Package ‘FLSSS’

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Type Package

Title Mining Rigs for Specialized Subset Sum, Multi-Subset Sum, Multidimensional Subset Sum, Multidimensional Knapsack, Generalized Assignment Problems

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Description Specialized solvers for combinatorial optimization problems in the Subset Sum family. These solvers differ from the mainstream in the options of (i) restricting subset size, (ii) bounding subset elements, (iii) mining real-value sets with predefined subset sum errors, and (iv) finding one or more subsets in limited time. A novel algorithm for mining the one-dimensional Subset Sum induced algorithms for the multi-Subset Sum and the multidimensional Subset Sum. The multi-threaded framework for the latter offers exact algorithms to the multidimensional Knapsack and the Generalized Assignment problems. Historical updates include (a) renewed implementation of the multi-Subset Sum, multidimensional Knapsack and Generalized Assignment solvers; (b) availability of bounding solution space in the multidimensional Subset Sum; (c) fundamental data structure and architectural changes for enhanced cache locality and better chance of SIMD vectorization; (d) an option of mapping real-domain problems to the integer domain with user-controlled precision loss, and those integers are further zipped non-uniformly in 64-bit buffers. Arithmetic on compressed integers is done by bit-manipulation and the design has virtually zero speed lag relative to normal integer arithmetic. Reduction in dimensionality from the compression may yield substantial acceleration; (e) distributed computing infrastructure for multidimensional subset sum. Compilation with g++ '-Ofast' is recommended. See package vignette (<arXiv:1612.04484v3>) for details. Functions prefixed with 'aux' (auxiliary) are or will be implementations of existing foundational or cutting-edge algorithms for solving optimization problems of interest.

License GPL-3

Encoding UTF-8

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ByteCompile true

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LinkingTo Rcpp, RcppParallel

SystemRequirements GNU make

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`auxGAPbb` *Multithreaded generalized assignment problem solver via branch and bound*

Description

Multithreaded exact solver for the generalized assignment problem via decomposition to binary knapsack problems (branch), and Lagrangian relaxation (bound).

Usage

```
auxGAPbb(
  cost,
  profitOrLoss,
  budget,
  maxCore = 7,
  tlimit = 60,
  ub = "MT",
  greedyBranching = TRUE,
  optim = "max",
  multhreadOn = "nodes",
  threadLoad = 32
)
```

Arguments

- `cost` A numeric matrix. Dimensionality = N(agents) x N(tasks).
- `profitOrLoss` A numeric matrix of the same dimensionality of `cost`. Profit for maximum GAP. Loss for minimum GAP.
- `budget` A numeric vector. Size = N(agents).
- `maxCore` Maximal threads to invoke. No greater than the number of logical CPUs on machine.
- `tlimit` Return the best exsisting solution in `tlimit` seconds.
- `ub` Upper bound function. "MT" or "HS". See `auxKnapsack01bb()`.
- `greedyBranching` If `TRUE`, branch and bound in a greedy manner. See Details.
- `optim` A string. `optim = "max"` (`"min"`) solves the maximum (minimum) GAP.
- `multhreadOn` A string. The default `multhreadOn = "nodes"` multithreads over branching nodes. Internally, a single-threaded miner runs at first and stops once there are no less than `maxCore * threadLoad` latent trees stored in stack. The miner realizes those branches and distribute them to threads. Threads work on the subproblems sequentially and update the optimum supervised by a light mutex lock.

  Other values of `multhreadOn` assign threads to knapsack problems at each branching node, which is a historical remain and should always be avoided. It has overwhelming overheads because knapsack problems at those nodes are typically trivial.
- `threadLoad` An integer. Each thread is loaded with `threadLoad` sub-problems on average.

Details

A popular library of GAP instances can be found here: https://github.com/WhateverLiu/gapInstances.

This algorithm is based on a foundational paper by Ross and Soland (1975) and is carefully engineered towards speed. Implementation highlights include (i) decomposition for multithreading; (ii) a new branching method (`greedyBranching`) that pushes all candidate branching variables at each node into stack instead of pushing only those that have the highest desirabilities and would not affect the subsequent branching after being pushed; (iii) the return of current best solutions in time; (iv) the capability of taking real costs and profits. `greedyBranching` may considerably lower the number of nodes having the same series of knapsack problems to solve, thus accelerate the convergence speed.

Value

A list of 5:

- `totalProfitOrLoss` Total profit or loss generated from the assignment.
- `agentCost` A numeric vector of total costs for each agent.
- `assignment` An integer vector. `assignment[i]` indexes the agent assigned to the `i`th task.
- `nodes` The number of branching nodes generated in mining.
- `bkpSolved` The number of binary knapsack problems solved in mining.

Note

The C++ implementation is fully independent and borrows no code from any commercial or open source.

Examples

```
# =============================================================================
# Data source: http://people.brunel.ac.uk/~mastjjb/jeb/orlib/gapinfo.html,
# gap1 c515-1, 5 agents 15 tasks. Parsed instances from the library can be
# found here: https://github.com/WhateverLiu/gapInstances
# =============================================================================
profit = c(17,21,22,18,24,15,20,18,19,18,16,22,24,24,16,23,16,21,16,17,16,19,
           25,18,21,17,15,25,17,24,16,20,16,25,24,16,17,19,19,18,20,16,17,21,
           24,19,19,22,22,20,16,19,17,21,19,25,23,25,25,25,18,19,15,15,21,25,
           16,16,23,15,22,17,19,22,24)
profit = t(matrix(profit, ncol = 5))
cost = c(8,15,14,23,8,16,8,25,9,17,25,15,10,8,24,15,7,23,22,11,11,12,10,17,16,
         7,16,10,18,22,21,20,6,22,24,10,24,9,21,14,11,14,11,19,16,20,11,8,14,
         9,5,6,19,19,7,6,6,13,9,18,8,13,13,13,10,20,25,16,16,17,10,10,5,12,23)
cost = t(matrix(cost, ncol = 5))
budget = c(36, 34, 38, 27, 33)


sol = FLSSS::auxGAPbb(cost, profit, budget, maxCore = 2, tlimit = 4,
                      ub = "MT", greedyBranching = TRUE, optim = "max")




# =============================================================================
# Data source: http://support.sas.com/documentation/cdl/en/ormpug/65554/HTML
# /default/viewer.htm#ormpug_decomp_examples02.htm, an example made by SAS
# corporation. 24 tasks assigned to 8 agents.
# =============================================================================
cost = t(matrix(c(
  8,18,22,5,11,11,22,11,17,22,11,20,13,13,7,22,15,22,24,8,8,24,18,8,24,14,11,
  15,24,8,10,15,19,25,6,13,10,25,19,24,13,12,5,18,10,24,8,5,22,22,21,22,13,
  16,21,5,25,13,12,9,24,6,22,24,11,21,11,14,12,10,20,6,13,8,19,12,19,18,10,21,
  5,9,11,9,22,8,12,13,9,25,19,24,22,6,19,14,25,16,13,5,11,8,7,8,25,20,24,20,11,
  6,10,10,6,22,10,10,13,21,5,19,19,19,5,11,22,24,18,11,6,13,24,24,22,6,22,5,14,
  6,16,11,6,8,18,10,24,10,9,10,6,15,7,13,20,8,7,9,24,9,21,9,11,19,10,5,23,20,5,
  21,6,9,9,5,12,10,16,15,19,18,20,18,16,21,11,12,22,16,21,25,7,14,16,10),
  ncol = 8))
profit = t(matrix(c(
  25,23,20,16,19,22,20,16,15,22,15,21,20,23,20,22,19,25,25,24,21,17,23,17,16,
  19,22,22,19,23,17,24,15,24,18,19,20,24,25,25,19,24,18,21,16,25,15,20,20,18,
  23,23,23,17,19,16,24,24,17,23,19,22,23,25,23,18,19,24,20,17,23,23,16,16,15,23,
  15,15,25,22,17,20,19,16,17,17,20,17,17,18,16,18,15,25,22,17,17,23,21,20,24,22,
  25,17,22,20,16,22,21,23,24,15,22,25,18,19,19,17,22,23,24,21,23,17,21,19,19,17,
  18,24,15,15,17,18,15,24,19,21,23,24,17,20,16,21,18,21,22,23,22,15,18,15,21,22,
  15,23,21,25,25,23,20,16,25,17,15,15,18,16,19,24,18,17,21,18,24,25,18,23,21,15,
  24,23,18,18,23,23,16,20,20,19,25,21), ncol = 8))
```

```
budget = c(36, 35, 38, 34, 32, 34, 31, 34)


# Intel CPU i7-4770 3.4GHz, g++ '-Ofast', 64-bit Windows 7:
system.time({sol = FLSSS::auxGAPbb(
  cost, profit, budget, maxCore = 2, tlimit = 4, ub = "MT",
  greedyBranching = FALSE, optim = "max")})
# user  system elapsed
# 0.02    0.00    0.01
# The elapsed time is about 1% of that reported by the SAS proc with 8
# threads, although its hardware configuration is unknown.


system.time({sol2 = FLSSS::auxGAPbb(
  cost, profit, budget, maxCore = 2, tlimit = 4, ub = "MT",
  greedyBranching = TRUE, optim = "max")})
sol[c("nodes", "bkpSolved")]  # 4526, 14671, can be different.
sol2[c("nodes", "bkpSolved")] # 4517, 13115, can be different.
# Greedy branching may lower the numbers of branching nodes and
# knapsack problems to solve.




# ===============================================================================
# Play random numbers.
# ===============================================================================
set.seed(22) # A nontrivial instance searched via changing random seeds.
             # RNG in R 3.5.1 for Windows.
Nagent = 20L; Ntask = 200L
cost = matrix(runif(Nagent * Ntask, 1e3, 1e6), nrow = Nagent)
profit = matrix(abs(rnorm(Nagent * Ntask, 1e6, 1e6)) + 1000, nrow = Nagent)
budget = apply(cost, 1, function(x) runif(1, min(x), sum(x) / 2))


# Intel CPU i7-4770 3.4GHz, g++ '-Ofast', 64-bit Windows 7.
system.time({sol1 = FLSSS::auxGAPbb(
  cost, profit, budget,
  maxCore = 1, multhreadOn = "KPs",
  tlimit = 3600, ub = "MT", greedyBranching = TRUE, optim = "max")})
# user  system elapsed
# 9.17    0.00    9.19


# Multithread knapsack problems at each branching node.
# This does not accelerate the speed at all because threading overheads
# are overwhelming.
system.time({sol2 = FLSSS::auxGAPbb(
  cost, profit, budget,
  maxCore = 7, multhreadOn = "KPs",
  tlimit = 3600, ub = "MT", greedyBranching = TRUE, optim = "max")})
# user   system elapsed
# 39.02    5.24   11.12
```

```
# Multithread nodes.
system.time({sol3 = FLSSS::auxGAPbb(
  cost, profit, budget,
  maxCore = 7, multhreadOn = "nodes", threadLoad = 32L,
  tlimit = 3600, ub = "MT", greedyBranching = TRUE, optim = "max")})
#  user  system elapsed
# 14.62    0.00    2.13
```

`auxGAPbbDp` *Multithreaded generalized assignment problem solver via a hybrid of branch-and-bound and dynamic programming.*

Description

Multithreaded exact solver for the generalized assignment problem via decomposition to binary knapsack problems (branch), and Lagrangian relaxation (bound). Knapsack problems are solved via dynamic programming.

Usage

```
auxGAPbbDp(
  cost,
  profitOrLoss,
  budget,
  maxCore = 7L,
  tlimit = 60,
  greedyBranching = TRUE,
  optim = "max",
  multhreadOn = "nodes",
  threadLoad = 32
)
```

Arguments

`cost`	An integer matrix. Dimensionality = N(agents) x N(tasks).
`profitOrLoss`	A numeric matrix of the same dimensionality of `cost`. Profit for maximum GAP. Loss for minimum GAP.
`budget`	An integer vector. Size = N(agents).
`maxCore`	Maximal threads to invoke. No greater than the number of logical CPUs on machine.
`tlimit`	Return the best exsisting solution in `tlimit` seconds.
`greedyBranching`	See `greedyBranching` in `auxGAPbb()`.

`optim`	A string. `optim` = "max" ("min") solves the maximum (minimum) GAP.
`multhreadOn`	See `multhreadOn` in `auxGAPbb()`.
`threadLoad`	See `threadLoad` in `auxGAPbb()`.

Details

For instances with integral `cost` and `budget` of small magnitudes, knapsack problems from the decomposition could be solved faster via dynamic programming than branch and bound. See `auxKnapsack01dp()`. Implementation highlights include (i) only `maxCore` many lookup matrices exist in memory; (ii) a lookup matrix is recycled if it is sufficiently large to support solving the current knapsack problem, so as to minimize potential contentious memory allocations in multithreading. These management rules for economical memories propagate through all package functions. See more details in `auxGAPbb()`.

Value

See Value of `auxGAPbb()`.

Note

`cost` and `budget` are integers. The C++ implementation is fully independent and borrows no code from any commercial or open source.

Examples

```
# ===============================================================================
# Data source: http://support.sas.com/documentation/cdl/en/ormpug/65554/HTML
# /default/viewer.htm#ormpug_decomp_examples02.htm, an example made by SAS
# corporation. 24 tasks assigned to 8 agents.
# ===============================================================================
cost = t(matrix(as.integer(c(
  8,18,22,5,11,11,22,11,17,22,11,20,13,13,7,22,15,22,24,8,8,24,18,8,24,14,11,
  15,24,8,10,15,19,25,6,13,10,25,19,24,13,12,5,18,10,24,8,5,22,22,21,22,13,
  16,21,5,25,13,12,9,24,6,22,24,11,21,11,14,12,10,20,6,13,8,19,12,19,18,10,21,
  5,9,11,9,22,8,12,13,9,25,19,24,22,6,19,14,25,16,13,5,11,8,7,8,25,20,24,20,11,
  6,10,10,6,22,10,10,13,21,5,19,19,19,5,11,22,24,18,11,6,13,24,24,22,6,22,5,14,
  6,16,11,6,8,18,10,24,10,9,10,6,15,7,13,20,8,7,9,24,9,21,9,11,19,10,5,23,20,5,
  21,6,9,9,5,12,10,16,15,19,18,20,18,16,21,11,12,22,16,21,25,7,14,16,10)),
  ncol = 8))
profit = t(matrix(c(
  25,23,20,16,19,22,20,16,15,22,15,21,20,23,20,22,19,25,25,24,21,17,23,17,16,
  19,22,22,19,23,17,24,15,24,18,19,20,24,25,25,19,24,18,21,16,25,15,20,20,18,
  23,23,23,17,19,16,24,24,17,23,19,22,23,25,23,18,19,24,20,17,23,23,16,16,15,23,
  15,15,25,22,17,20,19,16,17,17,20,17,17,18,16,18,15,25,22,17,17,23,21,20,24,22,
  25,17,22,20,16,22,21,23,24,15,22,25,18,19,19,17,22,23,24,21,23,17,21,19,19,17,
  18,24,15,15,17,18,15,24,19,21,23,24,17,20,16,21,18,21,22,23,22,15,18,15,21,22,
  15,23,21,25,25,23,20,16,25,17,15,15,18,16,19,24,18,17,21,18,24,25,18,23,21,15,
  24,23,18,18,23,23,16,20,20,19,25,21), ncol = 8))
budget = as.integer(c(36, 35, 38, 34, 32, 34, 31, 34))
```

```
system.time({sol = FLSSS::auxGAPbbDp(
  cost, profit, budget,
  maxCore = 2, tlimit = 4, greedyBranching = TRUE, optim = "max")})
sol[c("nodes", "bkpSolved")] # 2630, 8102




set.seed(8) # A nontrivial instance searched via changing random seeds.
            # RNG in R 3.5.1 for Windows.
Nagent = 20L; Ntask = 200L
cost = matrix(as.integer(runif(Nagent * Ntask, 1, 50)), nrow = Nagent)
budget = as.integer(apply(cost, 1, function(x) runif(1, min(x), sum(x) / 2)))
profit = matrix(abs(rnorm(Nagent * Ntask, 1e6, 1e6)) + 1000, nrow = Nagent)


# Intel CPU i7-4770 3.4GHz, g++ '-Ofast', 64-bit Windows 7.
system.time({sol1 = FLSSS::auxGAPbb(
  cost, profit, budget,
  maxCore = 7, multhreadOn = "nodes",
  tlimit = 3600, greedyBranching = TRUE, optim = "max")})
# user  system elapsed
# 14.43    0.00    2.11


system.time({sol2 = FLSSS::auxGAPbbDp(
  cost, profit, budget,
  maxCore = 7, multhreadOn = "nodes",
  tlimit = 3600, greedyBranching = TRUE, optim = "max")})
# user  system elapsed
# 5.77    0.00    0.87
# Dynamic programming for solving knapsack problems could be faster
# for integral costs and budgets of small magnitudes.
```

---

auxGAPga — *Multithreaded generalized assignment problem solver via genetic algorithm*

Description

A genetic algorithm with local heuristics for GAP.

Usage

```
auxGAPga(
  cost,
  profitOrLoss,
  budget,
  trials,
```

```
  populationSize,
  generations,
  randomSeed = NULL,
  maxCore = 7,
  optim = "max"
)
```

Arguments

cost	A numeric matrix. Dimensionality = N(agents) x N(tasks).
profitOrLoss	A numeric matrix of the same dimensionality of `cost`. Profit for maximum GAP. Loss for minimum GAP.
budget	A numeric vector. Size = N(agents).
trials	An integer. Number of trials, aka the number of population sets.
populationSize	An integer. Size of each population.
generations	An integer. As reproduction iterates, if there have been `generations` many children produced and accepted in population but no update on the current optimum, function quits.
randomSeed	An integer or `NULL`. `randomSeed` seeds the random number generator in R, generates `trials` many integers to seed the `mt19937_64` (Mersenne Twister) engine for each trial.
maxCore	Maximal threads to invoke. No greater than the number of logical CPUs on machine. The algorithm multithreads over trials.
optim	A string. `optim = "max"` (`"min"`) solves the maximum (minimum) GAP.

Details

This algorithm is based on a foundational paper by Chu and Beasley (1997) and is carefully engineered towards speed. Besides the standard cross-over and mutation operations, the algorithm applies two local heuristics for educating the new borns. The first is to randomly pick a task from each overloaded agent and reassign the task to the next budget-sufficient agent — if there is any. The second is to raise the total profit by reassigning another agent for each task — if the reassignment would not result in overload. The algorithm outperforms most peer metaheuristics such as variants of simulated annealing and tabu search (Osman), and is highly effective for large and hard instances.

Value

A list of 4:

`totalProfitOrLoss`
: Total profit or loss generated from the assignment. Negative infinity if no solution found.

`agentCost`
: A numeric vector of total costs for each agent. Empty if no solution found.

`assignment`
: An integer vector. `assignment[i]` indexes the agent assigned to the `i`th task. Empty if no solution found.

populationInfo
: A list of 3:

allGenes
: An N(task) x (`populationSize` x `trials`) integer matrix recording genes in all population sets upon completion. Each column represents a gene, namely a tentative assignment.

allBudgetExceedance
: A numeric vector of the size of `populationSize` x `trials`. `allBudgetExceedance[i]` equals the total budget exceedance of tentative assignment `allGenes[,i]`.

allProfitOrLoss
: A numeric vector of the size of `allBudgetExceedance`. `allProfitOrLoss[i]` equals the total profit or loss of tentative assignment `allGenes[,i]`.

Note

The C++ implementation is fully independent and borrows no code from any commercial or open source.

Examples

```
# ===============================================================================
# A trivial instance
# ===============================================================================
profit = c(17,21,22,18,24,15,20,18,19,18,16,22,24,24,16,23,16,21,16,17,16,19,
           25,18,21,17,15,25,17,24,16,20,16,25,24,16,17,19,19,18,20,16,17,21,
           24,19,19,22,22,20,16,19,17,21,19,25,23,25,25,25,18,19,15,15,21,25,
           16,16,23,15,22,17,19,22,24)
profit = t(matrix(profit, ncol = 5))
cost = c(8,15,14,23,8,16,8,25,9,17,25,15,10,8,24,15,7,23,22,11,11,12,10,17,16,
         7,16,10,18,22,21,20,6,22,24,10,24,9,21,14,11,14,11,19,16,20,11,8,14,
         9,5,6,19,19,7,6,6,13,9,18,8,13,13,13,10,20,25,16,16,17,10,10,5,12,23)
cost = t(matrix(cost, ncol = 5))
budget = c(36, 34, 38, 27, 33)


Nagent = 5L; Ntask = 15L
rst = FLSSS::auxGAPga(
  cost, profit, budget, trials = 2, populationSize = 100, generations = 10000,
  randomSeed = 42, maxCore = 2, optim = "max")


# ===============================================================================
# A relatively hard instance.
# ===============================================================================
# Download gapInstances.Rdata from
# https://github.com/WhateverLiu/gapInstances. Load it in R.

cost = gapC[[3]]$cost
loss = gapC[[3]]$loss
budget = gapC[[3]]$budget
# Intel CPU i7-4770 3.4GHz, g++ '-Ofast', 64-bit Windows 7.
system.time({rst = FLSSS::auxGAPga(cost, loss, budget, trials = 7,
```

```
              randomSeed = 42, populationSize = 100, generations = 500000,
              optim = "min", maxCore = 7)})
rst$totalProfitOrLoss # 1416
#  user  system elapsed
# 69.24    0.17   11.61
# The known optimum equals 1402 as the total loss.
```

---

auxKnapsack01bb *Multithreaded binary knapsack problem solver via branch and bound*

Description

Given items' weights and values, concurrently solve 0-1 knapsack problems to optimality via branch and bound for multiple knapsacks of different capacities.

Usage

```
auxKnapsack01bb(
  weight,
  value,
  caps,
  itemNcaps = integer(0),
  maxCore = 7L,
  tlimit = 60,
  ub = "MT",
  simplify = TRUE
)
```

Arguments

`weight`	A numeric vector.
`value`	A numeric vector. The size equals that of `weight`.
`caps`	A numeric vector of knapsack capacities.
`itemNcaps`	An integer vector of upper bounds on the number of selected items. `itemNcaps[i]` corresponds to instance `caps[i]`. Empty `itemNcaps` implies no size restriction.
`maxCore`	Maximal threads to invoke. No greater than the number of logical CPUs on machine.
`tlimit`	Return the best exsisting solution in `tlimit` seconds.
`ub`	Upper bound function.
`simplify`	If `length(caps) == 1`, simplify the output.

Details

The algorithm takes the Horowitz-Sahni (1974) and the Martello-Toth (1977) upper bound functions and is carefully engineered towards speed. Implementation highlights include (i) an extra option of upper bounding the number of selected items, which only adds trivial overhead; (ii) the return of existing best solutions in time; (iii) the capability of taking numeric weights and values.

Value

A list of 2:

maxValue: a numeric vector. maxValue[i] equals the sum of values of items selected for capacity caps[i].

selection: a list of integer vectors. selection[i] indexes the items selected for capacity caps[i].

Note

The function is not to solve the 0-1 multiple knapsack problem. The C++ implementation is fully independent and borrows no code from any open or commercial source.

Examples

```
set.seed(42)
weight = runif(100, min = 1e3, max = 1e6)
value = weight ^ 0.5 * 100 # Higher correlation between item weights and values
                           # typically implies a harder knapsack problem.
caps = runif(10, min(weight), sum(weight))
rst = FLSSS::auxKnapsack01bb(weight, value, caps, maxCore = 2, tlimit = 2)
str(rst)
```

---

auxKnapsack01dp *Multithreaded binary knapsack problem solver via dynamic programming*

Description

Given items' weights and values, concurrently solve 0-1 knapsack problems to optimality via dynamic programming for multiple knapsacks of different capacities.

Usage

```
auxKnapsack01dp(
  weight,
  value,
  caps,
  maxCore = 7L,
  tlimit = 60,
  simplify = TRUE
)
```

Arguments

weight	An integer vector.
value	A numeric vector. The size equals that of weight.
caps	An integer vector of knapsack capacities.

maxCore	Maximal threads to invoke. No greater than the number of logical CPUs on machine.
tlimit	Return the best exsisting solution in tlimit seconds.
simplify	If length(caps) == 1, simplify the output.

Details

Implementation highlights include (i) lookup matrix is only of space complexity O(N * [max(C) - min(W)]), where N = the number of items, max(C) = maximal knapsack capacity, min(W) = minimum item weight; (ii) threads read and write the same lookup matrix and thus accelerate each other; (iii) the return of existing best solutions in time.

Value

A list of 3:

maxValue: a numeric vector. maxValue[i] equals the sum of values of items selected for capacity caps[i].

selection: a list of integer vectors. selection[i] indexes the items selected for capacity caps[i].

lookupTable: a numeric matrix.

Note

The function is not to solve the 0-1 multiple knapsack problem. weight and caps are integers. Be cautioned that dynamic programming is not suitable for problems with weights or capacities of high magnitudes due to its space complexity. Otherwise it could outperform branch-and-bound especially for large instances with highly correlated item weights and values.

Examples

```
set.seed(42)
weight = sample(10L : 100L, 600L, replace = TRUE) # Dynamic programming
                                                  # solution requires integer
                                                  # weights.
value = weight ^ 0.5 * 100 # Higher correlation between item weights and values
                           # typically implies a harder knapsack problem.
caps = as.integer(runif(10, min(weight), 600L))
system.time({rstDp = FLSSS::auxKnapsack01dp(
  weight, value, caps, maxCore = 2, tlimit = 4)})
system.time({rstBb = FLSSS::auxKnapsack01bb(
  weight, value, caps, maxCore = 2, tlimit = 4)})
# Dynamic programming can be faster than branch-and-bound for integer weights
# and capacity of small magnitudes.
```

decomposeMflsss *mFLSSS decomposition*

Description

Decompose an mFLSSS instance into sub-problems for distributed computing.

Usage

```
decomposeMflsss(
  len,
  mV,
  mTarget,
  mME,
  solutionNeed = 1L,
  dl = ncol(mV),
  du = ncol(mV),
  useBiSrchInFB = FALSE,
  approxNinstance = 50000L
  )
```

Arguments

len	See the same argument in mFLSSSpar().
mV	See the same argument in mFLSSSpar().
mTarget	See the same argument in mFLSSSpar().
mME	See the same argument in mFLSSSpar().
solutionNeed	See the same argument in mFLSSSpar().
dl	See the same argument in mFLSSSpar().
du	See the same argument in mFLSSSpar().
useBiSrchInFB	See the same argument in mFLSSSpar().
approxNinstance	Approximately how many instances should the problem be decomposed into.

Details

This function and mFLSSSobjRun() constitute a multi-process counterpart of mFLSSSpar(). It decomposes a multidimensional subset sum problem into numerous independent instances that can be submitted to any computing resource of CPU threads, where mFLSSSobjRun() receives and solves the instance.

For example, if 1000 threads are available, either on a computing cluster integrated by LAN or on 1000 PCs connected by the Internet, one could (i) decompose the problem of interest into 100000 instances using decomposeMflsss(), (ii) transmit each instance and an R script that calls mFLSSSobjRun() on the instance to any available thread, (iii) collect the results from all threads. A good practice is to decompose the problem of interest into much more instances than the threads, provided that an automatic queueing system exists, so there would be less chance of having idling threads during computation — if the number of instances equals the number of threads, some threads may finish much earlier than others due to the heterogeneous nature of the instances, thus the waste.

The pair `decomposeMflsss()` and `mFLSSSobjRun()` is designed for exploiting distrbuted resource to solve large and hard multidimensional subset sum instances.

Value

A list of two:

`$mflsssObjects`: a list. Each element is an `mFLSSS` object that would be supplied to `mFLSSSobjRun()`.

`$solutionsFound`: solutions found during decomposition.

Examples

```
N = 30L # Superset size.
len = 6L # Subset size.
dimen = 5L # Dimension.
set.seed(8120)
v = matrix(runif(N * dimen) * 1000, nrow = N) # Superset.
sol = sample(N, len)
target = colSums(v[sol, ]) # Target sum.
ME = target * 0.03 # Error threshold.
approxNinstance = 1000


validate = function(len, v, target, ME, result)
{
  all(unlist(lapply(result, function(x)
    all(abs(colSums(v[x, ]) - target) <= ME))))
}


decompedFlsss = FLSSS::decomposeMflsss(
  len = len, mV = v, mTarget = target, mME = ME, solutionNeed = 1e6,
  approxNinstance = approxNinstance)


str(decompedFlsss$solutionsFound) # See if the agent already found
# some solutions and validate them.
if(length(decompedFlsss$solutionsFound) > 0)
  print(validate(len, v, target, ME, decompedFlsss$solutionsFound))


length(decompedFlsss$mflsssObjects) # Number of independent small jobs.
someOtherSolutions = FLSSS::mFLSSSobjRun(
  decompedFlsss$mflsssObjects[[620]], tlimit = 3, solutionNeed = 1e6)


if(length(someOtherSolutions) > 0) # Validate solutions.
```

```
{
  print(someOtherSolutions)
  print(validate(len, v, target, ME, someOtherSolutions))
}
```

FLSSS *One-dimensional Subset Sum given error threshold*

Description

Given subset size `len`, sorted superset `v`, subset sum `target` and error `ME`, find at least `solutionNeed` index (integer) vector(s) `x`, such that `target -ME <= sum(v[x]) <= target + ME`. To mine subsets that sum in a given range, set `target` to the midpoint and `ME` to half of the range width.

Usage

```
FLSSS(
  len,
  v,
  target,
  ME,
  solutionNeed = 1L,
  LB = 1L : len,
  UB = (length(v) - len + 1L) : length(v),
  viaConjugate = FALSE,
  tlimit = 60,
  useBiSrchInFB = FALSE,
  useFloat = FALSE
  )
```

Arguments

`len`	An integer as the subset size: `0 <= len < length(v)`. If `len == 0`, `FLSSS()` mines subets without size restriction. `len <-0` would be most likely slower than looping `len` over `1 : (length(v) -1)`. See Details.
`v`	A sorted numeric vector, the superset. `v` can be negative and nonunique.
`target`	A numeric value, the subset sum target.
`ME`	A positive numeric value, the error threshold.
`solutionNeed`	An integer, the least number of solutions wanted. If the function returns fewer solutions, either `tlimit` is up or less than `solutionNeed` solutions exist. The function may also return more than `solutionNeed` solutions.
`LB`	An integer vector of size `len` as the lower bounds of the solution space: for any solution `x`, `LB[i] <= x[i]`. Custom `LB` should be no less than `1L : len` element-wisely. Every element in `v` should be within the range enclosed by `LB` and `UB`.

UB — An integer vector of size `len` as the upper bounds of the solution space: for any solution `x`, `x[i] <= UB[i]`. Custom `UB` should be no greater than `(length(v) - len + 1L ) : length(v)` element-wisely. Every element in `v` should be within the range enclosed by `LB` and `UB`.

viaConjugate — A boolean value. If `TRUE`, `FLSSS()` mines susbets of size `length(v) -len` that sum to `sum(v) -target` with the same `ME`. Let `x` be the integer vector indexing a qualified subset. `FLSSS()` returns `(1L : length(v))[-x]`. Simulations show that `FLSSS()` often finds the first qualified conjugate subset faster if `len` is much less than `length(v) / 2`.

tlimit — A numeric value. Enforce function to return in `tlimit` seconds.

useBiSrchInFB — A boolean value. If `TRUE`, the function performs binary search for index bounds in the auxiliary triangle matrix of continuous sequence sums. This argument is mainly for research. Simulations show binary search has no major advantage over linear search due to caching mechanisms. The advantage may be pronounced if `length(v)` is substantial (> 10000) while `len` is small (< 5).

useFloat — A boolean value. If `TRUE`, convert data to single-precision floats. This argument is mainly for research. `useFloat = TRUE` is highly unrecommended.

Details

If `len == 0`, `FLSSS()` would (1) reset `len` to `length(v)`, (2) pad `len` zeros at the beginning of `v` and sort `v`, (3) search for size-`len` subsets, and (4) for an index vector that represents a subset, erases elements pointing to zeros in `v`. See the package documentation for more details.

Value

A list of index vectors.

Examples

```
# ===============================================================================
# Example I: play random numbers.
# ===============================================================================
rm(list = ls()); gc()
subsetSize = 200L
supersetSize = 1000L
superset = 10000 * sort(rnorm(supersetSize) ^ 3 + 2 * runif(supersetSize) ^ 2 +
           3 * rgamma(supersetSize, 5, 1) + 4)
subsetSum = runif(1, sum(superset[1L : subsetSize]), sum(superset[(supersetSize -
            subsetSize + 1L) : supersetSize]))
subsetSumError = 1e-3


# Mine 3 subsets
rst1 = FLSSS::FLSSS(len = subsetSize, v = superset, target = subsetSum,
                    ME = subsetSumError, solutionNeed = 3, tlimit = 4)


# Mine 3 subsets via solving the conjugate problem
rst2 = FLSSS::FLSSS(len = subsetSize, v = superset, target = subsetSum,
```

```
                    ME = subsetSumError, solutionNeed = 3, tlimit = 4,
                    viaConjugate = TRUE)


# Verify uniqueness
cat("rst1 number of solutions =",
    length(unique(lapply(rst1, function(x) sort(x)))), "\n")
cat("rst2 number of solutions =",
    length(unique(lapply(rst2, function(x) sort(x)))), "\n")


# Verify solutions
if(length(rst1) > 0)
  all(unlist(lapply(rst1, function(x)
    abs(sum(superset[x]) - subsetSum) <= subsetSumError)))
if(length(rst2) > 0)
  all(unlist(lapply(rst2, function(x)
    abs(sum(superset[x]) - subsetSum) <= subsetSumError)))


# Mine 3 subsets in bounded solution space.
# Make up the lower and upper bounds for the solution space:
tmp = sort(sample(1L : supersetSize, subsetSize))
tmp2 = sort(sample(1L : supersetSize, subsetSize))
lowerBounds = pmin(tmp, tmp2)
upperBounds = pmax(tmp, tmp2)
rm(tmp, tmp2)


# 'FLSSS()' does not work if there are elements not under the hood of
# lowerBounds + upperBounds. Exclude those elements:
remainIndex = unique(unlist(apply(cbind(lowerBounds, upperBounds), 1,
  function(x) x[1] : x[2])))
lowerBounds = match(lowerBounds, remainIndex)
upperBounds = match(upperBounds, remainIndex)
superset = superset[remainIndex]


# Plant a subset sum:
solution = integer(subsetSize)
solution[1] = sample(lowerBounds[1] : upperBounds[1], 1)
for(i in 2L : subsetSize)
{
  l = max(lowerBounds[i], solution[i - 1] + 1L)
  u = upperBounds[i]
  if(l == u) solution[i] = u
  else solution[i] = sample(l : u, 1)
}
subsetSum = sum(superset[solution])
subsetSumError = abs(subsetSum) * 0.01 # relative error within 1%
rm(solution)
```

```
rst3 = FLSSS::FLSSS(len = subsetSize, v = superset, target = subsetSum,
                    ME = subsetSumError, solutionNeed = 2, tlimit = 4,
                    LB = lowerBounds, UB = upperBounds, viaConjugate = TRUE)


print(length(rst3))


# Verify solutions
if(length(rst3) > 0)
  cat(all(unlist(lapply(rst3, function(x)
    abs(sum(superset[x]) - subsetSum) <= subsetSumError))), "\n")




# ===============================================================================
# Example II: mine a real-world dataset.
# ===============================================================================
rm(list = ls()); gc()
superset = c(
  -1119924501, -793412295, -496234747,  -213654767,   16818148,   26267601,   26557292,
     27340260,   28343800,   32036573,    32847411,   34570996,   34574989,   43633028,
     44003100,   47724096,   51905122,    52691025,   53600924,   56874435,   58207678,
     60225777,   60639161,   60888288,    60890325,   61742932,   63780621,   63786876,
     65167464,   66224357,   67198760,    69366452,   71163068,   72338751,   72960793,
     73197629,   76148392,   77779087,    78308432,   81196763,   82741805,   85315243,
     86446883,   87820032,   89819002,    90604146,   93761290,   97920291,   98315039,
    310120088, -441403864, -548143111,  -645883459, -149110919,  305170449, -248934805,
  -1108320430, -527806318, -192539936, -1005074405, -101557770, -156782742, -285384687,
   -418917176,   80346546, -273215446,  -552291568,   86824498,  -95392618, -707778486)
superset = sort(superset)
subsetSum = 139254953
subsetSumError = 0.1


# Find a subset of size 10.
subsetSize = 10L
rst = FLSSS::FLSSS(len = subsetSize, v = superset, target = subsetSum,
                   ME = subsetSumError, solutionNeed = 1, tlimit = 4)
# Verify:
all(unlist(lapply(rst, function(x)
  abs(sum(superset[x]) - subsetSum) <= subsetSumError)))


# Find a subset without size specification.
rst = FLSSS::FLSSS(len = 0, v = superset, target = subsetSum,
                   ME = subsetSumError, solutionNeed = 1, tlimit = 4)
# Verify:
all(unlist(lapply(rst, function(x)
  abs(sum(superset[x]) - subsetSum) <= subsetSumError)))
```

```
# Find a subset via looping subset size over 2L : (length(v)).
for(len in 2L : length(superset))
{
  rst = FLSSS::FLSSS(len = subsetSize, v = superset, target = subsetSum,
                     ME = subsetSumError, solutionNeed = 1, tlimit = 4)
  if(length(rst) > 0) break
}
# Verify:
all(unlist(lapply(rst, function(x)
  abs(sum(superset[x]) - subsetSum) <= subsetSumError)))


# Find as many qualified susbets as possible in 2 seconds
rst = FLSSS::FLSSS(len = subsetSize, v = superset, target = subsetSum,
                   ME = subsetSumError, solutionNeed = 999999L, tlimit = 2)
cat("Number of solutions =", length(rst), "\n")


# Verify:
all(unlist(lapply(rst, function(x)
  abs(sum(superset[x]) - subsetSum) <= subsetSumError)))




# ==========================================================================================
# Example III: solve a special knapsack problem.
# Given the knapsack's capacity, the number of catagories, the number of items in each
# catagory, select the least number of items to fulfill at least 95% of the knapsack's
# capacity.
# ==========================================================================================
rm(list = ls()); gc()
capacity = 361
catagories = LETTERS[1L : 10L] # A, B, ..., J, 10 catagories
catagoryMasses = round(runif(length(catagories)) * 20 + 1)
catagoryItems = sample(1L : 20L, length(catagories))


itemLabel = unlist(mapply(function(x, i) rep(i, x), catagoryItems, catagories))
itemMasses = unlist(mapply(function(x, i) rep(x, i), catagoryMasses, catagoryItems))
vorder = order(itemMasses)
itemLabel = itemLabel[vorder]


superset = itemMasses[vorder]
rate = 0.95
subsetSum = (capacity * rate + capacity) / 2
subsetSumError = capacity - subsetSum
for(subsetSize in 1L : length(itemMasses))
{
  rst = FLSSS::FLSSS(len = subsetSize, v = superset, target = subsetSum,
                     ME = subsetSumError, solutionNeed = 1, tlimit = 4)
  if(length(rst) > 0) break
```

```
}


# There may exist no qualified subsets. One can lower 'rate' until a solution
# shows up.
if(length(rst) == 0L)
{
  cat("No solutions. Please lower rate and rerun.\n")
} else
{
  cat("A solution:\n")
  print(table(itemLabel[rst[[1]]]))
}


rm(list = ls()); gc()
```

FLSSSmultiset *Multi-Subset Sum given error threshold*

Description

Find a subet of a given size for each of multiple supersets such that all the subsets sum in a given range.

Usage

```
FLSSSmultiset(
  len,
  buckets,
  target,
  ME,
  solutionNeed = 1L,
  tlimit = 60,
  useBiSrchInFB = FALSE,
  useFloat = FALSE
  )
```

Arguments

`len`	A positive integer vector as the subset sizes for the supersets.
`buckets`	A list of the supersets. `buckets[[i]]` is an unsorted numeric vector of size `len[i]`.
`target`	See `target` in `FLSSS()`.
`ME`	See `ME` in `FLSSS()`.
`solutionNeed`	See `solutionNeed` in `FLSSS()`.
`tlimit`	See `tlimit` in `FLSSS()`.
`useBiSrchInFB`	See `useBiSrchInFB` in `FLSSS()`.
`useFloat`	See `useFloat` in `FLSSS()`.

Value

A list of solutions. Each solution is a list of index vectors. Assume `X` is a solution. `X[[i]]` indexes the subset of superset `buckets[[i]]`.

Examples

```
# rm(list = ls()); gc()
Nsupersets = 30L
supersetSizes = sample(5L : 20L, Nsupersets, replace = TRUE)
subsetSizes = sapply(supersetSizes, function(x) sample(1L : x, 1))


# Create supersets at random:
supersets = lapply(supersetSizes, function(n)
{
  1000 * (rnorm(n) ^ 3 + 2 * runif(n) ^ 2 + 3 * rgamma(n, 5, 1) + 4)
})
str(supersets) # see the structure


# Give a subset sum
solution = mapply(function(n, l) sample(1L : n, l), supersetSizes, subsetSizes)
str(solution) # See structure
subsetsSum = sum(mapply(function(x, s) sum(x[s]), supersets, solution, SIMPLIFY = TRUE))
subsetsSumError = abs(subsetsSum) * 1e-7 # relative error within 0.00001%
rm(solution)


# Mine subsets:
rst = FLSSS::FLSSSmultiset(len = subsetSizes, buckets = supersets, target = subsetsSum,
                           ME = subsetsSumError, solutionNeed = 3, tlimit = 4)
cat("Number of solutions =", length(rst), "\n")


# Verify:
ver = all(unlist(lapply(rst, function(sol)
{
  S = sum(unlist(mapply(function(x, y) sum(x[y]), supersets, sol)))
  abs(S - subsetsSum) <= subsetsSumError
})))
cat("All subsets are qualified:", ver)
```

`GAP` *Generalized Assignment Problem solver*

Description

Given a number of agents and a number of tasks. An agent can finish a task with certain cost and profit. An agent also has a budget. Assign tasks to agents such that each agent costs no more than its budget while the total profit is maximized.

Usage

```
GAP(
  maxCore = 7L,
  agentsCosts,
  agentsProfits,
  agentsBudgets,
  heuristic = FALSE,
  tlimit = 60,
  threadLoad = 8L,
  verbose = TRUE
  )
```

Arguments

`maxCore`	Maximal threads to invoke. Ideally `maxCore` should not surpass the total logical processors on machine.
`agentsCosts`	A numeric matrix. `agentsCosts[i,j]` is the cost for agent `i` to finish task `j`.
`agentsProfits`	A numeric matrix. `agentsProfits[i,j]` is the profit from agent `i` finishing task `j`.
`agentsBudgets`	A numeric vector. `agentsBudgets[i]` is agent `i`'s budget.
`heuristic`	A boolean value. If `TRUE`, the function returns once it has found a solution whose sum of ranks of the profits becomes no less than that of the optimal. See `heuristic` in `mmKnapsack()`.
`tlimit`	A numeric value. Enforce function to return in `tlimit` seconds.
`threadLoad`	See `avgThreadLoad` in `mFLSSSpar()`.
`verbose`	If `TRUE`, function prints progress.

Value

A list of size nine.

`assignedAgents`	is a 2-column data frame, the mining result. The 1st column is task indexes. The 2nd column is agent indexes.
`assignmentProfit`	is the profit resulted from such assignment.
`assignmentCosts`	is a numeric vector. `Value$assignmentCosts[i]` is the cost of agent `i`.
`agentsBudgets`	is a numeric vector. `Value$agentsBudgets[i]` shows the budget of agent `i`.
`unconstrainedMaxProfit`	is the would-be maximal profit if agents had infinite budgets.
`FLSSSsolution`	is the solution from mining the corresponding multidimensional Subset Sum problem.
`FLSSSvec`	is the multidimensional vector (a matrix) going into the multidimensional Subset Sum miner.

MAXmat
: is the subset sum targets' upper bounds going into the multidimensional Subset Sum miner.

foreShadowFLSSSvec
: is the multidimensional vector before comonotonization.

Examples

```
# ===============================================================================
# Play random numbers
# ===============================================================================
rm(list = ls()); gc()
agents = 5L
tasks = 12L
costs = t(as.data.frame(lapply(1L : agents, function(x) runif(tasks) * 1000)))
budgets = apply(costs, 1, function(x) runif(1, min(x), sum(x)))
profits = t(as.data.frame(lapply(1L : agents, function(x)
  abs(rnorm(tasks) + runif(1, 0, 4)) * 10000)))


# A dirty function for examining the result's integrity. The function takes in
# the task-agent assignment, the profit or cost matrix M, and calculates the cost
# or profit generated by each agent. 'assignment' is a 2-column data
# frame, first column task, second column agent.
agentCostsOrProfits <- function(assignment, M)
{
  n = ncol(M) * nrow(M)
  M2 = matrix(numeric(n), ncol = tasks)
  for(i in 1L : nrow(assignment))
  {
    x = as.integer(assignment[i, ])
    M2[x[2], x[1]] = M[x[2], x[1]]
  }
  apply(M2, 1, function(x) sum(x))
}


dimnames(costs) = NULL
dimnames(profits) = NULL
names(budgets) = NULL


rst = FLSSS::GAP(maxCore = 7L, agentsCosts = costs, agentsProfits = profits,
                 agentsBudgets = budgets, heuristic = FALSE, tlimit = 60,
                 threadLoad = 8L, verbose = TRUE)
# Function also saves the assignment costs and profits
rst$assignedAgents
rst$assignmentProfit
rst$assignmentCosts


# Examine rst$assignmentCosts
if(sum(rst$assignedAgents) > 0) # all zeros mean the function has not found a solution.
  agentCostsOrProfits(rst$assignedAgents, costs)
```

```
# Should equal rst$assignmentCosts and not surpass budgets


# Examine rst$assignmentProfits
if(sum(rst$assignedAgents) > 0)
  sum(agentCostsOrProfits(rst$assignedAgents, profits))
# Should equal rst$assignmentProfit





# =======================================================================================
# Test case P03 from
# https://people.sc.fsu.edu/~jburkardt/datasets/generalized_assignment/
# =======================================================================================
agents = 3L
tasks = 8L
profits = t(matrix(c(
27, 12, 12, 16, 24, 31, 41, 13,
14,  5, 37,  9, 36, 25,  1, 34,
34, 34, 20,  9, 19, 19,  3, 34), ncol = agents))
costs = t(matrix(c(
21, 13,  9,  5,  7, 15,  5, 24,
20,  8, 18, 25,  6,  6,  9,  6,
16, 16, 18, 24, 11, 11, 16, 18), ncol = agents))
budgets = c(26, 25, 34)


rst = FLSSS::GAP(maxCore = 2L, agentsCosts = costs, agentsProfits = profits,
                 agentsBudgets = budgets, heuristic = FALSE, tlimit = 2,
                 threadLoad = 8L, verbose = TRUE)
agentCostsOrProfits(rst$assignedAgents, costs)
# Should equal rst$assignmentCosts and not surpass budgets


knownOptSolution = as.integer(c(3, 3, 1, 1, 2, 2, 1, 2))
knownOptSolution = data.frame(task = 1L : tasks, agent = knownOptSolution)


# Total profit from knownOptSolution:
sum(agentCostsOrProfits(knownOptSolution, profits))
# Total profit from FLSSS::GAP():
rst$assignmentProfit
```

`mFLSSSobjRun` *Run an* `mFLSSS` *instance*

Description

Run a multidimensional subset sum instance decomposed from `decomposeMflsss()`.

Usage

```
mFLSSSobjRun(
  mflsssObj,
  solutionNeed = 1,
  tlimit = 60
  )
```

Arguments

mflsssObj	An mFLSSS object.
solutionNeed	See the same argument in mFLSSSpar().
tlimit	See the same argument in mFLSSSpar().

Details

See the details about decomposeMflsss().

Value

See the value of mFLSSSpar().

Examples

```
# See the example for decomposeMflsss().
```

---

mFLSSSpar *Multithreaded multidimensional Subset Sum given error thresholds*

Description

The multidimensional version of FLSSS(). See decomposeMflsss() for the multi-process version.

Usage

```
mFLSSSpar(
  maxCore = 7L,
  len,
  mV,
  mTarget,
  mME,
  solutionNeed = 1L,
  tlimit = 60,
  dl = ncol(mV),
  du = ncol(mV),
  useBiSrchInFB = FALSE,
  avgThreadLoad = 8L
  )
```

Arguments

maxCore	Maximal threads to invoke. Ideally maxCore should not surpass the total logical processors on machine.
len	An integer as the subset size. See len in FLSSS().
mV	A data frame or a matrix as the multidimensional set, columns as dimensions.
mTarget	A numeric vector of size ncol(mV) as the subset sum.
mME	A numeric vector of size ncol(mV) as the subset sum error thresholds.
solutionNeed	See solutionNeed in FLSSS().
tlimit	See tlimit in FLSSS().
dl	An integer no greater than ncol(mV). Let sol be the index vector of a solution. Let dls <-1L : dl. The following is true: colSums(mV[sol,dls]) >= mTarget[dls] -mME[dls].
du	An integer no greater than ncol(mV). Let sol be the index vector of a solution. Let dus <-(ncol(mV) -du + 1) : ncol(mV). The following is true: colSums(mV[sol,dus]) <= mTarget[dus] + mME[dus].
useBiSrchInFB	See useBiSrchInFB in FLSSS().
avgThreadLoad	If mV is comonotonic, mFLSSSpar() warms up with a breadth-first search and then spawns at least B branches for parallelization. B equals the first power-of-two integer no less than avgThreadLoad * maxCore.

Value

A list of index vectors.

Examples

```
rm(list = ls()); gc()
subsetSize = 7L
supersetSize = 60L
dimension = 5L # dimensionality


# Create a supertset at random:
N = supersetSize * dimension
superset = matrix(1000 * (rnorm(N) ^ 3 + 2 * runif(N) ^ 2 +
  3 * rgamma(N, 5, 1) + 4), ncol = dimension)
rm(N)


# Plant a subset sum:
solution = sample(1L : supersetSize, subsetSize)
subsetSum = colSums(superset[solution, ])
subsetSumError = abs(subsetSum) * 0.01 # relative error within 1%
rm(solution)


# Mine subsets, dimensions fully bounded
```

```
rst = FLSSS::mFLSSSpar(maxCore = 2, len = subsetSize, mV = superset,
                       mTarget = subsetSum, mME = subsetSumError,
                       solutionNeed = 2, dl = ncol(superset), du = ncol(superset),
                       tlimit = 2, useBiSrchInFB = FALSE, avgThreadLoad = 8L)


# Verify:
cat("Number of solutions = ", length(rst), "\n")
if(length(rst) > 0)
{
  cat("Solutions unique: ")
  cat(length(unique(lapply(rst, function(x) sort(x)))) == length(rst), "\n")
  cat("Solutions correct: ")
  cat(all(unlist(lapply(rst, function(x)
    abs(colSums(superset[x, ]) - subsetSum) <= subsetSumError))), "\n")
} else
{
  cat("No solutions exist or timer ended too soon.\n")
}




# Mine subsets, the first 3 dimensions lower bounded,
# the last 4 dimension upper bounded
rst = FLSSS::mFLSSSpar(maxCore = 2, len = subsetSize, mV = superset,
                       mTarget = subsetSum, mME = subsetSumError,
                       solutionNeed = 2, dl = 3L, du = 4L,
                       tlimit = 2, useBiSrchInFB = FALSE, avgThreadLoad = 8L)


# Verify:
cat("Number of solutions = ", length(rst), "\n")
if(length(rst) > 0)
{
  cat("Solutions unique: ")
  cat(length(unique(lapply(rst, function(x) sort(x)))) == length(rst), "\n")
  cat("Solutions correct: ")
  cat(all(unlist(lapply(rst, function(x)
  {
    lowerBoundedDim = 1L : 3L
    lowerBounded = all(colSums(superset[x, lowerBoundedDim]) >=
      subsetSum[lowerBoundedDim] - subsetSumError[lowerBoundedDim])


    upperBoundedDim = (ncol(superset) - 3L) : ncol(superset)
    upperBounded = all(colSums(superset[x, upperBoundedDim]) <=
      subsetSum[upperBoundedDim] + subsetSumError[upperBoundedDim])


    lowerBounded & upperBounded
  }))), "\n")
} else
```

```
{
  cat("No solutions exist or timer ended too soon.\n")
}
```

---

mFLSSSparImposeBounds *Multithreaded multidimensional Subset Sum in bounded solution space given error thresholds*

Description

For comparison, function `mFLSSSpar()` puts no bounds on the solution space so it sorts `mV` internally in a special order for mining accerlation.

Usage

```
mFLSSSparImposeBounds(
  maxCore = 7L,
  len,
  mV,
  mTarget,
  mME,
  LB = 1L : len,
  UB = (nrow(mV) - len + 1L) : nrow(mV),
  solutionNeed = 1L,
  tlimit = 60,
  dl = ncol(mV),
  du = ncol(mV),
  targetsOrder = NULL,
  useBiSrchInFB = FALSE,
  avgThreadLoad = 8L
  )
```

Arguments

`maxCore`	See `maxCore` in `mFLSSSpar()`.
`len`	See `len` in `mFLSSSpar()`.
`mV`	See `mV` in `mFLSSSpar()`.
`mTarget`	See `mTarget` in `mFLSSSpar()`.
`mME`	See `mME` in `mFLSSSpar()`.
`LB`	See `LB` in `FLSSS()`.
`UB`	See `UB` in `FLSSS()`.
`solutionNeed`	See `solutionNeed` in `mFLSSSpar()`.
`tlimit`	See `tlimit` in `mFLSSSpar()`.
`dl`	See `dl` in `mFLSSSpar()`.

du — See du in mFLSSSpar().

targetsOrder — This argument is mainly for research and unrecommended for use. Depending on the structure of mV, mFLSSSpar() or mFLSSSparImposeBounds() would break the mining task into a collection of no more than len * (nrow(mV) -len) + 1 independent subtasks. Threads work on these subtasks, sequentially coordinated by an atomic counter [1]. Different subtasks have different probabilities of yielding a qualified subset, thus the order of subtasks matters to the mining speed. targetsOrder is an index vector of size len * (nrow(mV) - len) + 1 for ordering the subtasks. targetsOrder <-NULL makes a special order, and is implicitly the choice in mFLSSSpar(). This order is empirically optimal based on simulations. See the package documentation for details.

useBiSrchInFB — See useBiSrchInFB in mFLSSSpar().

avgThreadLoad — See avgThreadLoad in mFLSSSpar().

Value

A list of index vectors.

References

[1] Atomic template class in Intel TBB. An atomic counter is used to coordinate heterogeneous subtasks to avoid idle threads. The atomic operation overhead is negligible compared to the time cost of the lightest subtask.

Examples

```
rm(list = ls()); gc()
subsetSize = 7L
supersetSize = 60L
dimension = 5L # dimensionality


# Create a supertset at random:
N = supersetSize * dimension
superset = matrix(1000 * (rnorm(N) ^ 3 + 2 * runif(N) ^ 2 +
                  3 * rgamma(N, 5, 1) + 4), ncol = dimension)
rm(N)


# Make up the lower and upper bounds for the solution space:
tmp = sort(sample(1L : supersetSize, subsetSize))
tmp2 = sort(sample(1L : supersetSize, subsetSize))
lowerBounds = pmin(tmp, tmp2)
upperBounds = pmax(tmp, tmp2)
rm(tmp, tmp2)


# Exclude elements not covered by 'lowerBounds' and 'upperBounds':
remainIndex = unique(unlist(apply(cbind(lowerBounds, upperBounds), 1,
```

```
                                  function(x) x[1] : x[2])))
lowerBounds = match(lowerBounds, remainIndex)
upperBounds = match(upperBounds, remainIndex)
superset = superset[remainIndex, ]


# Plant a subset sum:
solution = apply(rbind(lowerBounds, upperBounds), 2, function(x)
  sample(x[1] : x[2], 1))
subsetSum = colSums(superset[solution, ])
subsetSumError = abs(subsetSum) * 0.01 # relative error within 1%
rm(solution)


rst = FLSSS::mFLSSSparImposeBounds(
  maxCore = 2L, len = subsetSize, mV = superset, mTarget = subsetSum,
  mME = subsetSumError, LB = lowerBounds, UB = upperBounds,
  solutionNeed = 1, tlimit = 2, dl = ncol(superset), du = ncol(superset),
  targetsOrder = NULL, useBiSrchInFB = FALSE, avgThreadLoad = 8L)


# Verify:
cat("Number of solutions = ", length(rst), "\n")
if(length(rst) > 0)
{
  cat("Solutions unique: ")
  cat(length(unique(lapply(rst, function(x) sort(x)))) == length(rst), "\n")
  cat("Solution in bounded space: ")
  cat(all(unlist(lapply(rst, function(x)
    sort(x) <= upperBounds & sort(x) >= lowerBounds))), "\n")
  cat("Solutions correct: ")
  cat(all(unlist(lapply(rst, function(x)
    abs(colSums(superset[x, ]) - subsetSum) <= subsetSumError))), "\n")
} else
{
  cat("No solutions exist or timer ended too soon.\n")
}
```

`mFLSSSparImposeBoundsIntegerized`
An advanced version of `mFLSSSparImposeBounds()`

Description

See the description of `mFLSSSparIntegerized()`.

Usage

```
mFLSSSparImposeBoundsIntegerized(
```

```
  maxCore = 7L,
  len,
  mV,
  mTarget,
  mME,
  LB = 1L:len,
  UB = (nrow(mV) - len + 1L) : nrow(mV),
  solutionNeed = 1L,
  precisionLevel = integer(ncol(mV)),
  returnBeforeMining = FALSE,
  tlimit = 60,
  dl = ncol(mV),
  du = ncol(mV),
  targetsOrder = NULL,
  useBiSrchInFB = FALSE,
  avgThreadLoad = 8L,
  verbose = TRUE)
```

Arguments

maxCore	See maxCore in mFLSSSpar().
len	See len in mFLSSSpar().
mV	See mV in mFLSSSpar().
mTarget	See mTarget in mFLSSSpar().
mME	See mME in mFLSSSpar().
LB	See LB in FLSSS().
UB	See UB in FLSSS().
solutionNeed	See solutionNeed in mFLSSSpar().
precisionLevel	See precisionLevel in mFLSSSparIntegerized().
returnBeforeMining	See returnBeforeMining in mFLSSSparIntegerized().
tlimit	See tlimit in mFLSSSpar().
dl	See dl in mFLSSSpar().
du	See dl in mFLSSSpar().
targetsOrder	See targetsOrder in mFLSSSparImposeBounds().
useBiSrchInFB	See useBiSrchInFB in mFLSSSpar().
avgThreadLoad	See avgThreadLoad in mFLSSSpar().
verbose	If TRUE, prints mining progress.

Value

See Value in mFLSSSparIntegerized().

Note

32-bit architecture unsupported.

Examples

```
if(.Machine$sizeof.pointer == 8L){
# =====================================================================================
# 64-bit architecture required.
# =====================================================================================
rm(list = ls()); gc()
subsetSize = 7L
supersetSize = 60L
dimension = 5L # dimensionality


# Create a superset at random:
N = supersetSize * dimension
superset = matrix(1000 * (rnorm(N) ^ 3 + 2 * runif(N) ^ 2 +
                  3 * rgamma(N, 5, 1) + 4), ncol = dimension)
rm(N)


# Make up the lower and upper bounds for the solution space:
tmp = sort(sample(1L : supersetSize, subsetSize))
tmp2 = sort(sample(1L : supersetSize, subsetSize))
lowerBounds = pmin(tmp, tmp2)
upperBounds = pmax(tmp, tmp2)
rm(tmp, tmp2)


# 'mFLSSSparImposeBoundsIntegerized()' does not work if there are elements not
# under the hood of 'lowerBounds' + 'upperBounds'. Exclude these elements first:
remainIndex = unique(unlist(
  apply(cbind(lowerBounds, upperBounds), 1, function(x) x[1] : x[2])))
lowerBounds = match(lowerBounds, remainIndex)
upperBounds = match(upperBounds, remainIndex)
superset = superset[remainIndex, ]


# Plant a subset sum:
solution = integer(subsetSize)
solution[1] = sample(lowerBounds[1] : upperBounds[1], 1)
for(i in 2L : subsetSize)
{
  l = max(lowerBounds[i], solution[i - 1] + 1L)
  u = upperBounds[i]
  if(l == u) solution[i] = u
  else solution[i] = sample(l : u, 1)
}
subsetSum = colSums(superset[solution, ])
subsetSumError = abs(subsetSum) * 0.01 # relative error within 1%
rm(solution)
```

```
system.time({rst = FLSSS::mFLSSSparImposeBoundsIntegerized(
  maxCore = 2L, len = subsetSize, mV = superset, mTarget = subsetSum,
  mME = subsetSumError, LB = lowerBounds, UB = upperBounds,
  solutionNeed = 1, tlimit = 3, dl = ncol(superset), du = ncol(superset),
  targetsOrder = NULL, useBiSrchInFB = FALSE, avgThreadLoad = 8L)})


# Compare the time cost of 'mFLSSSparImposeBoundsIntegerized()' and
# 'mFLSSSparImposeBounds()'. The speed advantage of 'mFLSSSparIntegerized()'
# may not be pronounced for toy examples.
system.time(FLSSS::mFLSSSparImposeBounds(
  maxCore = 2L, len = subsetSize, mV = superset, mTarget = subsetSum,
  mME = subsetSumError, LB = lowerBounds, UB = upperBounds,
  solutionNeed = 1, tlimit = 2, dl = ncol(superset), du = ncol(superset),
  targetsOrder = NULL, useBiSrchInFB = FALSE, avgThreadLoad = 8L))


# Verify:
cat("Number of solutions = ", length(rst$solution), "\n")
if(length(rst$solution) > 0)
{
  cat("Solutions unique: ")
  cat(length(unique(lapply(rst$solution, function(x)
    sort(x)))) == length(rst$solution), "\n")
  cat("Solution in bounded space: ")
  cat(all(unlist(lapply(rst$solution, function(x)
    sort(x) <= upperBounds & sort(x) >= lowerBounds))), "\n")


  cat("Solutions correct regarding integerized data: ")
  cat(all(unlist(lapply(rst$solution, function(x)
    abs(colSums(rst$INT$mV[x, ]) - rst$INT$mTarget) <= rst$INT$mME))), "\n")


  cat("Solutions correct regarding original data: ")
  boolean = all(unlist(lapply(rst$solution, function(x)
    abs(colSums(superset[x, ]) - subsetSum) <= subsetSumError)))
  cat(boolean, "\n")
  if(!boolean)
  {
    cat("The given error threshold relative to subset sum:\n")
    givenRelaErr = round(abs(subsetSumError / subsetSum), 5)
    cat(givenRelaErr, "\n")


    cat("Solution subset sum relative error:\n")
    tmp = lapply(rst$solution, function(x)
    {
      err = round(abs(colSums(superset[x, ]) / subsetSum -1), 5)
      for(i in 1L : length(err))
      {
```

```
        if(givenRelaErr[i] < err[i]) message(paste0(err[i], " "), appendLF = FALSE)
        else cat(err[i], "")
      }
      cat("\n")
    })
    cat("Integerization caused the errors. Future versions of")
    cat("'mFLSSSparIntegerized()' would have a parameter of precision level.\n")
  }
} else
{
  cat("No solutions exist or timer ended too soon.\n")
}

# ===========================================================================================
# ===========================================================================================
}
```

`mFLSSSparIntegerized` *An advanced version of* `mFLSSSpar()`

Description

This function maps a real-value multidimensional Subset Sum problem to the integer domain with minimal precision loss. Those integers are further compressed in 64-bit buffers for dimension reduction and SWAR (SIMD within a register) that could lead to substantial acceleration.

Usage

```
mFLSSSparIntegerized(
  maxCore = 7L,
  len,
  mV,
  mTarget,
  mME,
  solutionNeed = 1L,
  precisionLevel = integer(ncol(mV)),
  returnBeforeMining = FALSE,
  tlimit = 60,
  dl = ncol(mV),
  du = ncol(mV),
  useBiSrchInFB = FALSE,
  avgThreadLoad = 8L,
  verbose = TRUE
  )
```

Arguments

`maxCore` See `maxCore` in `mFLSSSpar()`.

`len` See `len` in `mFLSSSpar()`.

`mV` See `mV` in `mFLSSSpar()`.

`mTarget` See `mTarget` in `mFLSSSpar()`.

`mME` See `mME` in `mFLSSSpar()`.

`solutionNeed` See `solutionNeed` in `mFLSSSpar()`.

`precisionLevel` An integer vector of size equal to the dimensionality of `mV`. This argument controls the precision of real-to-integer conversion.

If `precisionLevel[i] = 0`, `mV[,i]` is shifted, scaled and rounded to the nearest integers such that the maximum becomes no less than `nrow(mV) * 8`.

If `precisionLevel[i] > 0`, e.g. `precisionLevel[i] = 1000`, `mV[,i]` is shifted, scaled and rounded to the nearest integers such that the maximum becomes no less than 1000.

If `precisionLevel[i] = -1`, `mV[,i]` is shifted, scaled and rounded to the nearest integers such that ranks of elements stay the same.

The shift operator contributes no precision loss. It only lowers the number of bits used for storing integers.

`returnBeforeMining`
A boolean value. If `TRUE`, function returns the integerized `mV`, `mTarget` and `mME`.

`tlimit` See `tlimit` in `mFLSSSpar()`.

`dl` See `dl` in `mFLSSSpar()`.

`du` See `du` in `mFLSSSpar()`.

`useBiSrchInFB` See `useBiSrchInFB` in `mFLSSSpar()`.

`avgThreadLoad` See `avgThreadLoad` in `mFLSSSpar()`.

`verbose` If TRUE, prints mining progress.

Value

A list of two.

`Value$solution` is a list of solution index vectors.

`Value$INT` is a list of three.

`Value$INT$mV` is the integerized superset.

`Value$INT$mTarget`
is the integerized subset sum.

`Value$INT$mME` is the integerized subset sum error threshold.

`Value$INT$compressedDim`
is the dimensionality after integerization.

Note

32-bit architecture unsupported.

Examples

```
if(.Machine$sizeof.pointer == 8L){
# =====================================================================================
# 64-bit architecture required.
# =====================================================================================
rm(list = ls()); gc()
subsetSize = 7L
supersetSize = 60L
dimension = 5L # dimensionality


# Create a supertset at random:
N = supersetSize * dimension
superset = matrix(1000 * (rnorm(N) ^ 3 + 2 * runif(N) ^ 2 + 3 * rgamma(N, 5, 1) + 4),
                  ncol = dimension)
rm(N)


# Plant a subset sum:
solution = sample(1L : supersetSize, subsetSize)
subsetSum = colSums(superset[solution, ])
subsetSumError = abs(subsetSum) * 0.01 # relative error within 1%
rm(solution)


# Mine subsets, dimensions fully bounded
system.time({rst = FLSSS::mFLSSSparIntegerized(
  maxCore = 2, len = subsetSize, mV = superset, mTarget = subsetSum,
  mME = subsetSumError, solutionNeed = 2, dl = ncol(superset),
  du = ncol(superset), tlimit = 2, useBiSrchInFB = FALSE, avgThreadLoad = 8L)})


# Compare the time cost of 'mFLSSSparIntegerized()' and 'mFLSSSpar()'. The
# speed advantage of 'mFLSSSparIntegerized()' may not be pronounced for toy
# examples.
system.time(FLSSS::mFLSSSpar(
  maxCore = 2, len = subsetSize, mV = superset, mTarget = subsetSum,
  mME = subsetSumError, solutionNeed = 2, dl = ncol(superset),
  du = ncol(superset), tlimit = 2, useBiSrchInFB = FALSE, avgThreadLoad = 8L))


# Verify:
cat("Number of solutions = ", length(rst$solution), "\n")
if(length(rst$solution) > 0)
{
  cat("Solutions unique: ")
  cat(length(unique(lapply(rst$solution, function(x)
    sort(x)))) == length(rst$solution), "\n")


  cat("Solutions correct regarding integerized data: ")
  cat(all(unlist(lapply(rst$solution, function(x)
```

```
    abs(colSums(rst$INT$mV[x, ]) - rst$INT$mTarget) <= rst$INT$mME))), "\n")


  cat("Solutions correct regarding original data: ")
  boolean = all(unlist(lapply(rst$solution, function(x)
    abs(colSums(superset[x, ]) - subsetSum) <= subsetSumError)))
  cat(boolean, "\n")
  if(!boolean)
  {
    cat("The given error threshold relative to subset sum:\n")
    givenRelaErr = round(abs(subsetSumError / subsetSum), 5)
    cat(givenRelaErr, "\n")


    cat("Solution subset sum relative error:\n")
    tmp = lapply(rst$solution, function(x)
    {
      err = round(abs(colSums(superset[x, ]) / subsetSum -1), 5)
      for(i in 1L : length(err))
      {
        if(givenRelaErr[i] < err[i]) message(paste0(err[i], " "), appendLF = FALSE)
        else cat(err[i], "")
      }
      cat("\n")
    })
    cat("Integerization caused the errors. Future versions of")
    cat("'mFLSSSparIntegerized()' would have a parameter of precision level.\n")
  }
} else
{
  cat("No solutions exist or time ended too soon.\n")
}


# Mine subsets, the first 3 dimensions lower bounded,
# the last 4 dimension upper bounded
rst = FLSSS::mFLSSSparIntegerized(
  maxCore = 2, len = subsetSize, mV = superset, mTarget = subsetSum,
  mME = subsetSumError, solutionNeed = 2, dl = 3L, du = 4L, tlimit = 2,
  useBiSrchInFB = FALSE, avgThreadLoad = 8L)


# Verify:
cat("Number of solutions = ", length(rst$solution), "\n")
if(length(rst$solution) > 0)
{
  cat("Solutions unique: ")
  cat(length(unique(lapply(rst$solution, function(x)
    sort(x)))) == length(rst$solution), "\n")


  cat("Solutions correct regarding integerized data: ")
  cat(all(unlist(lapply(rst$solution, function(x)
```

```
  {
    lowerBoundedDim = 1L : 3L
    lowerBounded = all(colSums(rst$INT$mV[x, lowerBoundedDim]) >=
      rst$INT$mTarget[lowerBoundedDim] - rst$INT$mME[lowerBoundedDim])


    upperBoundedDim = (ncol(rst$INT$mV) - 3L) : ncol(rst$INT$mV)
    upperBounded = all(colSums(rst$INT$mV[x, upperBoundedDim]) <=
      rst$INT$mTarget[upperBoundedDim] + rst$INT$mME[upperBoundedDim])


    lowerBounded & upperBounded
  }))), "\n")
} else
{
  cat("No solutions exist or timer ended too soon.\n")
}
# =====================================================================================
# =====================================================================================
}
```

---

mmKnapsack *Multithreaded multidimensional Knapsack problem solver*

Description

Given a set of items characterized by a profit attribute and multiple cost attributes, `mmKnapsack()` seeks a subset that maximizes the total profit while the subset sum in each cost dimension is upper bounded. The function applies to the 0-1 Knapsack problem. For the bounded or unbounded Knapsack problem, one can replicate items as needed and turn the problem into 0-1 Knapsack. Profits and costs should be nonnegative. Negative values in data can be neutralized by shifting and scaling.

Usage

```
mmKnapsack(
  maxCore = 7L,
  len,
  itemsProfits,
  itemsCosts,
  capacities,
  heuristic = FALSE,
  tlimit = 60,
  useBiSrchInFB = FALSE,
  threadLoad = 8L,
  verbose = TRUE
  )
```

Arguments

`maxCore`	Maximal threads to invoke. Ideally `maxCore` should not surpass the total logical processors on machine.
`len`	An integer as the subset size. See `len` in `FLSSS()`.
`itemsProfits`	A nonnegative numeric vector of size equal to the number of items.
`itemsCosts`	A nonnegative numeric matrix. Number of rows equals number of items. Number of columns equals number of cost dimensions.
`capacities`	A numeric vector of size equal to the number of cost dimensions. `capacities[i]` upper-bounds the total cost in `itemsCosts[,i]`.
`heuristic`	A boolean value. If `TRUE`, the function returns once it has found a solution whose sum of ranks of the profits is no less than that of the optimal. See Examples.
`tlimit`	A numeric value. Enforce function to return in `tlimit` seconds.
`useBiSrchInFB`	See `useBiSrchInFB` in `FLSSS()`.
`threadLoad`	See `avgThreadLoad` in `mFLSSSpar()`.
`verbose`	If `TRUE`, function prints progress.

Value

If no solution, an empty list, otherwise a list of five:

`solution`	The optimal solution.
`selectionCosts`	Solution costs.
`budgets`	Knapsack capacities.
`selectionProfit`	Solution total profit.
`unconstrainedMaxProfit`	Maximal profit given infinite budgets.

Examples

```
# ===============================================================================
# Play random numbers
# ===============================================================================
rm(list = ls()); gc()
subsetSize = 6
supersetSize = 60
NcostsAttr = 4


  # Make up costs for each item.
  costs = abs(6 * (rnorm(supersetSize * NcostsAttr) ^ 3 +
                   2 * runif(supersetSize * NcostsAttr) ^ 2 +
                   3 * rgamma(supersetSize * NcostsAttr, 5, 1) + 4))
  costs = matrix(costs, ncol = NcostsAttr)
```

```
  # Make up cost limits.
  budgets = apply(costs, 2, function(x)
  {
    x = sort(x)
    Min = sum(x[1L : subsetSize])
    Max = sum(x[(supersetSize - subsetSize + 1L) : supersetSize])
    runif(1, Min, Max)
  })


  # Make up item profits.
  gains = rnorm(supersetSize) ^ 2 * 10000 + 100


  rst1 = FLSSS::mmKnapsack(
    maxCore = 2L, len = subsetSize, itemsProfits = gains, itemsCosts = costs,
    capacities = budgets, heuristic = FALSE, tlimit = 60, useBiSrchInFB = FALSE,
    threadLoad = 4L, verbose = TRUE)


  # Let 'x' be the solution given 'heuristic = TRUE'. The sum of ranks of the
  # profits subsetted by 'x' would be no less than that of the optimal solution.
  rst2 = FLSSS::mmKnapsack(
    maxCore = 2L, len = subsetSize, itemsProfits = gains, itemsCosts = costs,
    capacities = budgets, heuristic = TRUE, tlimit = 60, useBiSrchInFB = FALSE,
    threadLoad = 4L, verbose = TRUE)


  # Exam difference in total profits given by the heuristic and the optimal:
  cat(length(rst1$solution)); cat(length(rst2$solution)) # See if solution exists.
  if(length(rst1$solution) > 0 & length(rst2$solution) > 0)
    sum(gains[rst2$solution]) / sum(gains[rst1$solution])




# ============================================================================
# Test case P08 from
# https://people.sc.fsu.edu/~jburkardt/datasets/knapsack_01/knapsack_01.html
# ============================================================================
rm(list = ls()); gc()
costs = matrix(c(382745, 799601, 909247, 729069, 467902,  44328,  34610, 698150,
                 823460, 903959, 853665, 551830, 610856, 670702, 488960, 951111,
                 323046, 446298, 931161,  31385, 496951, 264724, 224916, 169684),
               ncol = 1)


gains = c( 825594, 1677009, 1676628, 1523970,  943972,   97426,  69666, 1296457,
          1679693, 1902996, 1844992, 1049289, 1252836, 1319836, 953277, 2067538,
           675367,  853655, 1826027,   65731,  901489,  577243, 466257,  369261)
```

```
budgets = 6404180


# 'mmKnapsack()' is designed for the multidimensional Knapsack and may not
# be ideal for one-dimensional 0-1 Knapsack regarding computing speed.
# 'len = 0' causes substantial deceleration. Looping 'len' over possible
# values is recommended if 'len' is ungiven.
rst1 = FLSSS::mmKnapsack(
  maxCore = 2L, len = 12L, itemsProfits = gains, itemsCosts = costs,
  capacities = budgets, heuristic = FALSE, tlimit = 2, threadLoad = 4L,
  verbose = TRUE)
rst1 = sort(rst1$solution)


cat("Correct solution:\n1 2 4 5 6 10 11 13 16 22 23 24\nFLSSS solution =\n")
cat(rst1, "\n")




# ===================================================================================
# Test case P07 from
# https://people.sc.fsu.edu/~jburkardt/datasets/knapsack_01/knapsack_01.html
# ===================================================================================
costs = matrix(c(70, 73, 77, 80, 82, 87, 90, 94, 98, 106, 110, 113, 115, 118, 120),
               ncol = 1)


gains = c(135, 139, 149, 150, 156, 163, 173, 184, 192, 201, 210, 214, 221, 229, 240)


budgets = 750


rst2 = FLSSS::mmKnapsack(
  maxCore = 2L, len = 8L, itemsProfits = gains, itemsCosts = costs,
  capacities = budgets, heuristic = FALSE, tlimit = 2,
  threadLoad = 4L, verbose = TRUE)
rst2 = sort(rst2$solution)


cat("Correct solution:\n1 3 5 7 8 9 14 15\nFLSSS solution =\n")
cat(rst2, "\n")
```

`mmKnapsackIntegerized` *An advanced version of* `mmKnapsack()`

Description

See the description of `mFLSSSparIntegerized()`.

Usage

```
mmKnapsackIntegerized(
  maxCore = 7L,
  len,
  itemsProfits,
  itemsCosts,
  capacities,
  heuristic = FALSE,
  precisionLevel = integer(length(capacities)),
  returnBeforeMining = FALSE,
  tlimit = 60,
  useBiSrchInFB = FALSE,
  threadLoad = 8L,
  verbose = TRUE
  )
```

Arguments

`maxCore`	See `maxCore` in `mmKnapsack()`.
`len`	See `len` in `mmKnapsack()`.
`itemsProfits`	See `itemsProfits` in `mmKnapsack()`.
`itemsCosts`	See `itemsCosts` in `mmKnapsack()`.
`capacities`	See `capacities` in `mmKnapsack()`.
`heuristic`	See `heuristic` in `mmKnapsack()`.
`precisionLevel`	See `precisionLevel` in `mFLSSSparIntegerized()`.
`returnBeforeMining`	See `returnBeforeMining` in `mFLSSSparIntegerized()`.
`tlimit`	See `tlimit` in `mmKnapsack()`.
`useBiSrchInFB`	See `useBiSrchInFB` in `FLSSS()`.
`threadLoad`	See `avgThreadLoad` in `mFLSSSpar()`.
`verbose`	If `TRUE`, function prints progress.

Value

A list of six:

`solution`	The optimal solution.
`selectionCosts`	Solution costs.
`budgets`	Knapsack capacities.
`selectionProfit`	Solution total profit.
`unconstrainedMaxProfit`	Maximal profit given infinite budgets.
`INT`	A list of four:

INT$mV The integerized superset.

INT$mTarget The integerized subset sum.

INT$mME The integerized subset sum error threshold.

INT$compressedDim
The dimensionality after integerization.

Note

32-bit architecture unsupported.

Examples

```
if(.Machine$sizeof.pointer == 8L){
# =====================================================================================
# 64-bit architecture required.
# =====================================================================================
# =====================================================================================
# Play random numbers
# =====================================================================================
rm(list = ls()); gc()
subsetSize = 6
supersetSize = 60
NcostsAttr = 4


# Make up costs for each item.
costs = abs(6 * (rnorm(supersetSize * NcostsAttr) ^ 3 +
  2 * runif(supersetSize * NcostsAttr) ^ 2 +
  3 * rgamma(supersetSize * NcostsAttr, 5, 1) + 4))
costs = matrix(costs, ncol = NcostsAttr)


# Make up cost limits.
budgets = apply(costs, 2, function(x)
{
  x = sort(x)
  Min = sum(x[1L : subsetSize])
  Max = sum(x[(supersetSize - subsetSize + 1L) : supersetSize])
  runif(1, Min, Max)
})


# Make up item profits.
gains = rnorm(supersetSize) ^ 2 * 10000 + 100


rst1 = FLSSS::mmKnapsackIntegerized(
  maxCore = 2L, len = subsetSize, itemsProfits = gains, itemsCosts = costs,
  capacities = budgets, heuristic = FALSE, tlimit = 2, useBiSrchInFB = FALSE,
  threadLoad = 4L, verbose = TRUE)
```

```
# Examine if 'mmKnapsackIntegerized()' gives the same solution as 'mmKnapsack()'.
rst2 = FLSSS::mmKnapsack(
  maxCore = 2L, len = subsetSize, itemsProfits = gains, itemsCosts = costs,
  capacities = budgets, heuristic = FALSE, tlimit = 2, useBiSrchInFB = FALSE,
  threadLoad = 4L, verbose = TRUE)
# Possible differences in solutions are due to real-integer conversion




# Let 'x' be the solution given 'heuristic = T'. The sum of ranks of the
# profits subsetted by 'x' would be no less than that of the optimal solution.
rst3 = FLSSS::mmKnapsackIntegerized(
  maxCore = 2L, len = subsetSize, itemsProfits = gains, itemsCosts = costs,
  capacities = budgets, heuristic = TRUE, tlimit = 2, useBiSrchInFB = FALSE,
  threadLoad = 4L, verbose = TRUE)


# Exam difference in total profits given by the heuristic and the optimal:
if(length(rst3$solution) > 0 & length(rst1$solution) > 0)
  sum(gains[rst3$solution]) / sum(gains[rst1$solution])





# ==========================================================================================
# Test case P08 from
# https://people.sc.fsu.edu/~jburkardt/datasets/knapsack_01/knapsack_01.html
# ==========================================================================================
costs = matrix(c(382745, 799601, 909247, 729069, 467902,  44328,  34610, 698150,
                 823460, 903959, 853665, 551830, 610856, 670702, 488960, 951111,
                 323046, 446298, 931161,  31385, 496951, 264724, 224916, 169684),
               ncol = 1)


gains = c( 825594, 1677009, 1676628, 1523970,  943972,   97426,  69666, 1296457,
          1679693, 1902996, 1844992, 1049289, 1252836, 1319836, 953277, 2067538,
           675367,  853655, 1826027,   65731,  901489,  577243, 466257,  369261)


budgets = 6404180


# 'mmKnapsackIntegerized()' is designed for the multidimensional Knapsack
# and may not be ideal for one-dimensional 0-1 Knapsack regarding computing speed.
# 'len = 0' would cause severe deceleration. Looping 'len' over possible
# values is recommended if 'len' is ungiven.
rst = FLSSS::mmKnapsackIntegerized(
  maxCore = 2L, len = 12L, itemsProfits = gains, itemsCosts = costs,
  capacities = budgets, heuristic = FALSE, tlimit = 2, threadLoad = 4L, verbose = TRUE)
rst = sort(rst$solution)
```

```
cat("Correct solution:\n1 2 4 5 6 10 11 13 16 22 23 24\nFLSSS solution =\n")
cat(rst, "\n")
# The difference is due to rounding errors in real-integer conversion. The default
# 'precisionLevel' shifts, scales and rounds 'itemCosts' such that its
# maximal element is no less than 8 times the number of items.


# Increase the precision level
rst = FLSSS::mmKnapsackIntegerized(
  maxCore = 2L, len = 12L, itemsProfits = gains, itemsCosts = costs,
  capacities = budgets, heuristic = FALSE, precisionLevel = rep(500L, 1),
  tlimit = 2, threadLoad = 4L, verbose = TRUE)
# 'precisionLevel = 500' shifts, scales and rounds 'itemCosts' such that its
# maximal element is no less than 500.
rst = sort(rst$solution)
cat("Correct solution:\n1 2 4 5 6 10 11 13 16 22 23 24\nFLSSS solution =\n")
cat(rst, "\n")
}
# ======================================================================================
# ======================================================================================
```

Index