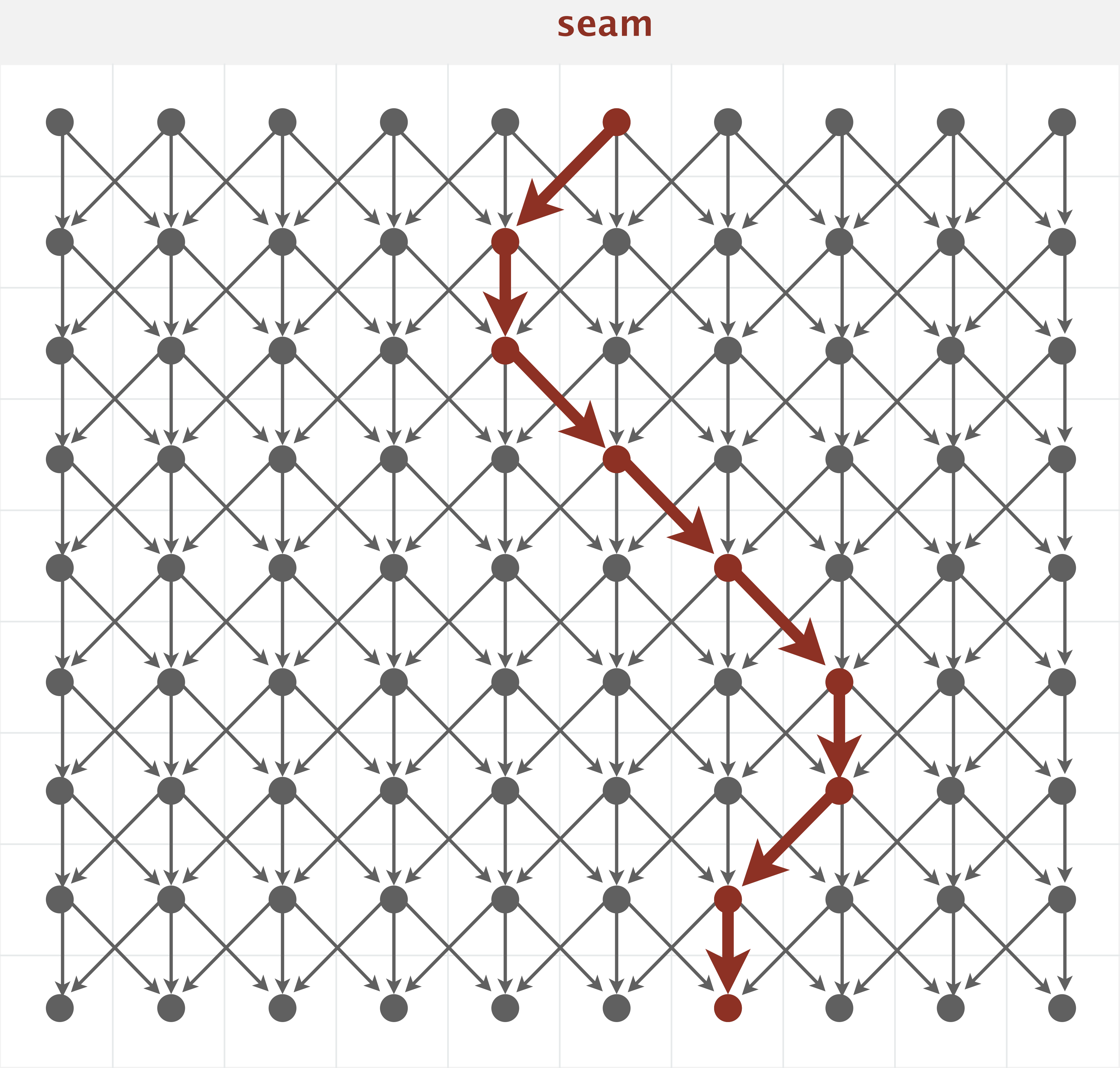


Content-aware resizing: dynamic programming formulation

Problem. Find a min energy path from top to bottom.

Subproblems. $distTo(col,\ row)$ = energy of min energy path from any top pixel to pixel (col, row).

Goal. $\min \{\ distTo(col, H-1)\ \}$.



Summary

How to design a dynamic programming algorithm.

- Find good subproblems.
- Develop DP recurrence for optimal value.
  - optimal substructure
  - overlapping subproblems
- Determine order in which to solve subproblems.
- Cache computed results to avoid unnecessary re-computation.
- Reconstruct the solution: backtrace or save extra state.