

Integer Programming for Student-Project Allocation

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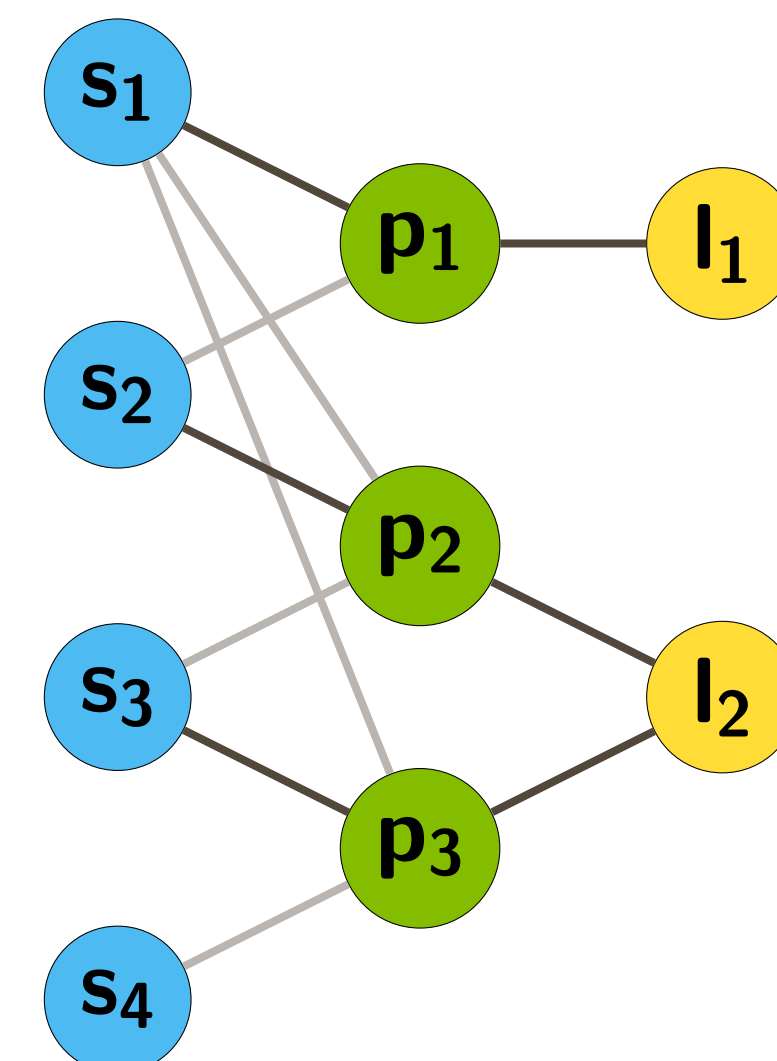


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The Student-Project Allocation Problem

The Student-Project Allocation problem with lecturer preferences over Students (SPA-S)

- A set of students $S = \{s_1, s_2, \dots, s_{n_1}\}$, projects $P = \{p_1, p_2, \dots, p_{n_2}\}$ and lecturers $L = \{l_1, l_2, \dots, l_{n_3}\}$
- Each project is offered by a unique lecturer
- Students have preferences over projects, lecturers have preferences over students
- Projects and lecturers have upper quotas



Stable Matching

A **stable matching** in SPA-S is an assignment of students to projects such that capacities are respected and there is no student-project pair (s_i, p_j) where s_i and l_k , the lecturer offering p_j , have an incentive to deviate from the assignments (if any) and form a pairing.

- Every instance of SPA-S must admit a stable matching [1]
- A stable matching can be found in linear time [1]

Adding Ties and Lecturer Targets

The Student-Project Allocation Problem with lecturer preferences over Students including Ties and Lecturer targets (SPA-STL) extends SPA-S.

- Ties are allowed in lecturer (and student) preference lists
- Projects and lecturers have lower quotas
- Lecturer targets indicate a target number of lecturer allocations

Optimisations

- Similar definition of **stability** for SPA-S applies to SPA-STL
- **maximum size** - maximum number of students are assigned
- **load balancing** - variety of comparisons between the number of lecturer allocations and the lecturer targets

New Integer Programming Model

Integer Programming (IP) is a computational technique which can deal with hard problems. Finding a maximum stable matching in an instance of SPA-STL is NP-hard and so an **IP model** was developed for instances of SPA-STL with the aim of investigating the scalability of the IP model with changes in instance complexity and size, and also investigating changes in matching characteristics when altering instance parameters such as preference list length and probability of ties.

- New integer inequalities and objective functions created for stability constraints and load balancing optimisations

Java Application

- Integer Program accessed by Java application
- Optimisations can be performed in any order

order of optimisations		
Linear constraints	1st	stability
	2nd	maximum sized
	4th	minimum cost
		generous
		minMaxLecDiff
Quadratic constraints		minSumLecDiff
	3rd	Q minSumSqLec
		Q minSumSqRanks
		Q minSumSqLecAndRanks
		Q minSumLecVar

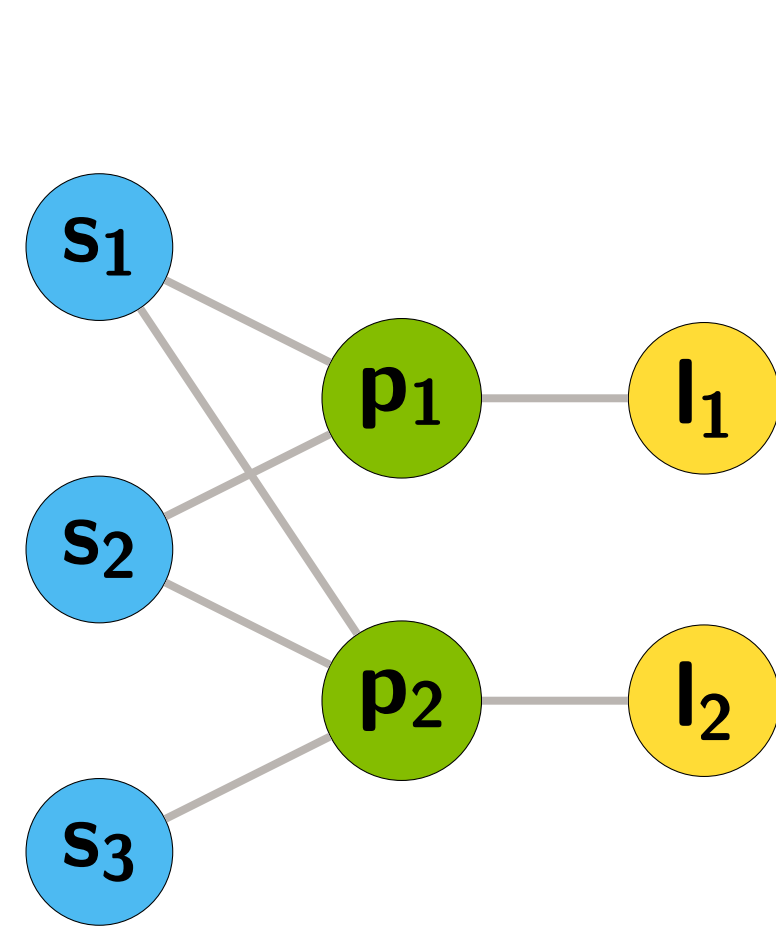
Minimises the number of students assigned to the worst ranked project, and subject to this, the second worst, and so on

Minimises the sum of the absolute difference between lecturer occupancy and targets

Minimises the sum of the squares of student-project pair ranks in the matching

Minimises variance of the proportion of lecturer occupancy compared to targets

Conflicting Objectives Example



$s_1: (p_1, p_2)$
 $s_2: p_2, p_1$
 $s_3: p_2$
 $p_1: \text{LQ: 0, UQ: 2}$
 $p_2: \text{LQ: 0, UQ: 2}$
 $l_1: (s_1, s_2) \text{ LQ: 0, UQ: 2}$
 $l_2: (s_3, s_1), s_2 \text{ LQ: 0, UQ: 2}$
 all lecturer targets 1

Objectives A:

Opt 1: stable
 Opt 2: maximum size
 $M = \{(s_1, p_1)(s_2, p_2)(s_3, p_2)\}$

Objectives B:

Opt 1: minimise the sum of lecturer differences
 Opt 2: maximum size
 $M = \{(s_1, p_1)(s_2, p_2)\}$

Generated Results

Input datasets were generated randomly and vary parameters such as the prevalence of ties in preference lists (Figure 1).

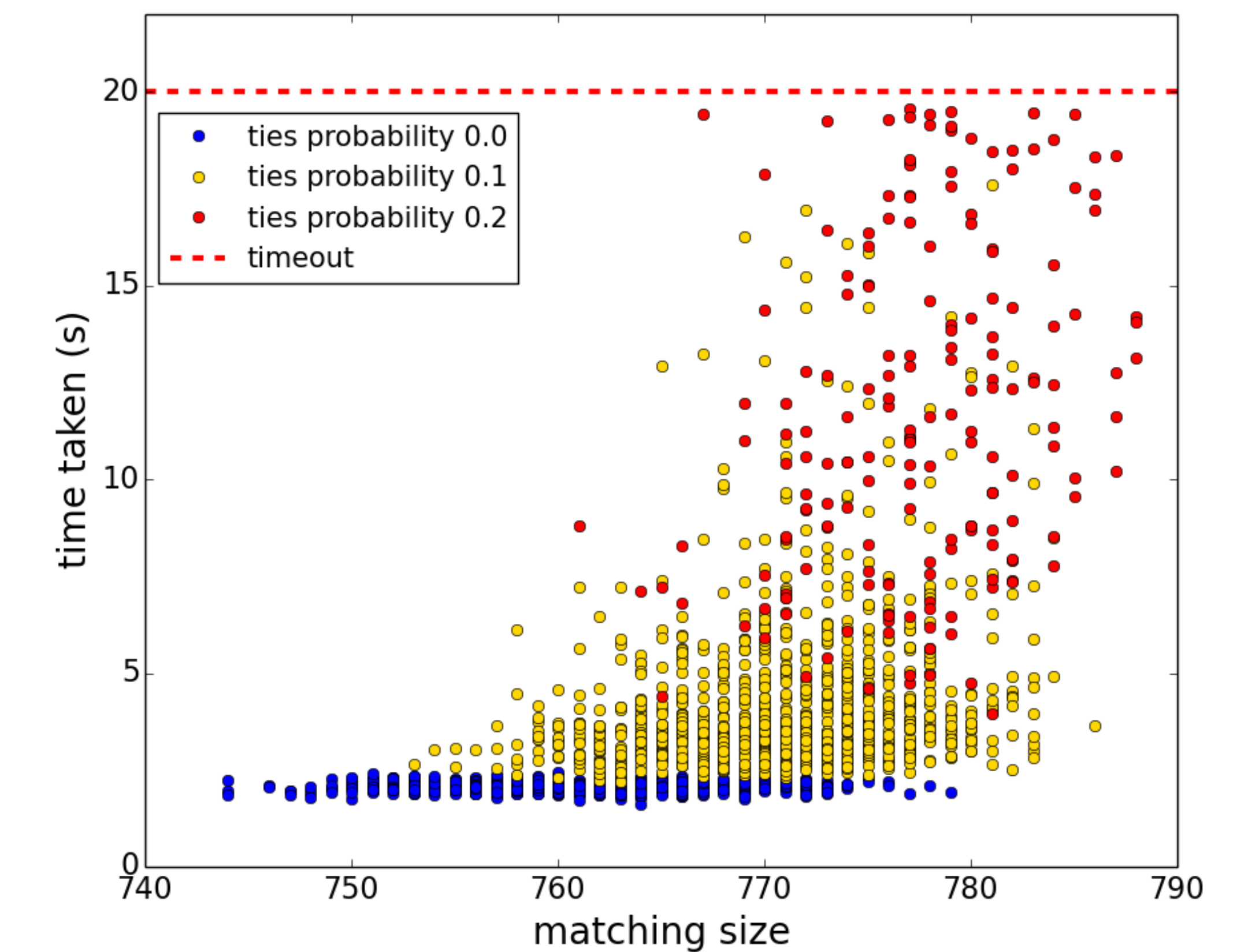


Figure 1: Preliminary results. Changes in time taken to solve instances versus matching size when varying preference list ties probability. In all cases there are 800 students, 350 projects, 200 lecturers, all lower quotas 0, all upper quotas 1000.

- 0%, 2.1% and 82% instances timeout for 0.0, 0.1 and 0.2 ties probability respectively
- As tie probability increased, matching size and time taken to solve also increased

Real World Results

In addition to generated data, the IP model has been used on **several real world scenarios** including student project allocations for the University of Glasgow, the University of Edinburgh and the University of Leeds, and teacher-region allocations for TeachFirst. Each scenario had varying requirements but in several instances the IP model replaced a manual allocation process which was both time-consuming and unlikely to result in an optimal outcome.



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References

[1] David J. Abraham, Robert W. Irving, and David F. Manlove. Two algorithms for the student-project allocation problem. Journal of Discrete Algorithms, 5:73-90, 2007.