Compare the performances of greedy, backtracking, dynamic programming, and brute-force approach to solve 0/1 knapsack problem.

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## Abstract:

A knapsack is a sack or bag that can be filled up to the given maximum weight. Here, each of the object have some value (i.e. worth) and some weight. Also, these objects are indivisible. So, we can't divide the object into its fractional parts accordingly to fill the sack. This is the reason why we give the name 0/1 knapsack, which means '0' indicates that the particular object is not taken and '1' indicates that the particular object is taken in the sack (like we use in digital logics). Our aim is to fill the sack such that we get the maximum profit(value) and the weight of all the objects that are taken should be less than are equal to the maximum capacity of the bag (i.e. maximum weight capacity). In mathematical terms,

Maximum( $\Sigma$ pixi) and  $\Sigma$ wixi <= W

Where,

pi = The profit of that particular object.

wi = The weight of that particular object.

xi = 1 or 0(i.e., object is taken or left behind respectively)

W = Maximum weight capacity of the sack.

For example, let us consider a situation where we need to pack a bag such that the contents provide maximum value without exceeding our bag's capacity. We assume that we have a Knapsack that can hold at most 5 Kgs and have the following items.

| THINGS     | VALUE | WEIGHT |
|------------|-------|--------|
| Clock      | 450   | 0.5 Kg |
| Painting   | 500   | 0.5 Kg |
| Radio      | 1250  | 1 Kg   |
| Laptop     | 45000 | 2 Kgs  |
| Grinder    | 5000  | 2 Kgs  |
| DVD Player | 5000  | 1 Kg   |

To solve this problem, we use different kinds of algorithms like backtracking, greedy, dynamic programming, brute-force etc.

The main goal is to present the comparative study of the approaches to find the performance of the different algorithms used to solve the 0/1 Knapsack problem, based on the time complexity of each algorithm.

### AIM:

To compare the performances of greedy, backtracking, dynamic programming, and brute-force approach to solve 0/1 knapsack problem.

## **APPLICABILITY:**

The knapsack problem can be widely applied in:

- 1. Resource Allocation
- 2. Job Scheduling
- 3. Capital Budgeting
- 4. Investment Decisions
- 5. Project Selection

# The proposed application is using knapsack in a startup company.

The initial investment is taken to be the maximum weight and the stock items have their own individual price(weight) and their own profit(value).

So being a member of the start up company, we need to utilize the initial investment in the best way possible by buying those stock items such that we get maximum profit.

Here we use the 0/1 knapsack problem and solve the issue such that the company benefits maximum from it.

In today's world where everyone is on a look out to start something new, something of their own, it is essential to have proper planning on what to invest on such that they benefit maximum from it. People invest a good amount but some end up with losses since they were unable to decide on the right stocks to invest on.

Since there is a large database available, it is also required to use an algorithm that works fast and efficiently. Hence, we compare the working of the four algorithms and find out the best algorithm in order to solve the above application of knapsack.

## **INTRODUCTION:**

In our program, we take-

Maximum weight: Initial Investment

Individual weights: Individual prices of the stock items

Individual values: Individual profits on selling the stock items.

So, our aim is to get maximum profit by using our investment wisely.

The program uses the concept of data structures as well as algorithms.

To solve the knapsack, we use the concept of queues and linked list data structures and do dynamic programming in order to get maximum profit for the company.

The comparison of the algorithms is the concept derived from algorithms where we compare the time taken to compile (time complexity) when the data is passed using brute force, dynamic programming, greedy and back tracking approaches.

While we do this, we find out that **dynamic programming is the fastest** and the most efficient way of solving the knapsack problem due to the least time taken to compile.

We have various member functions in order to add stock items, display stock items, delete stock items, alter the price or the profit of a stock item and so on, adding functionality to our program.

## EXISTING METHODS AND THEIR DRAWBACKS:

#### 1. THE BRUTE FORCE APPROACH

Brute force is a straightforward approach to solving a problem, usually directly based on the problem's statement and definitions of the concepts involved.

#### Algorithm:

- If there are n items to choose from, then there will be 2^n possible combinations of items for the knapsack.
- An item is either chosen or not chosen.
- A bit string of 0's and 1's is generated which is of length n.
- If the ith symbol of a bit string is 0, then the ith item is not chosen and if it is 1, the ith item is chosen.

#### **DRAWBACKS:**

- Rarely yields efficient algorithms
- Some brute-force algorithms are unacceptably slow
- Not as constructive as some other design techniques

Complexity: O(N\*2^N)

#### 2. GREEDY ALGORITHM

- In this approach, we first sort items by worth density, in descending order.
- Then we start with the highest worth item. Next, we put items into the bag until the next item on the list cannot fit.
- Then we try to fill the remaining capacity with any of the remaining items on the list that can fit.
- The greedy algorithm doesn't improve upon the solution it returns. It simply adds the next highest worth item it can to the bag.

### DRAWBACK:

- Hard to design: Once you have found the right greedy approach, designing greedy algorithms can be easy. However, finding the right approach can be hard.
- Hard to verify: Showing a greedy algorithm is correct often requires a nuanced argument.

Complexity : O(NlogN) + O(N) = O(NlogN)

## 3. BACKTRACKING APPROACH

The idea of backtracking is to construct solutions one component at a time and evaluate such partially constructed solutions. This partially constructed solution can be developed further without violating the problem constraints.

#### Algorithm:

- It is convenient to implement this kind of processing by constructing a tree of choices being made called the "State Space Tree".
- Its root represents an initial state before the search for the solution begins.
- The nodes of the first level in the tree represent the choices for the first component of a solution and the nodes of a second level represent the choices for the second component and so on.
- A node in the state space tree is promising if it corresponds to the partially constructed solution that may lead to the complete solution otherwise the nodes are called non-promising.
- Leaves of the tree represent either the non- promising dead end or complete solution found by the algorithm.

#### DRAWBACKS:

- One is thrashing, i.e., repeated failure due to the same reason. Thrashing occurs
  because the standard backtracking algorithm does not identify the real reason of the
  conflict, i.e., the conflicting variables. Therefore, search in different parts of the
  space keeps failing for the same reason. Thrashing can be avoided by intelligent
  backtracking, i.e., by a scheme on which backtracking is done directly to the variable
  that caused the failure.
- The other drawback of backtracking is having to perform redundant work. Even if the
  conflicting values of variables is identified during the intelligent backtracking, they
  are not remembered for immediate detection of the same conflict in a subsequent
  computation. However, there is a backtracking based method that eliminates both of
  the above drawbacks of backtracking. This method is traditionally called
  dependency-directed backtracking and is used in truth maintenance systems.
- It should be noted that using advanced techniques adds other expenses to the algorithm that has to be balanced with the overall advantage of using them.

### PROPOSED METHOD:

#### DYNAMIC PROGRAMMING

- Firstly, a dynamic programming bag packing solution enumerates the entire solution space with all possibilities of item combinations that could be used to pack our bag. Where a greedy algorithm chooses the most optimal local solution, dynamic programming algorithms are able to find the most optimal global solution.
- Secondly, dynamic programming uses memorization to store the results of previously computed operations and returns the cached result when the operation occurs again. This allows it to "remember" previous combinations. This takes less time than it would to recompute the answer again.

Dynamic Programming solves each of the smaller subproblems only once and records the results in a table rather than solving overlapping subproblems over and over again. The table is then used to obtain a solution to the original problem. The classical dynamic programming approach works bottom-up.

## Algorithm:

- Create a matrix representing all subsets of the items (the solution space) with rows representing items and columns representing the bag's remaining weight capacity
- Loop through the matrix and calculate the worth that can be obtained by each combination of items at each stage of the bag's capacity
- Examine the completed matrix to determine which items to add to the bag in order to produce the maximum possible worth for the bag in total.

In terms of memory, Dynamic Programming requires a two-dimensional array with rows equal to the number of items and columns equal to the capacity of the knapsack. This algorithm is probably one of the easiest to implement because it does not require the use of any additional structures.

Keywords: int, for, if, new, sizeof, return, strlen.

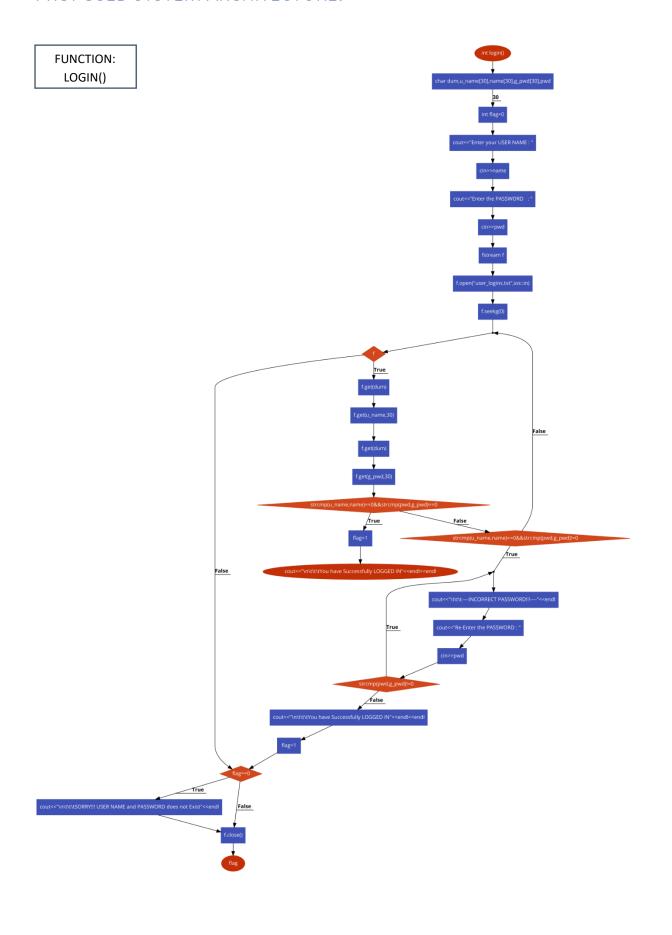
#### **ADVANTAGES:**

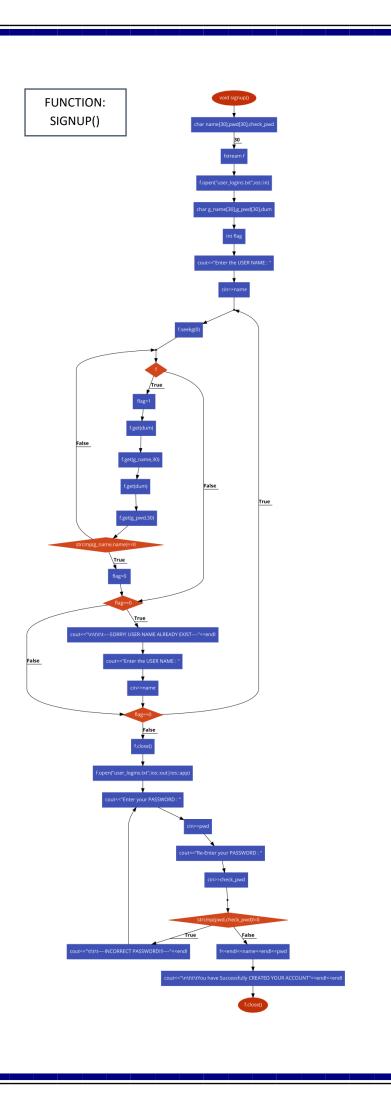
Dynamic programming means that you sort of have efficient access to already computed results for your algorithm inputs. Ideally, you may find a special order in which to perform the sub-problems computations, so that you don't have to remember much (and also eliminate any complicated searches for the results).

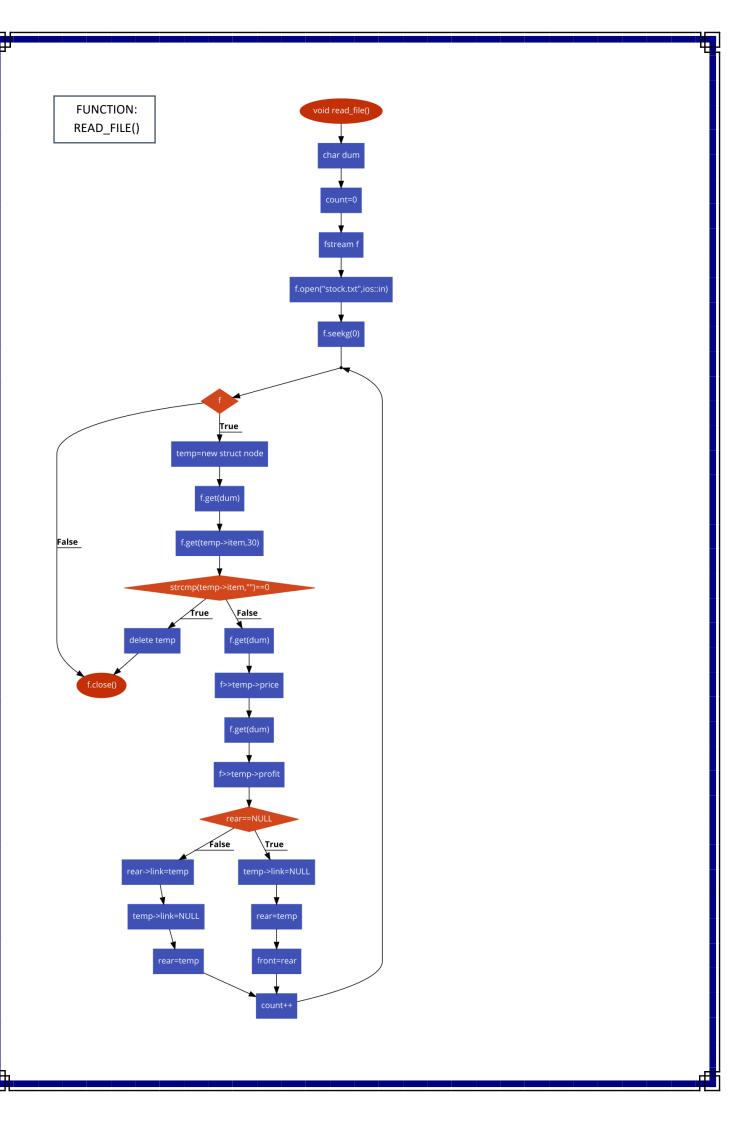
So, in short, dynamic programming has the advantage of **much greater efficiency** (where the simple divide-et-impera method would re-compute sub-problems solutions).

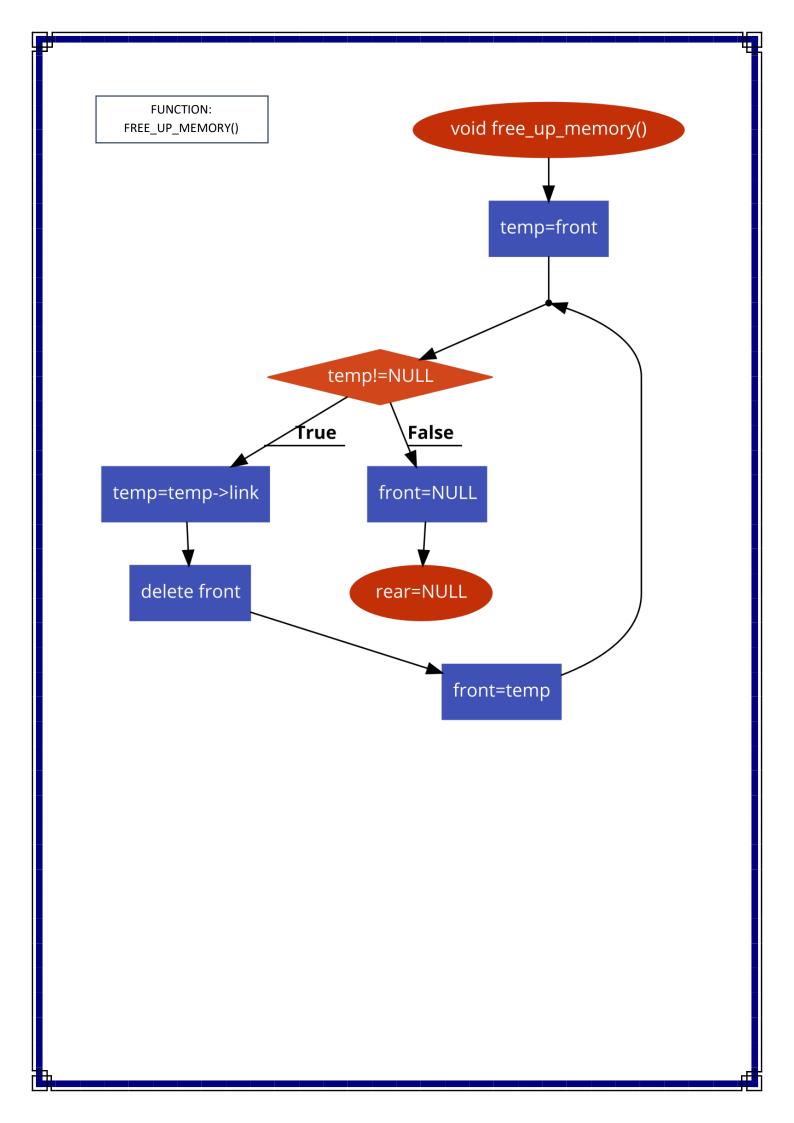
Complexity = O (N\*Capacity)

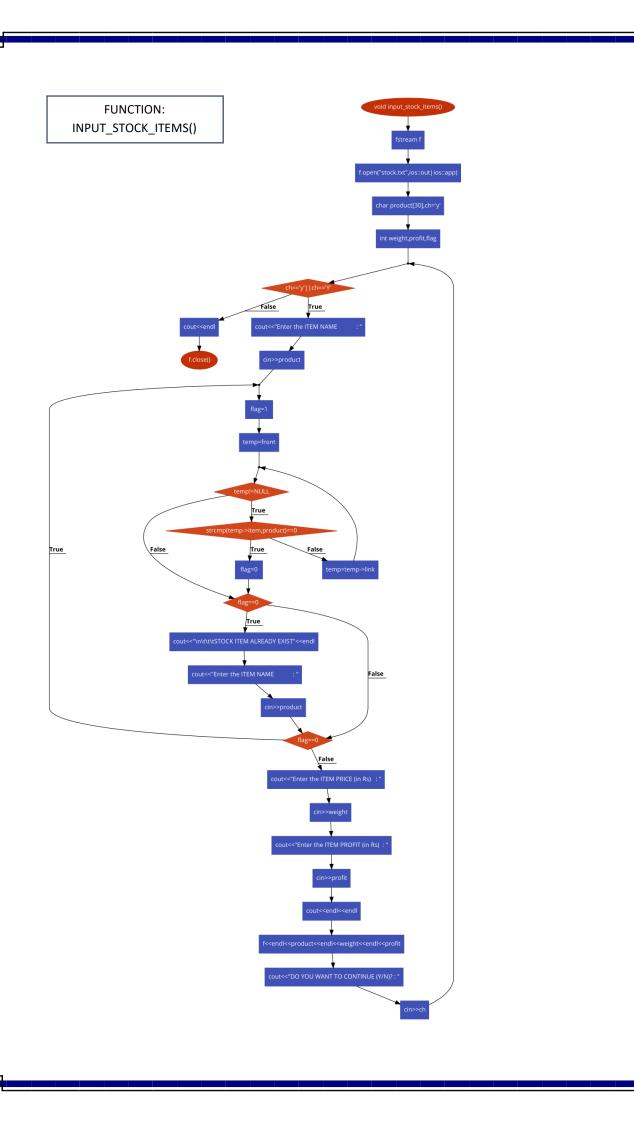
# PROPOSED SYSTEM ARCHITECTURE:

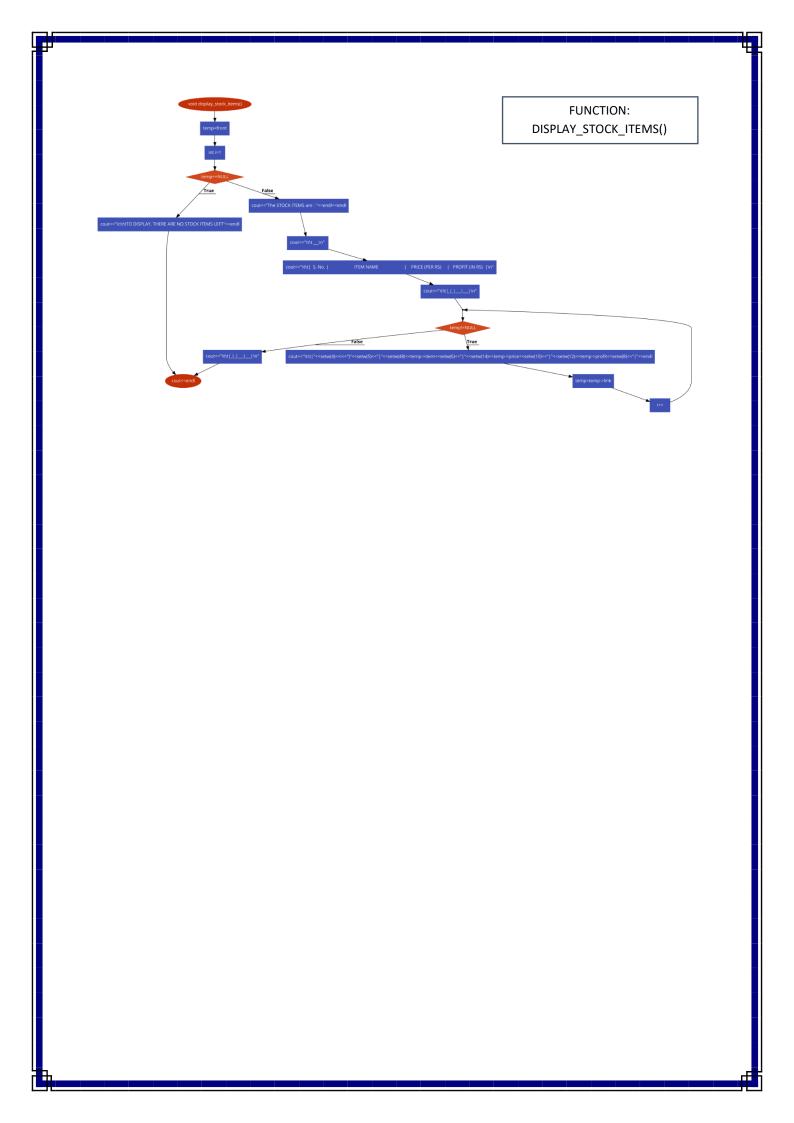


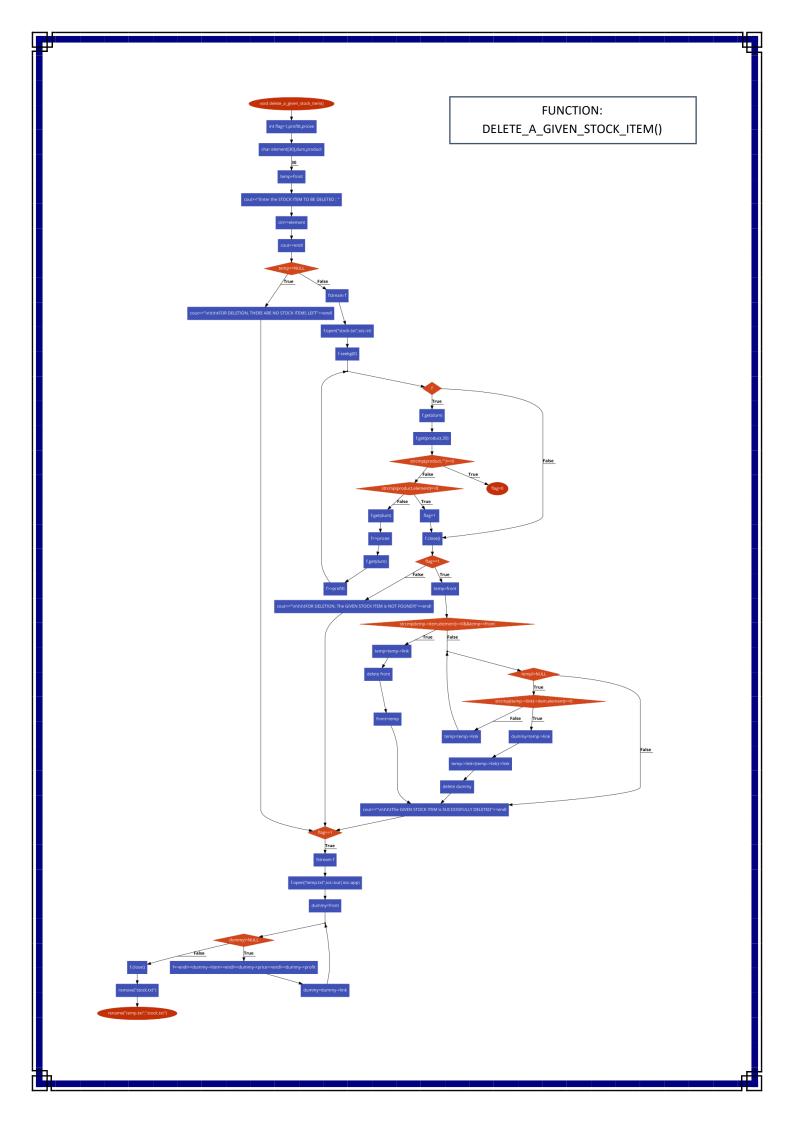


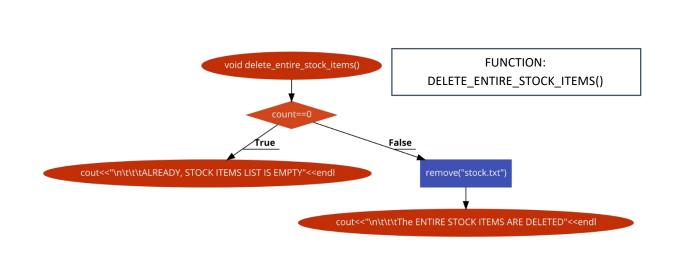


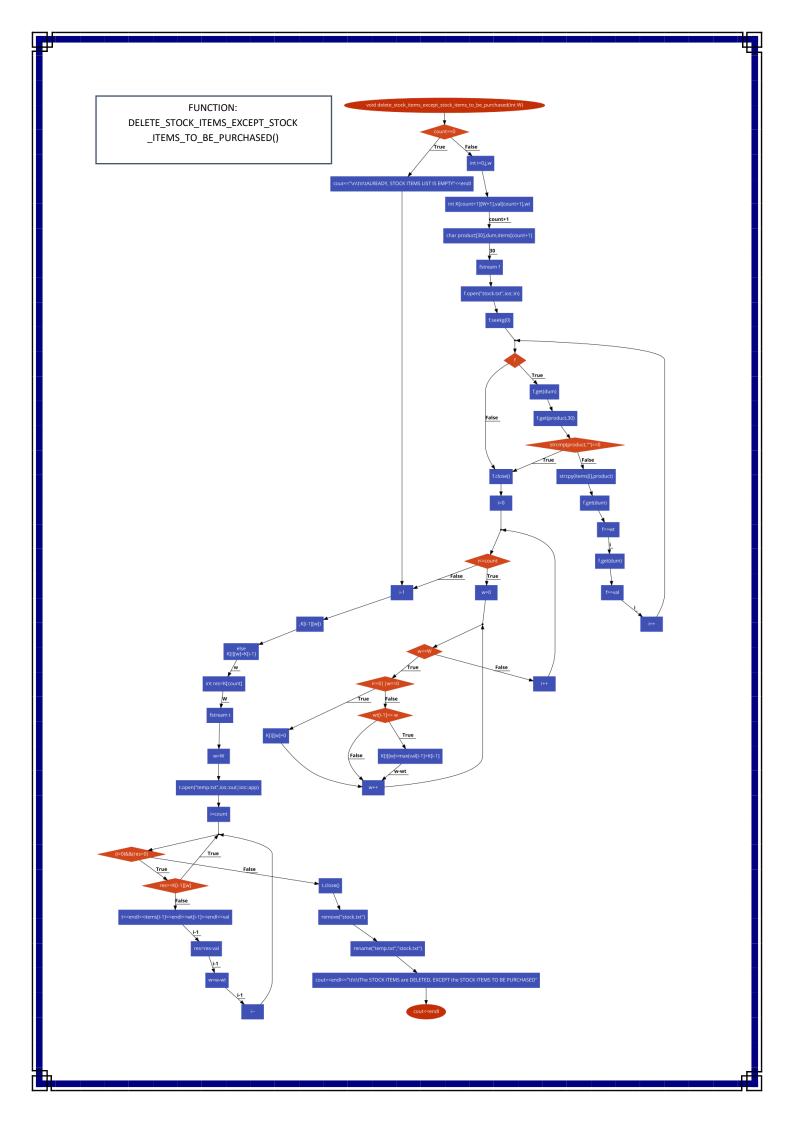


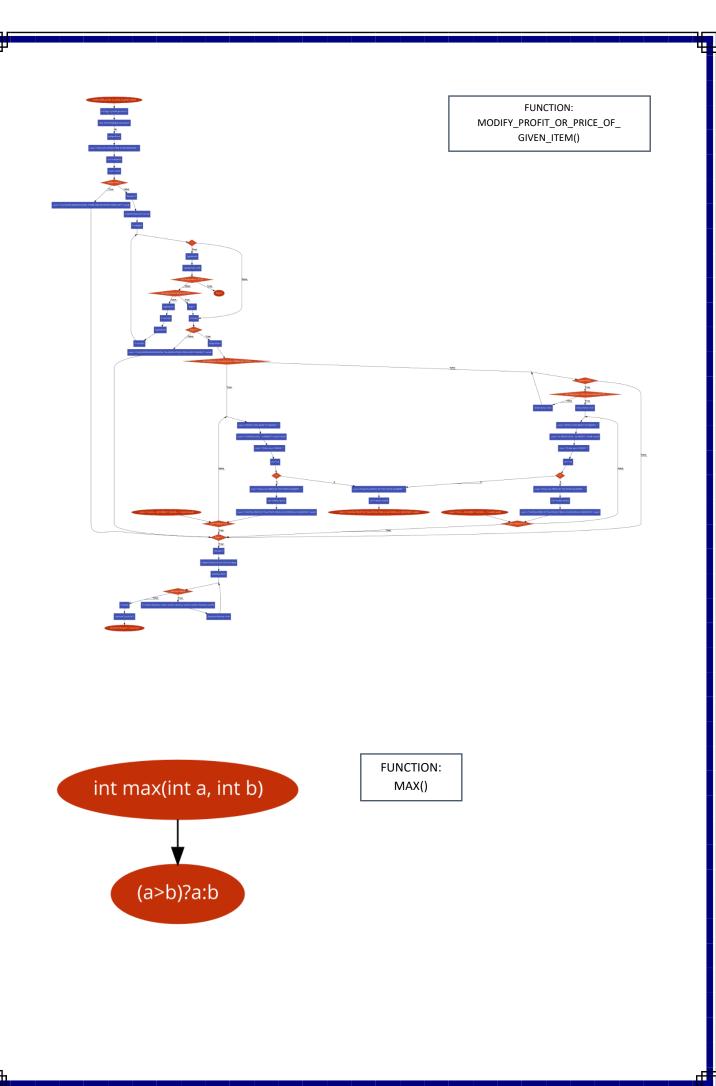


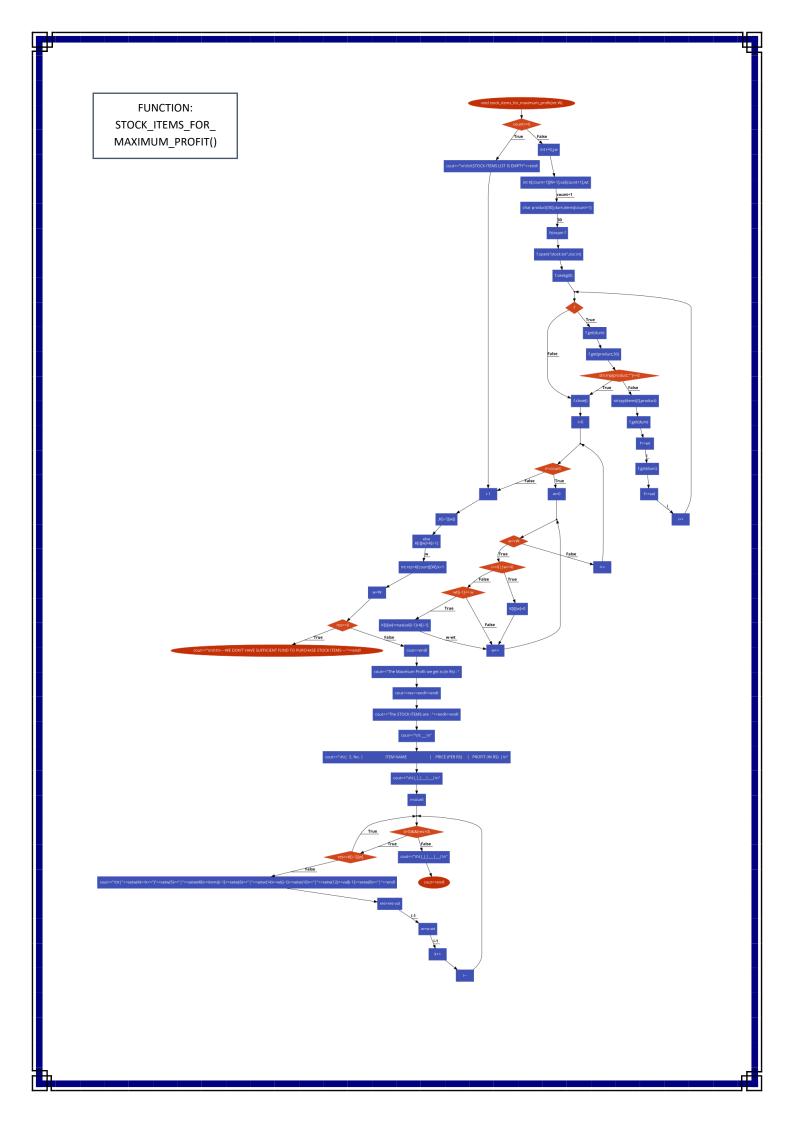


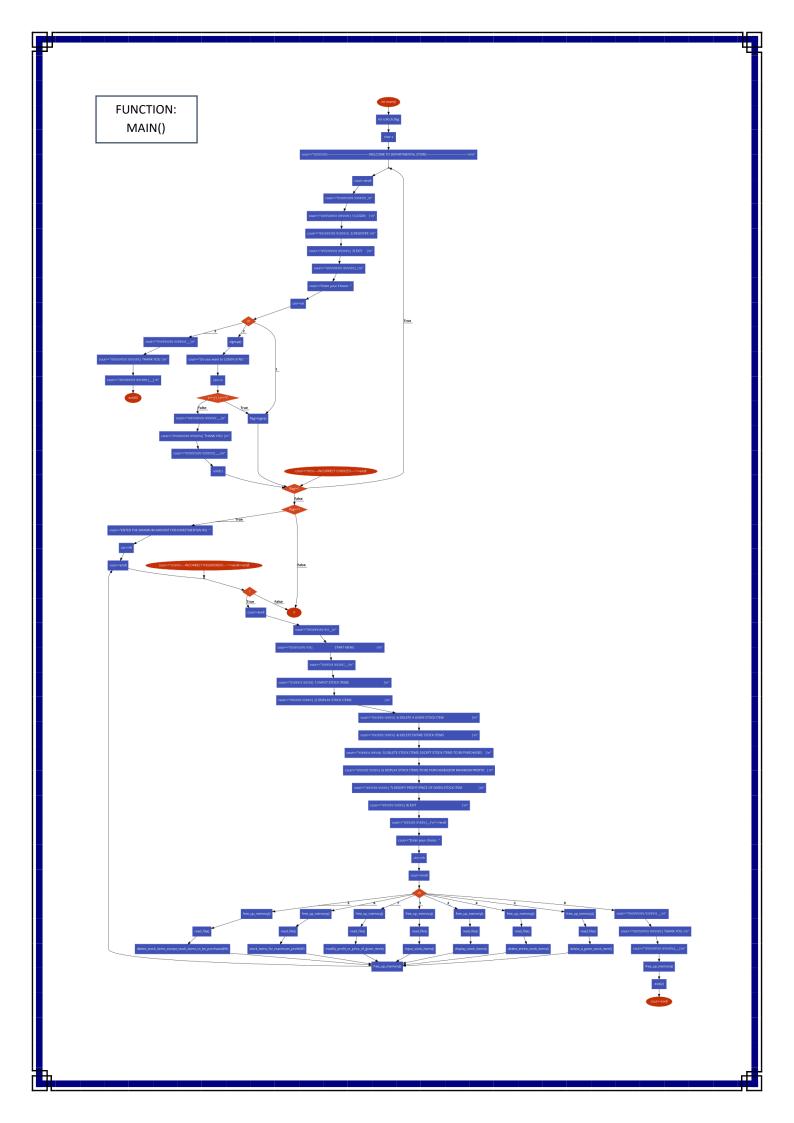








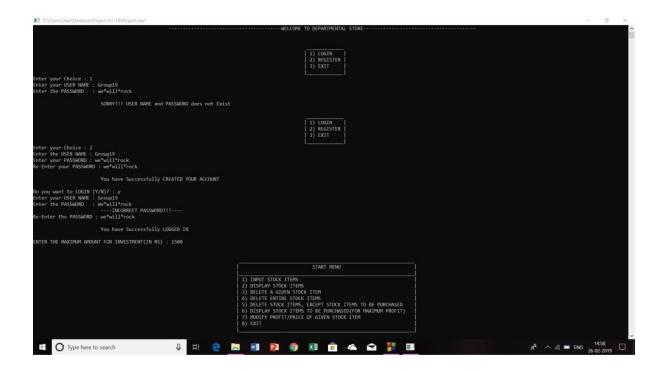


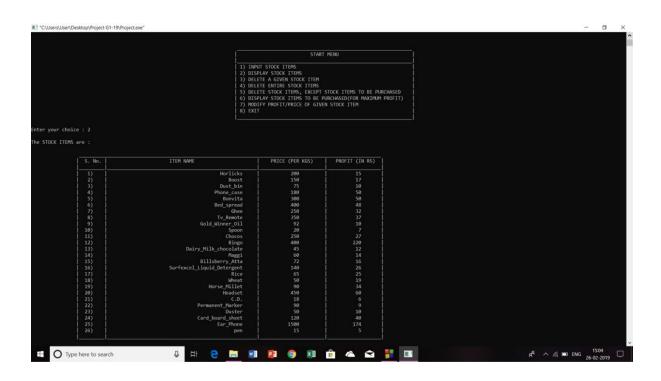


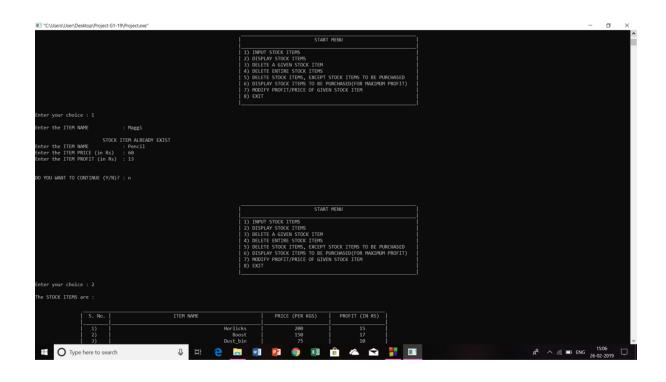
## **IMPLEMENTATION DETAILS**

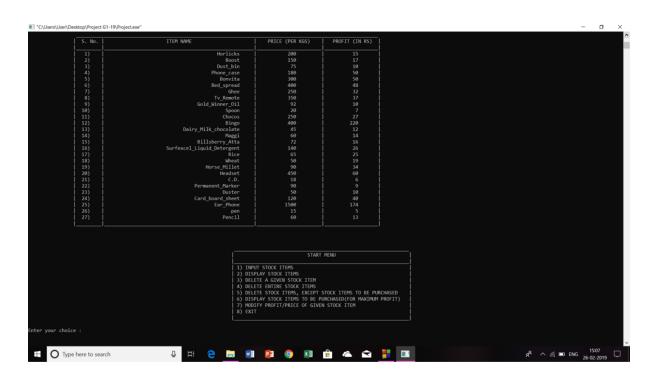
Please refer to my <u>GitHub</u> Repository.

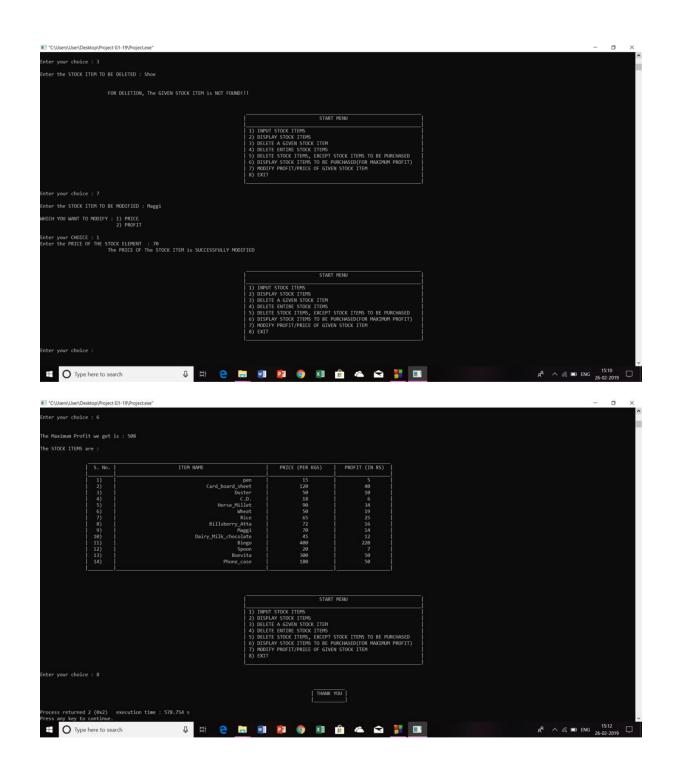
## TESTING AND SAMPLE SCREENSHOTS OF OUTPUT:











# CODE FOR COMPARISON OF DIFFERENT APPROACHES

```
#include<iostream>
#include<cstdlib>
#include<cstring>
#include<fstream>
#include<iomanip>
using namespace std;
struct items
{ char name[30];
 int price;
 int profit;
 float density;
}itm[50];
void greedy(items itm[], int num, int W);
int max(int a, int b) { return (a > b)? a : b; }
void dynamicProgramming(int W, items itm[], int n)
{
  int i, w;
  int K[n + 1][W + 1];
  for (i = 0; i \le n; i++) {
    for (w = 0; w \le W; w++) {
       if (i == 0 | | w == 0)
         K[i][w] = 0;
       else if (itm[i - 1].price <= w)
```

```
K[i][w] = max(itm[i-1].profit + K[i-1][w-itm[i-1].price], K[i-1][w]);
       else
         K[i][w] = K[i - 1][w];
    }
  }
  int res = K[n][W];
  cout<<"\nMaximum Profit= "<< res<<endl;</pre>
  w = W;
  for (i = n; i > 0 \&\& res > 0; i--)
        {
    if (res == K[i - 1][w])
       continue;
    else {
       res = res - itm[i-1].profit;
       w = w - itm[i - 1].price;
    }
  }
}
void bruteforce(items itm[],int c,int n)
{
        int i,j,isSelected=1,maxWt,maxProfit;
        int selected[n];
        int iter=2^n;
        int result=0;
        int temp[n];
        for(i =0;i<n;i++)
                 temp[i]=0;
```

```
for(i=0;i<iter;i++) {
                isSelected=1;
                maxProfit=0;
                maxWt=0;
        for(j=0;j< n;j++){
                        if(temp[j]==1){
                                maxWt+=itm[j].price;
                                maxProfit+= itm[j].profit;
                        }
                }
                if( maxWt <= c && maxProfit>result){
                        for(j=0;j<n;j++)
                                selected[j]=temp[j];
                        result=maxProfit;
                }
                for(j=0;j< n;j++){
                        temp[j]=temp[j]+isSelected;
                        isSelected = temp[j]/2;
                        temp[j]=temp[j]%2;
                }
        }
        cout<<"\nMaximum Profit="<< result<<endl;</pre>
}
void greedy( items itm[], int num, int W)
{
```

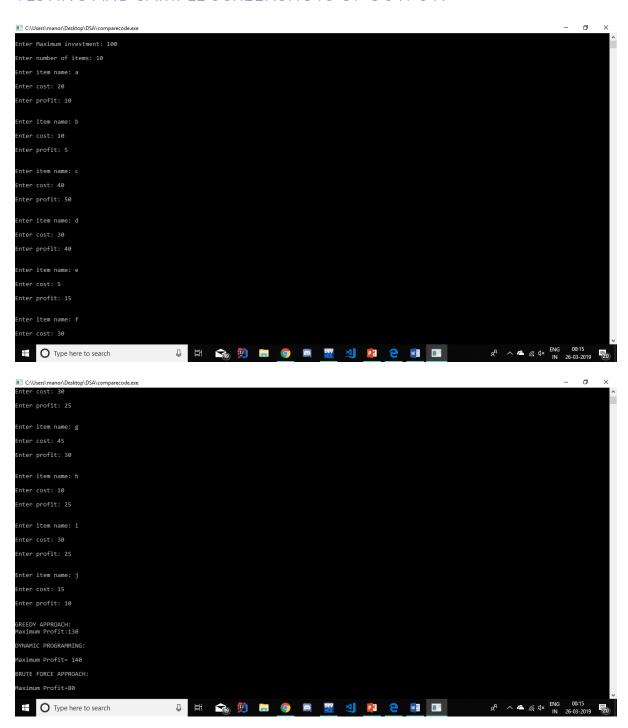
```
int i,j, wt,var[num];
float value;
float totalWeight = 0, totalBenefit = 0;
items temp;
for(i = 0; i < num; i++)
 itm[i].density = float(itm[i].profit) / itm[i].price;
 var[i]=0;
}
for(i = 1; i < num; i++) {
 for(j = 0; j < num - i; j++) {
  if(itm[j+1].density > itm[j].density) {
   temp = itm[j+1];
    itm[j+1] = itm[j];
    itm[j] = temp;
  }
int v=W;
for(i=0;i<num && itm[i].price<=v;i++)
{
       var[i]=1;
       v=v-itm[i].price;
for(i=0;i<num;i++)
         totalWeight=totalWeight+(itm[i].price*var[i]);
```

```
total Benefit = total Benefit + (itm[i].profit*var[i]);\\
 }
 cout<<"Maximum Profit:"<< totalBenefit<<endl;</pre>
}
int main(void)
{
 int i, j,W,num,choice;
 cout<<"\nEnter Maximum investment: ";</pre>
 cin>>W;
 char ch;
cout<<"\nEnter number of items: ";</pre>
cin>>num;
 for(i=0;i<num;i++)</pre>
 {
                 cout<<"\nEnter item name: ";</pre>
                 cin>>itm[i].name;
                 cout<<"\nEnter cost: ";</pre>
                 cin>>itm[i].price;
                 cout<<"\nEnter profit: ";</pre>
                 cin>>itm[i].profit;
                 cout << "\n";
        }
        cout<<"\nGREEDY APPROACH:\n";</pre>
        greedy(itm,num,W);
  cout<<"\nDYNAMIC PROGRAMMING:\n";</pre>
```

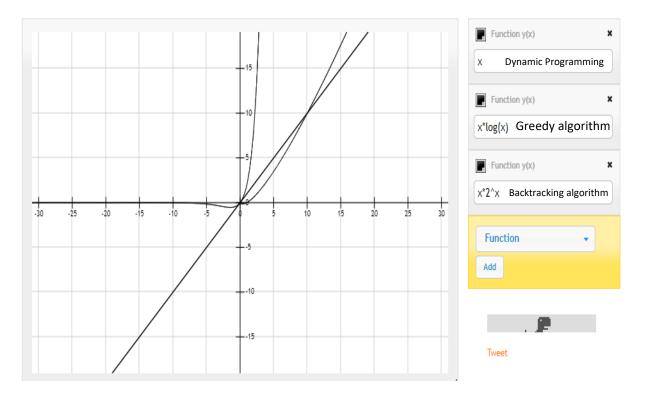
```
dynamicProgramming(W,itm,num);
    cout<<"\nBRUTE FORCE APPROACH:\n";
    bruteforce(itm,W,num);

return 0;
}</pre>
```

## TESTING AND SAMPLE SCREENSHOTS OF OUTPUT:



## GRAPH COMPARING THE DIFFERENT APPROACHES:



## **CONCLUSION:**

Clearly, from the given graph and output, we see that dynamic programming is the most efficient programming technique in order to solve the 0/1 Knapsack Problem. From the graph, we infer that the time complexity of dynamic programming for large outputs is least as compared to the rest.

Hence, using dynamic programming in knapsack, we solve the basic problem that a start-up company faces, that is, where to invest with the given initial investment such that we get maximum profit in the end and do not incur any loses.

## **REFERENCES:**

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- http://condor.depaul.edu/ichu/csc491/notes/wk8/knapsack.html
- http://www.micsymposium.org/mics 2005/papers/paper102.pdf