Steepest Descent Approaches for the Minimization of Open Stacks

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March 22, 2016

Outline

Introduction

- The problem of minimizing the maximum number of simultaneous open stacks arises in industrial environments:
  - A factory needs to supply specific combinations of products that have associated given demands;
  - A single machine manufactures all the products in batches and at each stage, a single product type is handled;
  - Whenever a customer places an order for a set of products, a new *open stack* is associated with it, meaning that physical space around the machine is assigned to it until the order is fulfilled - the *stack's closure*.

Introduction

- There is an implicit assumption of a physical limit on space around the machine because there is not enough free room around the machine to place all customers' orders simultaneously;
- Moving open stacks requires additional manpower and machinery, introducing risks to product's integrity;
- In order to better use that physical space, it is necessary to determine the sequence of the products' manufacturing.

Introduction

- The *Minimization of Open Stacks Problem* (MOSP) is defined on a binary sparse matrix M:
  - The n rows correspond to the customers's orders and the m columns correspond to each product type available;
  - Entry $m_{ij} = 1$ if customer i ordered product type j, and $m_{ij} = 0$ otherwise;
  - Matrix M holds the *consecutive ones property*[a].

[a] In each row all elements between two 1s are considered to have value 1, also called *fill-ins*. Those elements together define a *1-block*.

Formal Definition

- Given an $n \times m$ sparse binary matrix M, matrix M_π is the matrix obtained from a permutation π of the $\{1, 2, \ldots, m\}$ columns of matrix M, and M_π^1 is the matrix obtained from M_π that holds the consecutive ones property;
- The objective is to find a permutation π of columns of M such that the maximum sum of a column (including the fill-ins)[a] in M_π^1 is minimized.

[a] given by Z^π.

Example

Table 1 presents an example of sparse binary matrix M_π and M_π^1 for π=[5, 2, 4, 6, 3, 1]. $Z^\pi = 3$, on columns 2, 4, 6 and 3. Columns with maximum sum represent the bottleneck of problem and are called *critical columns*.

	1	2	3	4	5	6
1	1	1	0	0	0	0
2	1	0	1	0	0	0
3	0	0	0	1	1	0
4	0	0	0	1	0	1
5	0	1	0	0	1	0
6	0	0	1	0	0	1

	5	2	4	6	3	1
1	0	1	**1**	**1**	**1**	1
2	0	0	0	0	1	1
3	1	**1**	1	0	0	0
4	0	0	1	1	0	0
5	1	1	0	0	0	0
6	0	0	0	1	1	0

Table : M_π and M_π^1 for π=[5, 2, 4, 6, 3, 1]. Fill-ins are highlighted in bold font.

Motivation

- MOSP is a NP-hard problem;
- Its practical application;
- It models successfully a wide range of equivalent problems in a variety of contexts:
  - Interval Thickness;
  - Node Search Game;
  - Edge Search Game;
  - Narrowness;
  - Split Bandwidth;
  - Pathwidth;
  - Edge Separation;
  - Vertex Separation;
  - Modified Cutwidth;
  - Programmable Logic Array Folding;
  - Gate Matrix Layout.

Steepest Descent Approaches for the MOSP

Proposed Methods

- A graph search for generating an initial solution;
- A Variable Neighborhood Descent method;
- A simple Steepest Descent method.

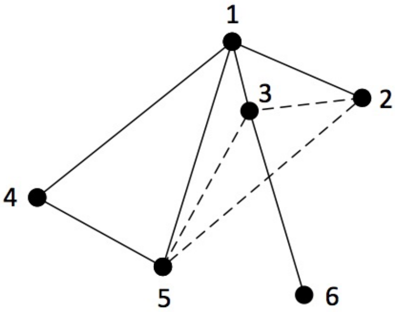
Current State of the Art

- Heuristic: Minimum Cost Node Heuristic (2004);
- Metaheuristic: Biased Random Key Genetic Algorithm (2014);
- Exact: A* (2009).

Graph Model

- Nodes represent customers;
- Edges represent products – no loops or parallel edges;
- Each customer induces a clique.

	1	2	3	4	5	6
1	1	0	0	1	1	0
2	1	1	0	0	1	0
3	0	0	1	0	0	1
4	1	1	1	0	0	0
5	0	1	1	0	1	0



Steepest Descent Approaches for the MOSP

Graph Search

- The main idea is to search for customers, rather than for products directly;
- Breadth-first search (BFS) in non-decreasing degree order.

Products Sequencing

- The BFS returns a list of customers;
- The products sequence is determined in a greedy fashion:
  - The list of customers is traversed, and once all customers that ordered a specific product are found, it is sequenced.

Steepest Descent Approaches for the MOSP

Variable Neighborhood Descent - VND

- Classic version – first time applied to the MOSP;
- Five neighborhood structures:
  - k-opt of grouped contiguous columns ($k = 2, 3, 4, 5$).
  - The best neighbor is improved by a insertion move (only bottleneck related columns).
- All possible movements explored partially
  - Randomly selected, within a limit (50%).
- All parameters tuned using the irace package.

Steepest Descent - SD

- Classic version;
- Local Search:
  - Insertion move – only bottleneck related columns;
  - Target position defined by similarity of nonzero elements.
- All possible movements explored partially
  - Randomly selected, within a limit (70%).
- All parameters tuned using the irace package.

Computational Environment

- Intel Core i7 3.6 GHz processor;
- 16 GB RAM;
- Ubuntu 14.04 LTS;
- Codes written in C++, compiled with gcc 4.8.4 and the -O3 optimization option.

Methods:

- Variable Neighborhood Descent (VND);
- Steepest Descent (SD);
- Minimum Cost Node heuristic (MCNh).

Instances

Six different data sets from the literature were considered, a total of 475 instances.

- SCOOP: 24 real world MOSP instances;
- Faggioli & Bentivoglio: 300 artificial MOSP instances;
- Challenge: 126 artificial MOSP instances;
- VLSI: 25 real world Gate Matrix Layout instances.

Steepest Descent Approaches for the MOSP

Average gap from Optimal Solutions (20 runs)

Method	SCOOP	Faggioli & Bentivoglio	Challenge	VLSI
VND	3.76%	2.04%	7.39%	3.93%
SD	2.15%	0.75%	0.6%	1.12%
MCNh	25.27%	13.72%	2.0%	12.92%

Steepest Descent Approaches for the MOSP

Average Running Times (20 runs)

Method	SCOOP	Faggioli & Bentivoglio	Challenge	VLSI
VND	12ms	19.46ms	215ms	64ms
SD	138ms	479ms	18s	4.08s
MCNh	<1ms	<1ms	<1ms	<1ms

Optimal Solutions Found

Method	SCOOP	Faggioli & Bentivoglio	Challenge	VLSI
VND	70.83%	81.33%	6.52%	76.00%
SD	87.50%	93.33%	86.96%	92.00%
MCNh	36.00%	37.00%	78.00%	72.00%

Conclusions

- This is the first time a VND application on MOSP is reported;
- The best heuristic in literature performed poorly on 3 problem sets – first time reported;
- VND is faster, but less accurate;
- Surprisingly, SD presented a very low gap and a good rate of optimal solutions found for most problem sets;
- Future work includes:
  - Variable Neighborhood Search;
  - Matheuristic – poor models currently.

Acknowledgments

This research has been supported by the National Council for Scientific and Technological Development (CNPq).

Questions?


рахмат
danke
謝謝
ngiyabonga
teşekkür ederim
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