Algorithmic Optimization of Patient Allocation at Medical Schools

Which Patient Is the Best Fit for Undergraduate Training?

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***Abstract*—Limited access to patients is an increasing problem in medical education. In order to reduce patient shortage, we previously proposed a strategy for assigning patients to courses based on routinely available patient and educational data. However, the previous work showed deficiencies in terms of practical applicability with existing curricula. This paper introduces a corresponding refinement of the algorithm together with its implementation and an evaluation of three algorithm variants approaches for resolving medical school courses that are affected by patient shortage.**

Keywords: knowledge management for patient allocation in medical education; computer-assisted curriculum organisation

I. Introduction

A student-centred approach of learning is the basis of modern undergraduate education and is facilitated by an environment in which the needs of the learner are met by the provision of appropriate learning material. In the course of medical education, training opportunities and assessment methods should reflect the reality of clinical routine as closely as possible for optimal preparation of students, to provide them with the opportunity to develop professional and social skills and to acquire essential competence and confidence for clinical reasoning and decision-making [1, 2, 3]. Patient contact and exposure to a wide spectrum of pathologies is at the heart of the practical aspect of medical curricula, but decreasing durations of patient stay and extensive teaching loads of clinicians often interfere with ideal training conditions in university hospitals [4]. Addressing this issue, we have recently proposed that patient access should already be considered during curriculum design [7]. This way patient availability would determine the structure of the learning session for specific topics, which could range from lecture based demonstrations of patients to a clinical setting with a dedicated teaching ward. By combining learning objectives defined by the curriculum with available patient data, we proposed a strategy that optimizes patient access, student-patient interaction and learning outcomes. In this paper, we present a method for adapting this strategy to the requirements of an existing curriculum, we describe an implementation of the algorithm and discuss results of an evaluation of the approach.

II. Related Work

When resources are scarce, optimal distribution and allocation is paramount to guarantee highest benefit. In recent years, computer-based methods have proven to be superior to traditional processes in a range of different areas in medicine. As an example, using discrete-event simulation, a prioritization system was introduced to reduce waiting times for cataract surgeries, which represent a resource in low supply. Compared to routinely used first-in first-out systems, the computer-based method represented a significant improvement and waiting time reduction [8]. In a different setting, a variety of simulation algorithms have been applied to compare different models of resource allocation and prioritization in cases of natural disasters in order to optimize the number of saved lives while taking into account ethical aspects of prioritization [9]. Advances in medical research, treatment options and techniques have improved general medical care, but have put an increasing financial burden on the healthcare systems of many countries. Several computer-based solutions for the optimal use of necessary resources have been proposed to address this. One area of interest are hospital beds, a fluctuating and limited resource. Optimization of bed occupancy improves health care efficiency and reduces costs. A recent approach utilises a combination of different methodologies, a queuing system, a compartmental model and evolutionary-based optimisation for optimal resource allocation in a hospital setting [10].

Another critical aspect of the provision of quality patient care is the minimum amount of nursing staff that needs to be present at any time. An NHS Foundation Trust in the UK has recently introduced an electronic workload management tool to ensure efficient resource allocation and continuity of patient care [11]. As a step further, a computer-aided support system, which links a knowledge-driven reasoning process to a planning and scheduling domain has recently been proposed for automated planning and provision of patient-tailored individual medical care [12].

Furthermore, algorithms for resource allocations which have to be integrated into already existing schedules have also been successful in the scheduling of chemotherapy plans where sufficient flexibility has to be maintained to allow for individual changes in individuals' health and adjusted treatment regimes [13].

In summary, for the allocation of scarce resources in complex medical settings, computer-based methods prove to be more efficient than traditional distribution processes. However, the problem of patient allocation during medical education still represents an open issue which none of the known approaches addresses. The matchmaking of available, suitable patients and appropriate course sessions at the right point of medical training requires an integrative approach tailored to this specific learning environment. These requirements are not met by any of the currently available algorithmic approaches, neither in medicine nor in educational technology.

III. Results of Preliminary Studies

During medical education, patient availability represents a scarce resource, and its use and distribution is crucial for high standard medical training. Therefore, we developed a four-step process, which aims to prioritize learning opportunities (i.e. learning objectives taught in courses, seminars, lectures, etc. that involve patient contact) and hospital departments in order to maximize access to patients [7]. We will briefly sketch this process in the following:

First, learning opportunities of a medical curriculum need to be aligned with patient data (step I). For this, we mapped objectives of learning opportunities to codes of the International Statistical Classification of Diseases and Related Health Problems Version 10 (ICD-10), a terminology that is widely used to encode medical diagnosis in patient's records [14].

Second, we determined which learning opportunities need to be considered first for patient allocation in order to maximise overall benefit (step II). This was done by considering the highest student-to-patient ratio (e.g. lectures with hundreds of students before considering small bed-side teaching activities) and rareness of a pathology (e.g. a rare genetic disorder as opposed to common medical conditions like arterial hypertension).

Third, the most suitable hospital department for teaching a specific learning opportunity is determined (step III). As patients often have multiple diagnoses, the right patients might not be located in the expected departments. We therefore introduced a variable called department-expertise that was defined as the ratio of treated patients with a specific disease in a given department to all treated patients of the same department. If most of a department's patients are treated for a specific disease, one would expect relatively high expertise of that department to conduct a respective learning opportunity.

Fourth, the optimal patient of a department is determined (step IV). The most suitable patient would display the entire content of diseases covered in the specific learning opportunity, and the number of ICD-10 codes identified in the patient divided by the total number of ICD-10 codes of the learning module would equal 1.0, thus: adequacy = (number of shared ICDs by learning opportunities and patient)/(total number of ICDs of learning opportunities). As within the setting of our institution patients usually agree to assist in teaching twice, the number of patients must be re-calculated after each assignment.

This four-step process shown in [7] presents a first idealized allocation algorithm described for optimisation of access to crucial but scarce learning resources, and provides a method for the design of a new curriculum. It is, however, not suitable to be applied in the context of an existing curriculum. In the curricula of existing medical education, learning opportunities are already assigned to specific departments. Symptoms, diagnosis and treatment of hypertension, for example, are usually covered by the department of internal medicine. Any small changes to the curriculum would require a reassignment of teaching resources between departments, which would have budget impact and would thus be politically hard to implement in practice. Hence, a systematic evaluation of the depicted algorithm by comparing results of the traditional and the computer-based approach in a parallel setting is not feasible.

Furthermore, there are no objective criteria to determine the level of suitability of a patient for a specific learning objective. Defining diseases by ICD-10 codes is an attempt to break down the complexity of an ill patient to a couple of letters and numbers. Although the associated diagnoses should theoretically fit those of the learning objective, multiple interacting diseases make each patient an individual and incomparable case. In addition, teachers would hardly admit a lack of suitable patients, as this would discredit any medical education institution. The number of available patients can therefore not serve as an objective evaluation criterion.

IV. System Description

A. *Algorithmic aspects*

In order to account for the described obstacles for the utilisation of the allocation algorithm in existing curricula, we propose the following approach in order to use algorithm-based patient allocation in the context an existing curriculum. The algorithm aims to correct for bottleneck situations that are possible during patient allocation. Measures that are taken for resolving such situations aim to provide a more equal distribution of a department's teaching obligation over the course of the academic period.

In our algorithm, the steps I, II and IV of the previously described algorithm in [7] are applied as. Step III (the identification of the most suitable department for a specific learning opportunity) is no longer necessary if we already

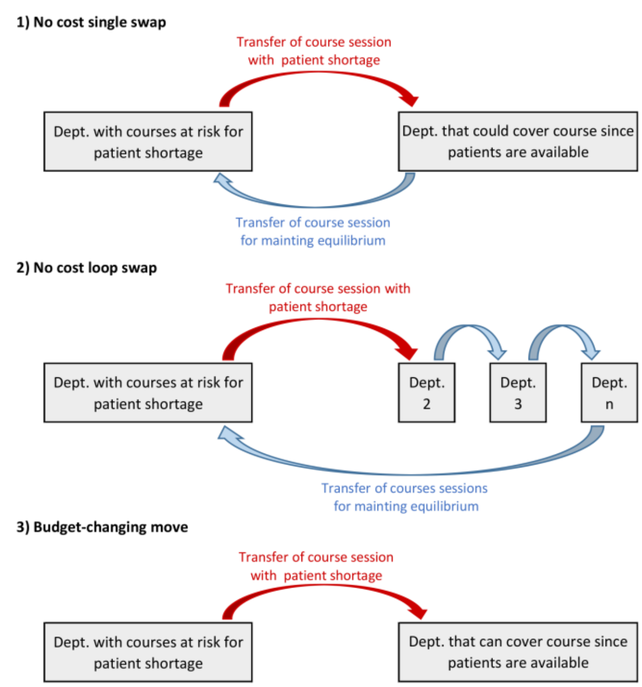

Figure 1: Three proposed strategies for the patient allocation algorithm

have an existing curriculum. Then, extending the previous algorithm, three different strategies may be applied to militate deficiencies in patient allocation and to provide an optimal patient-centred learning environment (Fig 1).

1) No cost single swap

If the department, which the existing curriculum assigned a specific learning opportunity (i.e. course session) to, encounters a shortage of patients and finds itself unable to provide an appropriate learning source, and another department is able to provide suitable patients, the respective course session is transferred to and covered by the newly appointed department ("second department"). In return, an equivalent course session is being transferred from the second to the first department in order to balance costs and to maintain equilibrium in resources. Selection of the course session of the second department is done under consideration of the respective workload in that week: Preference is given to course sessions that take place in weeks with high number of teaching obligations, thus soothing possible peaks.

2) No cost loop swap

If the second department has got the required patients to cover a learning opportunity, but no appropriate course session to transfer back to the first department for maintaining equilibrium, one or more departments are added to the exchange loop. This way, a course session can eventually be moved to the first department to balance costs and hereby education effort. Once again, selection of course sessions to be transferred is based on teaching workloads in the respective weeks.

3) Budget-changing move

If the second department receiving the course session is not able to provide a suitable learning opportunity to transfer to either the original department or to a third interposed department, a simple transfer of the course from the donor to the recipient department is conducted, and the learning opportunity is covered by the institution holding the necessary learning source. As no balancing course transfer is made, the budgets of both departments have to be adjusted accordingly.

In order to determine the utility of the algorithm, the following criteria are introduced for measuring outcome: The first effect variable is the number of departments or institutions with a potential deficit in learning sources before and after the application of one of the swap models. The ideal outcome and full effectiveness of the measure should result in no learning opportunities with potential shortage of patients, therefore the number should equal 0, independent of the initial value. In this case, all courses with a potential shortage of patients have been successfully transferred to institutions in which suitable patients are available. The second objective criterion and measurable value is the number of swaps or transfers needed to reach the optimal distribution of learning opportunities in order to allocate patients to all appropriate courses. A single no cost swap during which a course session is transferred to another department with suitable patients available, and another course session is transferred back in return, accounts for two shifts. A no cost loop swap, in which one (or more) additional departments are used to balance costs and education resources, accounts for three (or more) shifts. If all transactions are budget neutral, a low number of swaps is desirable, as this minimises administrative efforts. Additional considerations have to be made for budget changing swaps, as these require fewer shifts to reach the target of full course coverage, but might affect the overall cost of the education programme.

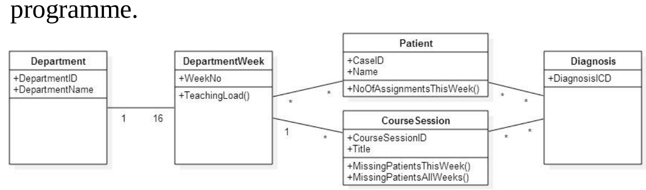

Figure 2: Main system classes

B. System implementation

The core classes and relationships for our algorithm implementation are illustrated in the class diagram in Figure 2. As the current curriculum extends over a semester of (in our case) 16 weeks, every department has 16 departmentWeeks. The operation 'TeachingLoad()'

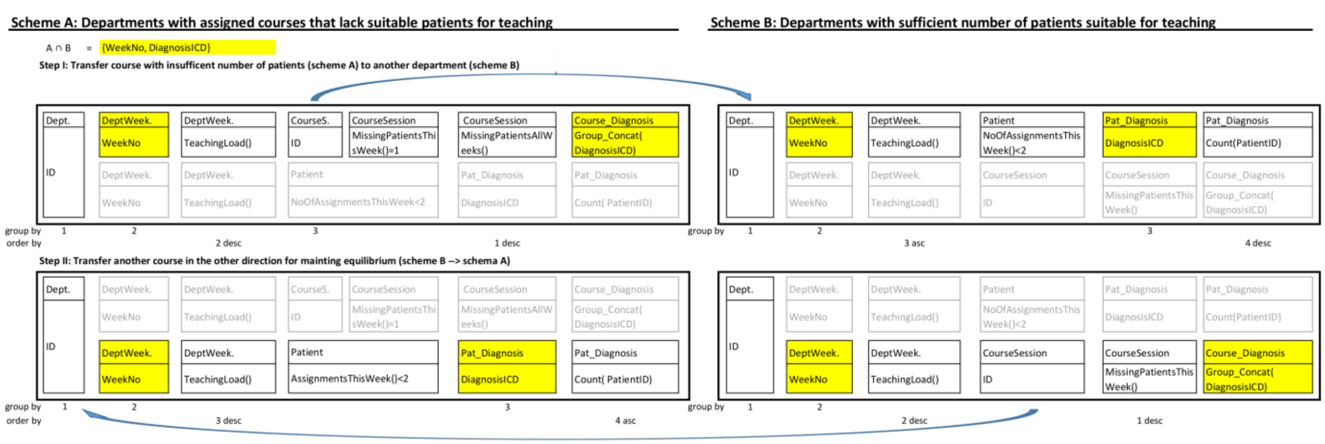

Figure 3: Illustration of the algorithm for the no cost single swap strategy. Schemes are joined by 'WeekNo' and 'Diagnosis ICD'.

Dept. ID	DeptWeek. WeekNo	DeptWeek. TeachingLoad()	CourseS. ID	...	CourseSession MissingPatientsAllWeeks()	Course_Diagnosis Group_Concat(DiagnosisICD)
123	2	1,5	333		8	I21;I50
123	3	1,2	555		8	J09;J12
123	4	1,9	444		7	F20;F32
234	1	1,1	666		6	K73
...	...	...	...		...	...
order by		2 desc			1 desc	

Dept. ID	DeptWeek. WeekNo	DeptWeek. TeachingLoad()	...	Pat_Diagnosis DiagnosisICD	Pat_Diagnosis Count(PatientID)
987	2	0,6		I21	6
876	2	0,6		I50	4
765	2	1,6		I21	7
...	...	...		...	...
		3 asc			4 desc

Figure 4: Example for the no cost single swap strategy. Possible swap combinations are outlined in colour.

calculates the departmental teaching load of the respective week, defined as the time effort of clinicians invested in student education in all teaching activities. Thereafter, a value of 1 is set for a balanced teaching load. If a department has a higher teaching load in a specific week, when compared to the other weeks of the semester (i.e. is responsible for many courses), the value is higher than 1. Accordingly, values of less than 1 represent weeks with a comparably low teaching load. As described above, the teaching load is one of the applied criteria for the selection of course session swaps from one department to another.

Each department week contains a variable number of patients. The operation 'NoAssignmentsThisWeek()' reflects how often a patient has already assisted in learning opportunities in that week. In COUNTRY, it seems acceptable for patients to assist twice a week in learning opportunities [15].

In addition, each department week is associated to a variable number of course sessions. We assume that exactly one patient is needed for each course session, so the value determined by the operation 'MissingPatientsThisWeek()' can be either 0 (=ok) or 1 (=patient missing). In order to determine the extent of patient shortage over the semester, the operation 'MissingPatientsAllWeeks()' is applied. This enables a prioritisation of courses in which many course sessions fail to be sufficiently staffed with patients.

The final class 'Diagnoses' is defined by ICD-10 classifications. Patients as well as course sessions are attributed with specific diagnoses.

The application of the above described classes and relationships for the algorithm is depicted in Figure 3, using the no cost single swap as a model example. Scheme A contains a list of all departments with respective course sessions with patient shortages. This includes the specification of the week, departmental teaching load in this week, the ID of the courses with patient shortage, the number of all missing patients of this course over the whole semester as well as the necessary diagnoses in the form of ICD-10 codes. Subsequently, scheme B illustrates the search for a suitable candidate for a swap for the same week with patients associated with the same diagnoses (outlined in colour).

The selection of swapping partners is based on the following prioritisation:

- Patient shortage is present (prerequisite) as well as a high teaching load in the department, from which the course session is transferred.
- Low teaching load and high number of suitable patients in the receiving department.

The lower part of figure 3 illustrates the return transaction: again, suitable swapping partners of the same departments are matched by weeks and diagnoses. Priority is given to a course session, which might also potentially experience patient shortage and which could also potentially be resolved by the transaction. Next, the teaching load is considered in order to balance this variable. Secondly, the items are sorted on the left side according to low teaching load and high number of available patients.

Figure 4 illustrates a simplified example: highest priority for the determination of a swapping partner is given to course session 333, as this course is experiencing the highest patient shortage across the semester (MissingPatientsAllWeeks()=8). In addition, the course session to be transferred is scheduled for a week of already high teaching load (TeachingLoad()=1.5). Determination of suitable swapping partners with matching diagnoses is outlined in respective colours. The best match for the course session is department 987, as it has a low associated teaching load (TeachingLoad()=0.6) as well as the highest number of available suitable patients (Count(PatientID)=6). The return transfer takes place accordingly (not shown).

The no cost loop swap follows the same principles as shown here, with the exception of the return transfer, which can be diverted via several departments. Theoretically the number of interposed departments is unlimited, but due to the associated increase in complexity it was here limited to three here.

V. EVALUATION DESIGN AND RESULTS

We tested the algorithm on existing patient data from the summer term 2014 (April to September 2014) and authentic curriculum data of XXX medical education institution. Patient data is naturally only available in retrospect (but typically relatively stable between years). The curriculum consisted of 1,471 courses. Thereof, 184 required patient access. These 184 courses consisted of 6,120 course sessions out of which 449 were affected by patient shortage. We tested the three different variants shown in section IV.A of this paper on this dataset. For this specific experiment we limited the number of departments involved in a no cost loop swap to three.

The results are shown in Table 1. Note that, since a shift from one department to another may consist of one or more course sessions of the same course, the number of resulting transactions does not necessarily equal the number of resolved course sessions.

	No cost single swap	No cost loop swap	Budget-changing move
Number of course sessions with missing patients	449	449	449
No. of resulting transactions	147 swaps	195 loops	117 moves
No. of resulting shifts	294	585	117
No. of resolved course sessions (%)	289 (=64.37%)	313 (=69.71%)	314 (=69.93%)
Shifts per resolved course session	1.02	1.87	1.0 (by design)

Table 1: Effectiveness (i.e. number of resolved course sessions) and efficiency (i.e. number of necessary transactions) of the strategies

Roughly two thirds of all course sessions could be resolved using our algorithmic approach, between 64.37% for the no cost single swap and 69.71% for the no cost loop and 69.93% for the budget-changing move. That means that the gain in resolved course session between the worst (no cost single swap) and the best (budget-changing move) is comparatively small, while all algorithms solve a considerable portion of missing patient situations. Note here that by design, the budget-changing move algorithm will solve all situations that are theoretically solvable. Applying the no cost loop yielded about the same effectiveness as the budget-changing approach. This suggests that (close to) the maximum number of course sessions may be resolved even without having to redistribute department teaching budgets – but at the cost of more shifts: in order to evaluate effectiveness, we calculated the ratio of shifts per resolved course session. This parameter is a surrogate for the administrative effort in terms of necessary course session moves for meeting the target of resolving the highest number of patient shortage issues. Theoretically, resolving the 449 course sessions with patient shortage by 449 shifts would be optimal. Comparing the two no cost approaches, this ratio shows that the no cost loop causes a far greater number of shifts per resolved section than the no cost single swap (1.87 vs. 1.02) for achieving a relatively small gain number of resolved course sessions.

In summary, none of the three algorithms was superior on all measures. In a typical medical education setting, the no cost single swap would likely be the most favorable approach, as it resolves many patient shortages while balancing the workload of a second involved department. The no cost loop swap strategy even resolves more cases, but will cause a lot of shifts and, thus, administrative efforts. Finally, the budget-changing move strategy is preferable if budget is not an issue in the medical department: this approach needs the minimal number of shifts for resolving all solvable issues. Yet, in practice, budget will often be an issue

VI. Conclusion

In this paper, we modified a previously proposed strategy for patient allocation in medical schools. In order to render the algorithm applicable to existing curricula, we developed, implemented and evaluated different strategies for the redistribution of learning opportunities to other hospital departments. An evaluation of the new approach yielded that approximately two thirds of all course sessions affected by patient shortage could be resolved by applying several variants of the algorithm, each of which proved to have different strengths. In our future work, we plan to test the algorithm with different datasets and to consider constraints that result from practical aspects of curriculum organisation in other countries and systems of medical education.

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