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 $c_j$. 
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

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 ← ∅
for \( j = 1 \) to \( n \) {
  if (job \( j \) compatible with \( A \))
    A ← A ∪ \{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 \( r \).

Greedy:

```
\( i_1 \)  \( i_2 \)  \( i_3 \)  \( i_r \)
```

\( j_{r+1} \)

OPT:

```
\( j_1 \)  \( j_2 \)  \( j_3 \)  \( j_r \)
```

job \( i_{r+1} \) finishes before \( j_{r+1} \)

why not replace job \( j_{r+1} \) with job \( i_{r+1} \)?

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.
- 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: 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.

```plaintext
Sort intervals by starting time so that s_1 ≤ s_2 ≤ ... ≤ 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.

**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 \( ⇒ \) all schedules use \( ≥ d \) 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:**

<table>
<thead>
<tr>
<th>( t_j )</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>( s_j )</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>( d_j )</td>
<td>6</td>
<td>8</td>
<td>9</td>
<td>9</td>
<td>14</td>
<td>15</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( d_j = 9 )</th>
<th>( d_j = 8 )</th>
<th>( d_j = 15 )</th>
<th>( d_j = 6 )</th>
<th>( d_j = 14 )</th>
<th>( d_j = 9 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>lateness = 2</td>
<td>lateness = 0</td>
<td>max lateness = 6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>
**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 $d_j - t_j$.

**Greedy algorithm.** Earliest deadline first.

```
Sort n jobs by deadline so that $d_1 \leq d_2 \leq ... \leq d_n$

$t \leftarrow 0$

for $j = 1$ to $n$

    Assign job $j$ to interval $[t, t + t_j]$

    $s_j \leftarrow t$, $f_j \leftarrow t + t_j$

    $t \leftarrow t + t_j$

output intervals $[s_j, f_j]$
```

**Minimizing Lateness: No Idle Time**

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

<table>
<thead>
<tr>
<th>$d_j$</th>
<th>$d_1$</th>
<th>$d_2$</th>
<th>$d_3$</th>
<th>$d_4$</th>
<th>$d_5$</th>
<th>$d_6$</th>
<th>$d_7$</th>
<th>$d_8$</th>
<th>$d_9$</th>
<th>$d_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>8</td>
<td>9</td>
<td>9</td>
<td>14</td>
<td>9</td>
<td>15</td>
<td>14</td>
<td>15</td>
<td>14</td>
<td>15</td>
</tr>
</tbody>
</table>

**Observation.** The greedy schedule has no idle time.
Minimizing Lateness: Inversions

**Def.** Given a schedule S, an inversion is a pair of jobs \(i\) and \(j\) such that:
\[i < j \text{ but } j \text{ scheduled before } i.\]

**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.

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:

\[
\ell_j' = f_j' - d_j \quad \text{(definition)}
\]
\[
= f_i - d_j \quad \text{(} j \text{ finishes at time } f_i \text{)}
\]
\[
\leq f_i - d_i \quad \text{(} i < j \text{)}
\]
\[
\leq \ell_i \quad \text{(definition)}
\]

Minimizing Lateness: Analysis of Greedy Algorithm

**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

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: $g \ a \ b \ c \ d \ a \ b \ c \ d \ e \ a \ f \ a \ d \ e \ f \ g \ h \ldots$

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.
Reduced Eviction Schedules

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

Proof. (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.

Farthest-In-Future: Analysis

Theorem. FF is optimal eviction algorithm.

Proof. (by induction on number of requests $j$)
- Consider $(j+1)$th 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.
- Case 3: $(d$ is not in the cache; $S_{FF}$ evicts $e$; $S$ evicts $f \neq e)$.

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 $S_{FF}$ 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 \( j' \).

\[
\begin{array}{c|c|c}
  j' & \text{some} & e \\ \hline
  S & \text{same} & f \\
  S' & \text{same} & \text{same} \\
\end{array}
\]

\( \text{otherwise } S' \text{ would take the same action} \)

Case 3c: \( g = e, f \). \( S \) 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.

FF with direction of time reversed!

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 network.
- Directed graph \( G = (V, E) \).
- Source \( s \), destination \( t \).
- Length \( l_e \) = length of edge \( e \).

Shortest path problem: find shortest directed path from \( s \) to \( t \).

\[
\text{Cost of path } = \text{sum of edge costs in path}
\]

shortest path from Princeton CS department to Einstein’s house

Cost of path s-2-3-5-t = 9 + 23 + 2 + 16 = 50.
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 $\pi(v)$, add $v$ to $S$, and set $d(v) = \pi(v)$.

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 $S$.

$\ell(P) \geq \ell(P') + \ell(x, y) \geq d(x) + \ell(x, y) = \pi(y) = \pi(v)$

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

---

**Coin Changing**

**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.

\[
\text{Sort coins denominations by value: } c_1 < c_2 < \ldots < c_n.
\]

\[
\text{coins selected}
\]

\[
S \leftarrow \phi
\]

\[
\text{while } (x \neq 0) \{
\]

\[
\text{let } k \text{ be largest integer such that } c_k \leq x
\]

\[
\text{if } (k = 0) \quad \text{return } "\text{no solution found}" \]

\[
x \leftarrow x - c_k
\]

\[
S \leftarrow S \cup \{k\}
\]

\[
\text{return } S
\]

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.

\[
Pf. \ (\text{by induction on } x)
\]

- 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 \( c_1, \ldots, c_{k-1} \) 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.

\[
\begin{array}{|c|c|c|c|}
\hline
k & c_k & \text{All optimal solutions must satisfy} & \text{Max value of coins } 1, 2, \ldots, k-1 \text{ in any OPT} \\
\hline
1 & 1 & P \leq 4 & - \\
2 & 5 & N \leq 1 & 4 \\
3 & 10 & N + D \leq 2 & 4 + 5 = 9 \\
4 & 25 & Q \leq 3 & 20 + 4 = 24 \\
5 & 100 & \text{no limit} & 75 + 24 = 99 \\
\hline
\end{array}
\]

Counterexample. 140¢.

- Greedy: 100, 34, 1, 1, 1, 1, 1, 1.
- Optimal: 70, 70.

Observation. Greedy algorithm is sub-optimal for US postal denominations: 1, 10, 21, 34, 70, 100, 350, 1225, 1500.

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.

Truck driver’s algorithm. 

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.

Greedy:

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

OPT:

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Why doesn’t optimal solution drive a little further?