

## Part 7

### Dynamic Programming Algorithm Description

To solve the knapsack problem using dynamic programming, I define a 2D table  $dp[i][w]$ , where  $i$  represents the number of experiments considered and  $w$  is the current weight capacity. Each cell  $dp[i][w]$  stores the maximum rating achievable using the first  $i$  experiments without exceeding weight  $w$ .

The algorithm works as follows:

#### 1. Initialization:

Set  $dp[0][w] = 0$  for all  $w$  from 0 to 700. This represents the case where no experiments are selected.

#### 2. Iteration:

For each experiment  $i$  from 1 to  $n$ , and for each weight  $w$  from 0 to 700:

- If the experiment's weight is more than  $w$ , we cannot include it:  
 $dp[i][w] = dp[i-1][w]$
- Otherwise, we choose the better of:
  - Excluding the experiment:  $dp[i-1][w]$
  - Including it:  $dp[i-1][w - \text{weight}[i]] + \text{rating}[i]$

#### 3. Result:

The final answer is stored in  $dp[n][700]$ , which gives the maximum rating achievable. We then backtrack through the table to find the subset of experiments that were selected.

## Part 8:

### Dynamic Programming Implementation Report

I implemented the dynamic programming solution in Java using a 2D array  $dp[i][w]$  to store the maximum rating for each weight capacity. Each experiment is represented by a class with fields for name, weight, and rating. After filling the DP table, I used backtracking to identify the selected experiments.

Java Code Summary:

- **Class:** Experiment stores name, weight, and rating.
- **DP Table:**  $dp[i][w]$  is a 2D array storing max ratings.

- **Backtracking:** After filling the table, we trace back to find which experiments were selected.

**Output:**

☒ **Maximum Rating Achieved:** 43

- **Selected Experiments:**

- Micrometeorites (170 kg, 9)
- Cosmic Rays (80 kg, 7)
- Mice Tumors (65 kg, 8)
- Relativity (104 kg, 8)
- Cloud Patterns (36 kg, 5)
- Seed Viability (7 kg, 4)
- Yeast Fermentation (27 kg, 4)

- **Total Weight Used:** 489 kg

Code Flexibility:

This implementation can be adapted to accept arbitrary rating functions by modifying the Experiment class to include a method such as `getAdjustedRating()`, which computes the rating dynamically based on user-defined logic.

**Part 9:**

## Walkthrough and Debugging Strategy

The DP table is initialized with zeros. For each experiment, we iterate through all weight capacities from 0 to 700. If the experiment fits, we update the table with the maximum of including or excluding it.

Example:

- After processing "Cloud Patterns" (36 kg, 5 rating), all weights  $\geq 36$  have a value of 5.
- After adding "Micrometeorites" (170 kg, 9 rating), weights  $\geq 170$  are updated to reflect the best combination of "Cloud Patterns" and "Micrometeorites".

Backtracking:

Starting from `dp[12][700]`, we trace back:

- If  $dp[i][w] \neq dp[i-1][w]$ , experiment i was included.
- We subtract its weight from w and continue.

#### Memory Considerations:

The current implementation uses a 2D array of size  $12 \times 701$ , which is approximately 8,400 integers (~33 KB). This is efficient for small datasets. For larger datasets, we can optimize to a 1D array:

```
int[] dp = new int[MAX_WEIGHT + 1];
```

#### Debugging Strategy:

1. Method 1: Print the DP Table
2. Print the values during execution to see how ratings are calculated. This helps verify that the table is filled correctly.
3. Method 2: Trace Backtracking
4. Print each experiment as it is selected during backtracking. This confirms that the final subset matches the expected rating.
5. Method 3: Use Smaller Test Cases
6. Run the algorithm with a smaller weight limit (e.g., 100 kg) and fewer experiments to manually verify the output.
7. Method 4: Graphical Visualization (Optional)
8. Export the DP table to a CSV file and visualize it using Excel or Python. A heatmap or line chart can show how ratings increase with weight.