Chapter 4

Greedy Algorithms
4.1 Interval Scheduling
Interval Scheduling

Interval scheduling.

- Job j starts at $s_j$ and finishes at $f_j$.
- Two jobs compatible if they don't overlap.
- Goal: find maximum subset of mutually compatible jobs.
Greedy template. Consider jobs in some natural order. Take each job provided it's compatible with the ones already taken.

- [Earliest start time] Consider jobs in ascending order of $s_j$.
- [Earliest finish time] Consider jobs in ascending order of $f_j$.
- [Shortest interval] Consider jobs in ascending order of $f_j - s_j$.
- [Fewest conflicts] For each job $j$, count the number of conflicting jobs $c_j$. Schedule in ascending order of $c_j$. 
Interval Scheduling: Greedy Algorithms

Greedy template. Consider jobs in some natural order. Take each job provided it's compatible with the ones already taken.

counterexample for earliest start time

counterexample for shortest interval

counterexample for fewest conflicts
Interval Scheduling: Greedy Algorithm

**Greedy algorithm.** Consider jobs in increasing order of finish time. Take each job provided it's compatible with the ones already taken.

Sort jobs by finish times so that $f_1 \leq f_2 \leq \ldots \leq f_n$.

(set of jobs selected)

$A \leftarrow \emptyset$

for $j = 1$ to $n$ {
    if (job $j$ compatible with $A$)
        $A \leftarrow A \cup \{j\}$
}

return $A$

**Implementation.** $O(n \log n)$.

- Remember job $j^*$ that was added last to $A$.
- Job $j$ is compatible with $A$ if $s_j \geq f_{j^*}$.
Theorem. Greedy algorithm is optimal.

Pf. (by contradiction)

- Assume greedy is not optimal, and let's see what happens.
- Let $i_1, i_2, \ldots, i_k$ denote set of jobs selected by greedy.
- Let $j_1, j_2, \ldots, j_m$ denote set of jobs in the optimal solution with $i_1 = j_1, i_2 = j_2, \ldots, i_r = j_r$ for the largest possible value of $r$. 

<table>
<thead>
<tr>
<th>Greedy:</th>
<th>OPT:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_1$</td>
<td>$j_1$</td>
</tr>
<tr>
<td>$i_2$</td>
<td>$j_2$</td>
</tr>
<tr>
<td>$i_r$</td>
<td>$j_r$</td>
</tr>
<tr>
<td>$i_{r+1}$</td>
<td>$j_{r+1}$</td>
</tr>
</tbody>
</table>

job $i_{r+1}$ finishes before $j_{r+1}$

why not replace job $j_{r+1}$ with job $i_{r+1}$?
Theorem. Greedy algorithm is optimal.

Pf. (by contradiction)
- Assume greedy is not optimal, and let's see what happens.
- Let $i_1, i_2, ... i_k$ denote set of jobs selected by greedy.
- Let $j_1, j_2, ... j_m$ denote set of jobs in the optimal solution with $i_1 = j_1, i_2 = j_2, ..., i_r = j_r$ for the largest possible value of $r$.

Greedy:

\[
\begin{aligned}
& i_1 & & i_2 & & i_r & & i_{r+1} \\
& j_1 & & j_2 & & j_r & & i_{r+1} & \ldots
\end{aligned}
\]

OPT:

\[
\begin{aligned}
& j_1 & & j_2 & & j_r & & i_{r+1} & \ldots
\end{aligned}
\]

job $i_{r+1}$ finishes before $j_{r+1}$

solution still feasible and optimal, but contradicts maximality of $r$. 
4.1 Interval Partitioning
Interval Partitioning

Interval partitioning.
- Lecture $j$ starts at $s_j$ and finishes at $f_j$.
- Goal: find minimum number of classrooms to schedule all lectures so that no two occur at the same time in the same room.

Ex: This schedule uses 4 classrooms to schedule 10 lectures.
Interval Partitioning

Interval partitioning.
- Lecture $j$ starts at $s_j$ and finishes at $f_j$.
- Goal: find minimum number of classrooms to schedule all lectures so that no two occur at the same time in the same room.

Ex: This schedule uses only 3.
Interval Partitioning: Lower Bound on Optimal Solution

**Def.** The depth of a set of open intervals is the maximum number that contain any given time.

**Key observation.** Number of classrooms needed $\geq$ depth.

**Ex:** Depth of schedule below = 3 $\Rightarrow$ schedule below is optimal.

Q. Does there always exist a schedule equal to depth of intervals?
Interval Partitioning: Greedy Algorithm

**Greedy algorithm.** Consider lectures in increasing order of start time: assign lecture to any compatible classroom.

```
Sort intervals by starting time so that $s_1 \leq s_2 \leq \ldots \leq s_n$.
d ← 0 ← number of allocated classrooms

for j = 1 to n {
    if (lecture j is compatible with some classroom k)
        schedule lecture j in classroom k
    else
        allocate a new classroom d + 1
        schedule lecture j in classroom d + 1
        d ← d + 1
}
```

**Implementation.** $O(n \log n)$.
- For each classroom $k$, maintain the finish time of the last job added.
- Keep the classrooms in a priority queue.
Interval Partitioning: Greedy Analysis

Observation. Greedy algorithm never schedules two incompatible lectures in the same classroom.

Theorem. Greedy algorithm is optimal.

Pf.

- Let \( d \) = number of classrooms that the greedy algorithm allocates.
- Classroom \( d \) is opened because we needed to schedule a job, say \( j \), that is incompatible with all \( d-1 \) other classrooms.
- These \( d \) jobs each end after \( s_j \).
- Since we sorted by start time, all these incompatibilities are caused by lectures that start no later than \( s_j \).
- Thus, we have \( d \) lectures overlapping at time \( s_j + \varepsilon \).
- Key observation \( \Rightarrow \) all schedules use \( \geq d \) classrooms.
4.2 Scheduling to Minimize Lateness
Minimizing lateness problem.
- Single resource processes one job at a time.
- Job j requires $t_j$ units of processing time and is due at time $d_j$.
- If j starts at time $s_j$, it finishes at time $f_j = s_j + t_j$.
- Lateness: $\ell_j = \max \{ 0, f_j - d_j \}$.
- Goal: schedule all jobs to minimize maximum lateness $L = \max \ell_j$.

Ex:

\[
\begin{array}{c|ccccccc}
& 1 & 2 & 3 & 4 & 5 & 6 \\
\hline
\text{t}_j & 3 & 2 & 1 & 4 & 3 & 2 \\
\text{d}_j & 6 & 8 & 9 & 9 & 14 & 15 \\
\end{array}
\]
Minimizing Lateness: Greedy Algorithms

**Greedy template.** Consider jobs in some order.

- **[Shortest processing time first]** Consider jobs in ascending order of processing time \( t_j \).

- **[Earliest deadline first]** Consider jobs in ascending order of deadline \( d_j \).

- **[Smallest slack]** Consider jobs in ascending order of slack \( d_j - t_j \).
Minimizing Lateness: Greedy Algorithms

Greedy template. Consider jobs in some order.

- [Shortest processing time first] Consider jobs in ascending order of processing time $t_j$.

  \[
  \begin{array}{cc}
  1 & 2 \\
  t_j & 1 & 10 \\
  d_j & 100 & 10 \\
  \end{array}
  \]

  counterexample

- [Smallest slack] Consider jobs in ascending order of slack $d_j - t_j$.

  \[
  \begin{array}{cc}
  1 & 2 \\
  t_j & 1 & 10 \\
  d_j & 2 & 10 \\
  \end{array}
  \]

  counterexample
Minimizing Lateness: Greedy Algorithm

**Greedy algorithm.** Earliest deadline first.

Sort n jobs by deadline so that \(d_1 \leq d_2 \leq ... \leq d_n\)

\[
t \leftarrow 0
\]
\[
\text{for } j = 1 \text{ to } n
\]
\[
\quad \text{Assign job } j \text{ to interval } [t, t + t_j]
\]
\[
\quad s_j \leftarrow t, \ f_j \leftarrow t + t_j
\]
\[
\quad t \leftarrow t + t_j
\]
\[
\text{output intervals } [s_j, f_j]
\]

\[
\begin{array}{cccccccc}
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 \\
\hline
\text{d}_1 = 6 & \text{d}_2 = 8 & \text{d}_3 = 9 & \text{d}_4 = 9 & \text{d}_5 = 14 & \text{d}_6 = 15
\end{array}
\]

max lateness = 1
Minimizing Lateness: No Idle Time

**Observation.** There exists an optimal schedule with no idle time.

- $d = 4$
- $d = 6$
- $d = 12$

**Observation.** The greedy schedule has no idle time.
**Def.** Given a schedule $S$, an **inversion** is a pair of jobs $i$ and $j$ such that: $i < j$ but $j$ scheduled before $i$.

**Observation.** Greedy schedule has no inversions.

**Observation.** If a schedule (with no idle time) has an inversion, it has one with a pair of inverted jobs scheduled consecutively.
**Def.** Given a schedule $S$, an inversion is a pair of jobs $i$ and $j$ such that: $i < j$ but $j$ scheduled before $i$.

![Diagram showing before and after swap of two inverted jobs]

**Claim.** Swapping two consecutive, inverted jobs reduces the number of inversions by one and does not increase the max lateness.

**Pf.** Let $\ell$ be the lateness before the swap, and let $\ell'$ be it afterwards.

- $\ell_k' = \ell_k$ for all $k \neq i, j$
- $\ell_i' \leq \ell_i$
- If job $j$ is late:

$$
\ell_j' = f_j' - d_j \quad \text{(definition)}
= f_i - d_j \quad \text{($j$ finishes at time $f_i$)}
\leq f_i - d_i \quad \text{($i < j$)}
\leq \ell_i \quad \text{(definition)}
$$
**Theorem.** Greedy schedule $S$ is optimal.

**Pf.** Define $S^*$ to be an optimal schedule that has the fewest number of inversions, and let's see what happens.

- Can assume $S^*$ has no idle time.
- If $S^*$ has no inversions, then $S = S^*$.
- If $S^*$ has an inversion, let $i-j$ be an adjacent inversion.
  - Swapping $i$ and $j$ does not increase the maximum lateness and strictly decreases the number of inversions
  - This contradicts definition of $S^*$
Greedy Analysis Strategies

**Greedy algorithm stays ahead.** Show that after each step of the greedy algorithm, its solution is at least as good as any other algorithm's.

**Structural.** Discover a simple "structural" bound asserting that every possible solution must have a certain value. Then show that your algorithm always achieves this bound.

**Exchange argument.** Gradually transform any solution to the one found by the greedy algorithm without hurting its quality.

**Other greedy algorithms.** Kruskal, Prim, Dijkstra, Huffman, ...
4.3 Optimal Caching
**Optimal Offline Caching**

**Caching.**
- Cache with capacity to store k items.
- Sequence of m item requests \(d_1, d_2, \ldots, d_m\).
- Cache hit: item already in cache when requested.
- Cache miss: item not already in cache when requested: must bring requested item into cache, and evict some existing item, if full.

**Goal.** Eviction schedule that minimizes number of cache misses.

**Ex:** \(k = 2\), initial cache = ab,
requests: a, b, c, b, c, a, a, b.

**Optimal eviction schedule:** 2 cache misses.
Optimal Offline Caching: Farthest-In-Future

**Farthest-in-future.** Evict item in the cache that is not requested until farthest in the future.

```
current cache:   a b c d e f
```

```
future queries:  g a b c e d a b b a c d e a f a d e f g h ...

  ^ cache miss

  ^ eject this one
```

**Theorem.** [Bellady, 1960s] FF is optimal eviction schedule.

**Pf.** Algorithm and theorem are intuitive; proof is subtle.
Reduced Eviction Schedules

Def. A reduced schedule is a schedule that only inserts an item into the cache in a step in which that item is requested.

Intuition. Can transform an unreduced schedule into a reduced one with no more cache misses.

\[
\begin{array}{cccc}
\text{a} & \text{a} & \text{b} & \text{c} \\
\text{a} & \text{a} & \text{x} & \text{c} \\
\text{c} & \text{a} & \text{d} & \text{c} \\
\text{d} & \text{a} & \text{d} & \text{b} \\
\text{a} & \text{a} & \text{c} & \text{b} \\
\text{b} & \text{a} & \text{x} & \text{b} \\
\text{c} & \text{a} & \text{c} & \text{b} \\
\text{a} & \text{a} & \text{b} & \text{c} \\
\text{a} & \text{a} & \text{b} & \text{c} \\
\end{array}
\quad
\begin{array}{cccc}
\text{a} & \text{a} & \text{b} & \text{c} \\
\text{a} & \text{a} & \text{b} & \text{c} \\
\text{c} & \text{a} & \text{b} & \text{c} \\
\text{d} & \text{a} & \text{d} & \text{c} \\
\text{a} & \text{a} & \text{d} & \text{c} \\
\text{b} & \text{a} & \text{d} & \text{b} \\
\text{c} & \text{a} & \text{c} & \text{b} \\
\text{a} & \text{a} & \text{c} & \text{b} \\
\text{a} & \text{a} & \text{c} & \text{b} \\
\end{array}
\]

an unreduced schedule 
a reduced schedule
Reduced Eviction Schedules

Claim. Given any unreduced schedule S, can transform it into a reduced schedule S' with no more cache misses.

Pf. (by induction on number of unreduced items)

- Suppose S brings d into the cache at time \( t \), without a request.
- Let \( c \) be the item S evicts when it brings d into the cache.
- Case 1: d evicted at time \( t' \), before next request for d.
- Case 2: d requested at time \( t' \) before d is evicted.

\[ S \]
\[ c \]
\[ t \]
\[ d \]
\[ e \]
\[ d \text{ evicted at time } t', \text{ before next request} \]
\[ t' \]

\[ S' \]
\[ c \]
\[ t \]
\[ d \]
\[ e \]

\[ S \]
\[ c \]
\[ t \]
\[ d \]
\[ t' \]
\[ d \text{ requested at time } t' \]

\[ S' \]
\[ c \]
\[ t \]
\[ d \]
\[ t' \]
Theorem. FF is optimal eviction algorithm.

Pf. (by induction on number or requests j)

Invariant: There exists an optimal reduced schedule S that makes the same eviction schedule as $S_{FF}$ through the first $j+1$ requests.

Let S be reduced schedule that satisfies invariant through j requests. We produce $S'$ that satisfies invariant after $j+1$ requests.

- Consider $(j+1)^{st}$ request $d = d_{j+1}$.
- Since S and $S_{FF}$ have agreed up until now, they have the same cache contents before request $j+1$.
- Case 1: (d is already in the cache). $S' = S$ satisfies invariant.
- Case 2: (d is not in the cache and S and $S_{FF}$ evict the same element). $S' = S$ satisfies invariant.
Farthest-In-Future: Analysis

Pf. (continued)

- **Case 3**: (d is not in the cache; $S_{FF}$ evicts e; $S$ evicts $f \neq e$).
  - begin construction of $S'$ from $S$ by evicting e instead of f

\[
\begin{array}{c|c|c|c}
  j & \text{same} & e & f \\
  \text{S} & \text{same} & e & f \\
  \text{j+1} & \text{same} & e & d \\
  \text{S} & \text{same} & d & f \\
  \text{S'} & \text{S'}
\end{array}
\]

- now $S'$ agrees with $S_{FF}$ on first j+1 requests; we show that having element f in cache is no worse than having element e
Farthest-In-Future: Analysis

Let $j'$ be the first time after $j+1$ that $S$ and $S'$ take a different action, and let $g$ be item requested at time $j'$.

- **Case 3a:** $g = e$. Can't happen with Farthest-In-Future since there must be a request for $f$ before $e$.

- **Case 3b:** $g = f$. Element $f$ can't be in cache of $S$, so let $e'$ be the element that $S$ evicts.
  - if $e' = e$, $S'$ accesses $f$ from cache; now $S$ and $S'$ have same cache
  - if $e' \neq e$, $S'$ evicts $e'$ and brings $e$ into the cache; now $S$ and $S'$ have the same cache

Note: $S'$ is no longer reduced, but can be transformed into a reduced schedule that agrees with $S_{\text{FF}}$ through step $j+1$.
Farthest-In-Future: Analysis

Let \( j' \) be the first time after \( j+1 \) that \( S \) and \( S' \) take a different action, and let \( g \) be item requested at time \( j' \).

- Case 3c: \( g \neq e, f \). \( S \) must evict \( e \).
  Make \( S' \) evict \( f \); now \( S \) and \( S' \) have the same cache.
Caching Perspective

Online vs. offline algorithms.
- Offline: full sequence of requests is known a priori.
- Online (reality): requests are not known in advance.
- Caching is among most fundamental online problems in CS.

LIFO. Evict page brought in most recently.
LRU. Evict page whose most recent access was earliest.

Theorem. FF is optimal offline eviction algorithm.
- Provides basis for understanding and analyzing online algorithms.
- LRU is k-competitive. [Section 13.8]
- LIFO is arbitrarily bad.
4.4 Shortest Paths in a Graph

shortest path from Princeton CS department to Einstein's house
Shortest Path Problem

**Shortest path network.**
- Directed graph $G = (V, E)$.
- Source $s$, destination $t$.
- Length $l_e = \text{length of edge } e$.

**Shortest path problem:** find shortest directed path from $s$ to $t$.

Cost of path $s-2-3-5-t$

\[= 9 + 23 + 2 + 16\]

\[= 50.\]
Dijkstra's Algorithm

Dijkstra's algorithm.
- Maintain a set of explored nodes $S$ for which we have determined the shortest path distance $d(u)$ from $s$ to $u$.
- Initialize $S = \{ s \}$, $d(s) = 0$.
- Repeatedly choose unexplored node $v$ which minimizes

$$\pi(v) = \min_{e = (u,v) : u \in S} d(u) + \ell_e,$$

add $v$ to $S$, and set $d(v) = \pi(v)$.

The diagram illustrates the process with a network of nodes and edges, where $s$ is the source node, $S$ is the set of explored nodes, $d(u)$ represents the shortest path distance to node $u$ from $s$, and $\ell_e$ is the weight of edge $e$. The algorithm proceeds by iteratively selecting the node $v$ that minimizes the expression $\pi(v)$ and adding it to the set of explored nodes $S$. The shortest path to some node $u$ in the explored set $S$ is then extended by a single edge $(u, v)$.
Dijkstra's algorithm.

- Maintain a set of explored nodes $S$ for which we have determined the shortest path distance $d(u)$ from $s$ to $u$.
- Initialize $S = \{ s \}$, $d(s) = 0$.
- Repeatedly choose unexplored node $v$ which minimizes
  
  $$\pi(v) = \min_{e = (u,v) : u \in S} d(u) + \ell_e,$$

  add $v$ to $S$, and set $d(v) = \pi(v)$.

![Diagram of Dijkstra's algorithm](image)
Dijkstra's Algorithm: Proof of Correctness

**Invariant.** For each node \( u \in S \), \( d(u) \) is the length of the shortest \( s-u \) path.

**Pf.** (by induction on \(|S|\))

**Base case:** \(|S| = 1\) is trivial.

**Inductive hypothesis:** Assume true for \(|S| = k \geq 1\).

- Let \( v \) be next node added to \( S \), and let \( u-v \) be the chosen edge.
- The shortest \( s-u \) path plus \((u, v)\) is an \( s-v \) path of length \( \pi(v) \).
- Consider any \( s-v \) path \( P \). We'll see that it's no shorter than \( \pi(v) \).
- Let \( x-y \) be the first edge in \( P \) that leaves \( S \), and let \( P' \) be the subpath to \( x \).
- \( P \) is already too long as soon as it leaves \( S \).

\[
\ell(P) \geq \ell(P') + \ell(x, y) \geq d(x) + \ell(x, y) \geq \pi(y) \geq \pi(v)
\]

- nonnegative weights
- inductive hypothesis
- defn of \( \pi(y) \)
- Dijkstra chose \( v \) instead of \( y \)
Dijkstra’s Algorithm: Implementation

For each unexplored node, explicitly maintain $\pi(v) = \min_{e = (u,v) : u \in S} d(u) + l_e$.

- Next node to explore = node with minimum $\pi(v)$.
- When exploring $v$, for each incident edge $e = (v, w)$, update
  $$\pi(w) = \min \{ \pi(w), \pi(v) + l_e \}.$$  

**Efficient implementation.** Maintain a priority queue of unexplored nodes, prioritized by $\pi(v)$.

<table>
<thead>
<tr>
<th>PQ Operation</th>
<th>Dijkstra</th>
<th>Array</th>
<th>Binary heap</th>
<th>d-way Heap</th>
<th>Fib heap $^\dagger$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Insert</td>
<td>$n$</td>
<td>$n$</td>
<td>$\log n$</td>
<td>$d \log_d n$</td>
<td>$1$</td>
</tr>
<tr>
<td>ExtractMin</td>
<td>$n$</td>
<td>$n$</td>
<td>$\log n$</td>
<td>$d \log_d n$</td>
<td>$\log n$</td>
</tr>
<tr>
<td>ChangeKey</td>
<td>$m$</td>
<td>$1$</td>
<td>$\log n$</td>
<td>$\log_d n$</td>
<td>$1$</td>
</tr>
<tr>
<td>isEmpty</td>
<td>$n$</td>
<td>$1$</td>
<td>$1$</td>
<td>$1$</td>
<td>$1$</td>
</tr>
<tr>
<td>Total</td>
<td>$n^2$</td>
<td>$m \log n$</td>
<td>$m \log_{m/n} n$</td>
<td>$m + n \log n$</td>
<td></td>
</tr>
</tbody>
</table>

$^\dagger$ Individual ops are amortized bounds
The question of whether computers can think is like the question of whether submarines can swim.

Do only what only you can do.

In their capacity as a tool, computers will be but a ripple on the surface of our culture. In their capacity as intellectual challenge, they are without precedent in the cultural history of mankind.

The use of COBOL cripples the mind; its teaching should, therefore, be regarded as a criminal offence.

APL is a mistake, carried through to perfection. It is the language of the future for the programming techniques of the past: it creates a new generation of coding bums.
Extra Slides
Greed is good. Greed is right. Greed works. Greed clarifies, cuts through, and captures the essence of the evolutionary spirit.

- Gordon Gecko (Michael Douglas)
Goal. Given currency denominations: 1, 5, 10, 25, 100, devise a method to pay amount to customer using fewest number of coins.

Ex: 34¢.

Cashier's algorithm. At each iteration, add coin of the largest value that does not take us past the amount to be paid.

Ex: $2.89.
Coin-Changing: Greedy Algorithm

Cashier's algorithm. At each iteration, add coin of the largest value that does not take us past the amount to be paid.

Sort coins denominations by value: \(c_1 < c_2 < \ldots < c_n\).

\[ S \leftarrow \phi \]

while \((x \neq 0)\) {
  let \(k\) be largest integer such that \(c_k \leq x\)
  if \((k = 0)\)
    return "no solution found"
  \(x \leftarrow x - c_k\)
  \(S \leftarrow S \cup \{k\}\)
}

return \(S\)

Q. Is cashier's algorithm optimal?
Coin-Changing: Analysis of Greedy Algorithm

**Theorem.** Greedy algorithm is optimal for U.S. coinage: 1, 5, 10, 25, 100.

**Pf.** (by induction on x)

- Consider optimal way to change $c_k \leq x < c_{k+1}$: greedy takes coin $k$.
- We claim that any optimal solution must also take coin $k$.
  - if not, it needs enough coins of type $c_1$, ..., $c_{k-1}$ to add up to $x$
  - table below indicates no optimal solution can do this
- Problem reduces to coin-changing $x - c_k$ cents, which, by induction, is optimally solved by greedy algorithm.

<table>
<thead>
<tr>
<th>$k$</th>
<th>$c_k$</th>
<th>All optimal solutions must satisfy</th>
<th>Max value of coins 1, 2, ..., k-1 in any OPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>$P \leq 4$</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>$N \leq 1$</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>$N + D \leq 2$</td>
<td>$4 + 5 = 9$</td>
</tr>
<tr>
<td>4</td>
<td>25</td>
<td>$Q \leq 3$</td>
<td>$20 + 4 = 24$</td>
</tr>
<tr>
<td>5</td>
<td>100</td>
<td>no limit</td>
<td>$75 + 24 = 99$</td>
</tr>
</tbody>
</table>
Observation. Greedy algorithm is sub-optimal for US postal denominations: 1, 10, 21, 34, 70, 100, 350, 1225, 1500.

Counterexample. 140¢.
- Greedy: 100, 34, 1, 1, 1, 1, 1, 1.
- Optimal: 70, 70.
Selecting Breakpoints
Selecting breakpoints.
- Road trip from Princeton to Palo Alto along fixed route.
- Refueling stations at certain points along the way.
- Fuel capacity = $C$.
- Goal: makes as few refueling stops as possible.

**Greedy algorithm.** Go as far as you can before refueling.
Selecting Breakpoints: Greedy Algorithm

Truck driver's algorithm.

Sort breakpoints so that: \( 0 = b_0 < b_1 < b_2 < \ldots < b_n = L \)

\[ S \leftarrow \{0\} \quad \text{breakpoints selected} \]
\[ x \leftarrow 0 \quad \text{current location} \]

\textbf{while} \ (x \neq b_n) \ \\
\quad \text{let} \ p \ \text{be largest integer such that} \ b_p \leq x + C \\
\quad \textbf{if} \ (b_p = x) \ \\
\quad \quad \text{return "no solution"} \\
\quad \quad x \leftarrow b_p \\
\quad \quad S \leftarrow S \cup \{p\} \\
\quad \text{return} \ S

Implementation. \( O(n \log n) \)

- Use binary search to select each breakpoint \( p \).
Selecting Breakpoints: Correctness

**Theorem.** Greedy algorithm is optimal.

**Pf.** (by contradiction)

- Assume greedy is not optimal, and let's see what happens.
- Let $0 = g_0 < g_1 < \ldots < g_p = L$ denote set of breakpoints chosen by greedy.
- Let $0 = f_0 < f_1 < \ldots < f_q = L$ denote set of breakpoints in an optimal solution with $f_0 = g_0, f_1 = g_1, \ldots, f_r = g_r$ for largest possible value of $r$.
- Note: $g_{r+1} > f_{r+1}$ by greedy choice of algorithm.
Theorem. Greedy algorithm is optimal.

Pf. (by contradiction)
- Assume greedy is not optimal, and let's see what happens.
- Let 0 = g_0 < g_1 < ... < g_p = L denote set of breakpoints chosen by greedy.
- Let 0 = f_0 < f_1 < ... < f_q = L denote set of breakpoints in an optimal solution with f_0 = g_0, f_1 = g_1, ..., f_r = g_r for largest possible value of r.
- Note: g_{r+1} > f_{r+1} by greedy choice of algorithm.

[Diagram showing comparison between Greedy and OPT solutions with timestamps and inequality relations between breakpoints.]

another optimal solution has one more breakpoint in common \[\Rightarrow\] contradiction