Greedy Algorithms

Thomas Schwarz, SJ

- A given country uses a weird set of coins
	- 1, 3, 5, 8
- How do you make change with the least number of coins?
	- With these coins, it is not so obvious
	- Normally, we can just start out with the largest coin that fits, but not in this case
	- Making change for 15:
		- Use an 8, a 5 and two 1s
		- But three 5s is better

- To solve the change making problem, we can use dynamic programming
- Some notation: v_i value of coin $i, i \in \{1,...,n\}$
	- Best number of coins for change of x is
		- Best number of coins for change of $x v_1$ plus one
		- Best number of coins for change of $x v_2$ plus one
		- …
		- Best number of coins for change of $x v_n$ plus one

- To organize the calculation
	- Create a tableau
		- For row *i*, column *j*:
			- How many coins to make change for an amount of i with coins $1, \ldots, j$

• Example: Coins with values 1, 3, 5, 8 to make change of

- Example: Coins with values 1, 3, 5, 8 to make change of
- First column is easy

- Second column asks how many threes I should use
	- Example for value 10:
		- Can use none
			- Cost is 10
		- Can use one three
			- Cost is $1+7$
		- Can use two threes
			- Cost is $2+4$
		- Can use three threes
			- Cost is 3+1

- Second column asks how many threes I should use
	- Formula is

$$
\min\{T_{i-v_j\nu,j-1} + \nu \mid \nu = 0,1,...,\lfloor \frac{i}{v_i} \rfloor \}
$$

 $T_{i-v_jv,j-1}$ costs of making change of $i-\nu v_j$ with coins up to $j-1$

+*ν* costs of using *ν* coins of value *vj*

- Our alternatives are:
	- No threes: 10
	- One three: $7+1=8$
	- Two threes $4+2=6$
	- Three threes $1+3=4$

• Filling in the other values

- Now on to five
	- The first values are simple since we cannot use a five

- Now on to five
	- The first values are simple since we cannot use a five

- Now on to five
	- At value 5:
		- Can use a five
		- Can not use a five:
			- 3 coins according to previous column

- Now on to five
	- At value 6:
		- Can use 5
			- Costs: 1+1
		- Cannot use 5
			- Costs 2

- Now on to five
	- At value 8:
		- Can use 5
			- Costs: 1+1
		- Cannot use 5
			- Costs 4

- Now on to five
	- At value 9:
		- Can use 5
			- Costs: 2+1
		- Cannot use 5
			- Costs 3

- Now on to five
	- At value 10:
		- Can use two 5s
		- Can use one 5
			- \bullet Costs: 3+1
		- Can use no 5s
			- Costs 3

- Now on to five
	- At value 11:
		- Can use two 5s
			- Costs 2+1
		- Can use one 5
			- Costs: 2+1
		- Can use no 5s
			- Costs 5

- Now on to five
	- At value 12:
		- Can use two 5s
			- Costs 2+2
		- Can use one 5
			- Costs: 3+1
		- Can use no 5s
			- Costs 4

- Now on to five
	- At value 13:
		- Can use two 5s
			- Costs 2+1
		- Can use one 5
			- Costs: 4+1
		- Can use no 5s
			- Costs 5

- Now on to five
	- At value 14:
		- Can use two 5s
			- \bullet Costs 2+2
		- Can use one 5
			- Costs: 3+1
		- Can use no 5s
			- Costs 6

- Now on to five
	- At value 15:
		- Can use three 5s
			- Costs 3
		- Can use two 5s
			- Costs 2+3
		- Can use one 5
			- \bullet Costs: 4+1
		- Can use no 5s
			- Costs 5

- Now on to eights
	- At value 15:
		- Can use one eight
			- Costs $1+3$
		- Can use no eights
			- Costs: 3

- Alternative: Memoization and Recursion
	- Instead of using a tableau
		- (or rather two, one to remember the best choice)
	- Can use recursion and memoization
		- Simplest form:
			- What was the last coin that was added
				- It has to be one of the coins: e.g. 1, 3, 5, or 8
				- The costs are the cost of making change for the amount minus the value of the coin plus one for the coin itself

- Alternative: Memoization and Recursion
	- Recursion

 $c(n) = \min\{c(n - v_i) + 1\}$

- where the minimum is taken over all different coin values
- We also write the coin which causes the minimum to be selected

- For memoization in Python:
	- have a global dictionary for the costs and the best choice of coin (last_coin)
	- Also, add the values of the coins in a list

```
last coin = \{0:0\}costs = {0:0}values = [1, 3, 5, 7, 8]
```
• Here is very simple Python code

```
def getChange(n): 
     if n in costs: 
         return costs[n] 
    best = 100000bestcoin = 0 for x in range(len(values)): 
         if values[x] > n: 
             break 
        alternativeCost = getChange(n-values[x])+1 if alternativeCost < best: 
             best = alternativeCost 
            bestcoin = values[x]costs[n] = bestlast coin[n] = bestcoin return best
```
• And here is the output • Amount to make change for • Number of coins needed • Last coin used • Example: • For 20, use a 5, left 15 • For 15, use a 7, left 8 • For 8, use 8

- But we do not have this problem with normal coin sets
	- US\$-cents: 1, 5, 10, 25, 100
	- Euro-cents: 1, 5, 10, 20, 50, 100, 200

- Cashier's Algorithm
	- Always select the largest coin smaller or equal the current amount
	- Will not always work
		- Another example: US Postage Stamps before forever
			- 1, 5, 25, 32, 100
			- Make change for 121
				- Cashier's algorithm: 100+5+5+5+5+1
				- Better choice 32+32+32+25

- But sometimes the Cashier's Algorithm is the best
	- Assume that we have coins of 1, 5, 10, 20, and 50
	- Proof by induction that the cashier's algorithm always give the best change
	- Represent the change as an array
		- Coefficient *i* of array: number of *i*-th coins
		- Example:

$$
\begin{array}{|c|c|c|c|}\n\hline\n1 & 5 & 10 & 20 & 50 \\
\hline\n3 & 2 & 4 & 8 & 0\n\end{array}
$$

• one way of making change for 213

- Proof:
- Assume $C = [c_1, c_5, c_{10}, c_{20}, c_{50}]$ is the result of the cashier's algorithm for an amount of

$$
c_1 + c_5 \cdot 5 + c_{10} \cdot 10 + c_{20} \cdot 20 + c_{50} \cdot 50
$$

• Assume $A = [a_1, a_5, a_{10}, a_{20}, a_{50}]$ is an alternative with less coins for the same amount

$$
a_1 + a_5 \cdot 5 + a_{10} \cdot 10 + a_{20} \cdot 20 + a_{50} \cdot 50
$$

but

 $a_1 + a_5 + a_{10} + a_{20} + a_{50} < c_1 + c_5 + c_{10} + c_{20} + c_{50}$

- Proof:
- Want to show that $A = C$.

- Proof:
	- Lemma 1: An optimal solutions has not more than four pennies
		- Otherwise replace with a 5 cent piece
	- Lemma 2: An optimal solution has not more than one 10 cent piece
		- Otherwise replace with a 20 cent piece
	- Lemma 3: An optimal solution cannot have two twenty cent pieces and one 10 cent piece
		- Otherwise replace with a 50 cent piece

- Proof:
	- Lemma 5: Maximum number of pennies in an optimal solution is four
		- Follows from Lemma 1
	- Lemma 6: If the optimal solution has only pennies and five cents, then the amount is at most nine
		- Follows from Lemma 2 and Lemma 5

- Lemma 7: The maximum amount for an optimal solution with only pennies, 5 cent and 10 cent pieces is 19
- Lemma 8: The maximum amount for an optimal solution with only 1 cent, 5 cent, 10 cent, and 20 cent pieces is 49

- Proof:
	- Assume that the number of 50 cent coins in A and C differ.
	- Because of how C is defined, the number of 50 cent coins in A has to be lower $a_{50} < c_{50}$.
	- However, the difference needs to be made up with coins of smaller value
	- But an optimal solution cannot have more than 49 cents in smaller coins
-

• Contradiction

• Proof:

• Et cetera

- So, the number of 50 cent coins does not differ
	- If there are x 50 cent coins, then look at the best solution for amount- x coins.
	- C and A with the 50 cent coins removed are still two different solutions for the same amount
- Now apply the same argument to the 20 cent coins.

- We call the cashier's algorithm a *greedy algorithm*:
	- We solve the problem by going to a smaller problem
		- E.g. Making change for 134 cents.
		- Lay out 50 cents
		- Making change for 84 cents.
		- …
	- At each step, we select something optimal

Greedy Algorithms

- Many algorithms run from stage to stage
	- At each stage, they make a decision based on the information available
- A Greedy algorithm makes decisions
	- At each stage, using locally available information, the greedy algorithm makes an optimal choice

- Sometimes, greedy algorithms give an overall optimal solution
- Sometimes, greedy algorithms will not result in an optimal solution but often in one good enough

Divisible Items Knapsack Problem

- Given a set of items *S*
	- Each item has a weight *w*(*x*)
	- Each item has a value $v(x)$
- Select a subset *M* ⊂ *S*
	- Constraint:

$$
\sum_{x \in M} w(x) < W
$$

Objective Function:

$$
\sum_{x \in M} v(x) \longrightarrow \max
$$

Divisible Items Knapsack Problem

- Order all items by impact
	- \bullet **impact** $(x) =$ *v*(*x*) *w*(*x*)
- In order of impact (highest first), ask whether you want to include the item
	- And you include it if the sum of the weights of the items already selected is smaller than *W*

- Set of activities $S = \{a_1, a_2, ..., a_n\}$
	- Each activity has a start time and a finish time
		- $0 \le s_i < f_i < \infty$
	- Each activity needs to use your facility
	- Only one activity at a time
	- Make the rental agreements that maximize the number of rentals

- Two activities a_i and a_j are compatible if
	- $[s_i, f_i) \cap [s_j, f_j] = \emptyset$

• This means that activity $i < j$ finishes before activity j

• A compatible set is $\{A_1, A_5, A_8, A_{10}\}$

• Another compatible set is $\{A_3, A_9\}$

- Optimal rental with a dynamic programming algorithm
	- Subproblems: Define S_{ik} to be the set of activities that start after a_i finishes and finish before a_k starts

$$
S_{1,8} = \{a_5\}
$$

- We want to find an optimal rental plan for *Sik*
	- Assume that there is an optimal solution that contains activity $a_j \in S_{i,k}$
	- By selecting a_j , we need to decide what to do with the time before $\vec{a_j}$ starts and after $\vec{a_j}$ finishes
	- These sets are S_{ij} and S_{jk}

- Assume that a_j is part of an optimal solution $A_{i,k}$ for $S_{i,k}$
	- Then $A_{i,k}$ is divided into the ones that end before a_j and the ones that start after *aj*

•
$$
A_{i,j} = A_{i,k} \cap S_{i,k} \quad A_{j,k} = A_{i,k} \cap S_{j,k}
$$

$$
A_{i,k} = A_{i,j} \cup \{a_j\} \cup A_{j,k}
$$

- Clearly, $A_{i,j}$ is an optimal solution for $S_{i,j}$
- $A_{j,k}$ is an optimal solution for $S_{j,k}$
- For if not, we could construct a better solution for *Si*,*k*

- We can therefore solve recursively the problem for $S_{i,k}$ by looking at all possible activities for *aj*
	- Define $C[i, k] =$ Max number of compatible activities in *Si*,*k*
	- Then:

 $C[i, k] = \max(0, \max(C[i, j] + C[j, k] + 1 | a_i \in S_{i,k}))$

• The 0 is necessary because there might be no activity in $S_{i,k}$

• The recursion leads to a nice dynamic programming problem

$$
C[i, k] = \max(0, \max\left(C[i, j] + C[j, k] + 1 \, | \, a_j \in S_{i,k}\right))
$$

• But can we do better?

- Start out with the initial problem
	- Select the activity that finishes first
		- this would be a_1
	- This leaves most space for all other activities
		- Call S_1 the set of activities compatible with a_1
			- These are those starting after a_1
		- Similarly, call S_k the set of activities starting after a_k

- Theorem: For any non-empty problem S_k let a_m be the activity with the smallest end time. Then a_m is contained in an optimal solution
- Proof:
	- Let A_k be a solution
		- \bullet i.e. the maximum sized compatible subset in S_k
		- Let $a_1 \in A_k$ be the activity with earliest finish time
		- If $a_m = a_1$ then we are done

- Theorem: For any non-empty problem S_k let a_m be the activity with the smallest end time. Then a_m is contained in an optimal solution
- Proof:
	- Otherwise replace a_1 with a_m in A_k

•
$$
A'_k = A_k - \{a_1\} \cup \{a_m\}
$$

- Since a_m is the first to finish, this is a set of compatible activities
- Therefore, there exists an optimal solution with a_m

- Result of the Theorem:
	- We can find an optimal solution (but not necessarily all optimal solutions) by always picking the first one to finish.

• Example

- Select a_1
- Exclude a_2 , a_3 , and a_4 as incompatible
- Choose a_5 , a_8 , and a_{10} for the complete solution

Greedy Algorithms

- Greedy algorithms
	- Determine the optimal substructure
	- Develop a recursive solution
	- Show that making the greedy choice is best
	- Show that making the greedy choice leads to a similar subproblem
	- Obtain a recursive algorithm
	- Convert the recursive algorithm to an iterative algorithm