

Dynamic Programming: Change Problem

Change problem

Input: An integer `money` and positive integers `coin[1], ..., coin[d]`

Output: The minimum number of coins with denominations `coin[1], ..., coin[d]` that changes `money`

Greedy algorithm picks the largest denomination available that does not exceed `money`.

```
GreedyChange(money) :  
Change <- empty collection of coins  
while money > 0:  
    coin <- largest denomination that does not exceed money  
    add coin to Change  
    money <- money - coin  
return Change
```

Recursive algorithm picks the denominations which yields the minimum number of coins used. For example, there are 9 cents given denominations 6, 5, and 1. We can have $3 + 6$, $4 + 5$ or $8 + 1$. Pick one that `money - coin[i]` requires the minimum number of coins used. In mathematics,

$$\text{MinNumCoins}(9) = \min \begin{cases} \text{MinNumCoins}(9 - 6) + 1 \\ \text{MinNumCoins}(9 - 5) + 1 \\ \text{MinNumCoins}(9 - 1) + 1 \end{cases}$$

In general,

$$\text{MinNumCoins}(\text{money}) = \min \begin{cases} \text{MinNumCoins}(\text{money} - \text{coin}[1]) + 1 \\ \text{MinNumCoins}(\text{money} - \text{coin}[2]) + 1 \\ \dots \\ \text{MinNumCoins}(\text{money} - \text{coin}[d]) + 1 \end{cases}$$

```
RecursiveChange(money, coins):  
if money = 0:  
    return 0  
MinNumCoins <- infinity  
for i from 1 to len(coins):  
    if money >= coin[i]:  
        NumCoins <- RecursiveChange(money - coin[i], coins)  
        if NumCoins + 1 < MinNumCoins:  
            MinNumCoins <- NumCoins + 1  
return MinNumCoins
```

Dynamic programming loops through each dollar. For each dollar, dynamic programming looks up the coins used by each possible coins, and records the best solution.

```
DPChange(money, coins):
MinNumCoins(0) <- 0
for m from 1 to money:
    MinNumCoins[m] <- infinity
    for i from 1 to len(coins):
        if m >= coin[i]:
            NumCoins <- MinNumCoins(m - coin[i]) + 1
            if NumCoins < MinNumCoins[m]:
                MinNumCoins[m] <- NumCoins
return MinNumCoins(money)
```

Dynamic Programming: String comparison

Alignment

An alignment of two strings is a two-row matrix:

1st row: symbols of the 1st string (in order) interspersed by "-"

2nd row: symbols of the 2nd string (in order) interspersed by "-"

Alignment score

Premium for every match (+1), and penalty for every mismatch ($-\mu$), indel ($-\sigma$).

Optimal alignment

Input: Two strings, mismatch penalty μ , and indel penalty σ .

Output: An alignment of the strings maximizing the score.

Longest common subsequence

Input: Two strings

Output: A longest common subsequence of these strings

Remark: It corresponds to maximizing the score of an alignment with $\mu = \sigma = 0$

Edit distance

Input: Two strings.

Output: The minimum number of operations (insertions, deletions, and substitutions of symbols) to transform one string into another.

Remark: Maximizing alignment score = maximizing edit distance

Suppose we want to transform A to B . Let $D(i, j)$ be the edit distance of an i -prefix $A[1...i]$ and a j -prefix $B[1...j]$.

$$D(i, j) = \min \begin{cases} D(i, j-1) + 1 \\ D(i-1, j) + 1 \\ D(i-1, j-1) + 1, A[i] \neq B[j] \\ D(i-1, j-1), A[i] = B[j] \end{cases}$$

```

EditDistance(A[1...n], B[1...m]):
D(i, 0) <- i and D(0, j) <- j for all i, j
for j from 1 to m:
    for i from 1 to n:
        insertion <- D(i, j - 1) + 1
        deletion <- D(i - 1, j) + 1
        match <- D(i - 1, j - 1)
        mismatch <- D(i - 1, j - 1) + 1
        if A[i] == B[j]:
            D(i, j) <- min(insertion, deletion, match)
        else:
            D(i, j) <- min(insertion, deletion, mismatch)
return D(n, m)

```

```

OutputAlignment(i, j):
if i == 0 and j == 0:
    return
if i > 0 and D(i, j) == D(i - 1, j) + 1:
    OutputAlignment(i - 1, j)
    print (A[i], '-')
else if j > 0 and D(i, j) == D(i, j - 1) + 1:
    OutputAlignment(i, j - 1)
    print('-', B[j])
else:
    OutputAlignment(i - 1, j - 1)
    print(A[i], B[j])

```

Dynamic Programming: Knapsack

Knapsack with repetitions problem

Input: Weights w_1, \dots, w_n and values v_1, \dots, v_n of n items; total weight W (v_i 's, w_i 's, and W are non-negative integers)

Output: The maximum value of items whose weight does not exceed W . Each item can be used any number of times.

```

Knapsack(W):
value[0] <- 0
for w from 1 to W:
    value[w] <- 0
    for i from 1 to n:
        if w[i] <= w:
            val <- value[w - w[i]] + v[i]
            if val > value[w]:
                value[w] <- val
return value[W]

```

Subproblem

Let $\text{value}[w]$ be the maximum value of knapsack of weight w .

$$\text{value}[w] = \max_{i:w_i \leq w} \{\text{value}[w - w_i] + v_i\}$$

Explanation: For each possible capacity up to W , all items which can be put into the knapsack are considered. We need to compare the current value of knapsack $\text{value}[w]$ and the optimal value of knapsack in previous step $\text{value}[w - w[i]]$ plus the corresponding item's value $v[i]$.

Knapsack without repetitions problem

Input: Weights w_1, \dots, w_n and values v_1, \dots, v_n of n items; total weight W (v_i 's, w_i 's, and W are non-negative integers)

Output: The maximum value of items whose weight does not exceed W . Each item can be used at most once.

```

Knapsack(W):
initialize all value[0, j] <- 0
initialize all value[w, 0] <- 0
for i from 1 to n:
    for w from 1 to W:
        value[w, i] <- value[w, i - 1]
        if w[i] <= w:
            val <- value[w - w[i], i - 1] + v[i]
            if value[w, i] < val:
                value[w, i] <- val
return value[W, n]

```

Subproblem

Let $\text{value}[w, i]$ be the maximum value of knapsack of weight w and items $1, \dots, i$.

$$\text{value}[w, i] = \max\{\text{value}[w - w_i, i - 1] + v_i, \text{value}[w, i - 1]\}$$

Explanation: Compare the previous optimal solution with weight $w - w_i$ and the value of item i with the value of doing nothing $\text{value}[w, i - 1]$.

To back trace the past, we need to compare $\text{value}[w - w_i, i - 1] + v_i$ and $\text{value}[w, i - 1]$, starting from the optimal value.

Memoization

```
Knapsack(w):
    if w is in hash table:
        return value[w]
    value[w] <- 0
    for i from 1 to n:
        if w[i] <= w:
            val <- Knapsack(v - w[i]) + v[i]
            if val > value[w]:
                value[w] <- val
    insert value[w] into hash table with key w
    return value[w]
```

The running time $O(nW)$ is not polynomial since the input size is proportion to $\log(W)$, but not W . In other words, the running time is $O(n2^{(\log W)})$ because the size of integer is represented in terms of $\log(W)$.

<https://stackoverflow.com/questions/4538581/why-is-the-knapsack-problem-pseudo-polynomial#answer-4538668>

Dynamic Programming: Placing Parentheses

Example: How to place parentheses in an expression $1 + 2 - 3 \times 4 - 5$ to maximize its value?

$$((((1 + 2) - 3) \times 4) - 5) = -5$$

$$((1 + 2) - ((3 \times 4) - 5)) = -4$$

$$((1 + 2) - (3 \times (4 - 5))) = 6$$

Placing parentheses

Input: A sequence of digits d_1, \dots, d_n and a sequence of operations $op_1, \dots, op_{n-1} \in \{+, -, \times\}$

Output: An order of applying these operations that maximizes the value of the expression $d_1 op_1 d_2 op_2 \dots op_{n-1} d_n$.

Subproblems

Let $E_{i,j}$ be the subexpression: $d_i op_i \dots op_{j-1} d_j$.

Let $M(i, j)$ be the maximum value of $E_{i,j}$ and $m(i, j)$ be the minimum value of $E_{i,j}$

$$M(i, j) = \max_{i \leq k \leq j-1} \begin{cases} M(i, k) \text{ op}_k M(k+1, j) \\ M(i, k) \text{ op}_k m(k+1, j) \\ m(i, k) \text{ op}_k M(k+1, j) \\ m(i, k) \text{ op}_k m(k+1, j) \end{cases}$$

$$m(i, j) = \min_{i \leq k \leq j-1} \begin{cases} M(i, k) \text{ op}_k M(k+1, j) \\ M(i, k) \text{ op}_k m(k+1, j) \\ m(i, k) \text{ op}_k M(k+1, j) \\ m(i, k) \text{ op}_k m(k+1, j) \end{cases}$$

```

MinAndMax(i, j):
max <- Inf
min <- -Inf
for k from i to j - 1:
    a <- M(i, k) op[k] M(k + 1, j)
    b <- M(i, k) op[k] m(k + 1, j)
    c <- m(i, k) op[k] M(k + 1, j)
    d <- m(i, k) op[k] m(k + 1, j)
    min <- min(min, a, b, c, d)
    max <- max(max, a, b, c, d)
return (min, max)

```

When computing $M(i, j)$, the values of $M(i, k)$ and $M(k + 1, j)$ should already be computed. Solve all subproblems in order of increasing $j - i$.

```

Parentheses(d[1]op[1]d[2]op[2]...d[n]):
for i from 1 to n:
    m(i, i) <- d[i], M(i, i) <- d[i]
for s from 1 to n - 1:
    for i from 1 to n - s:
        j <- i + s
        m(i, j), M(i, j) <- MinAndMax(i, j)
return M(1, n)

```