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Integrating Case-Based Reasoning and Tabu Search for University Makeup Class Scheduling

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ABSTRACT

Makeup class scheduling is a very time-consuming and highly constrained scheduling problem. It is similar in nature to course time tabling with different nature of hard and soft constraints. We focused on scheduling make up classes by using case-based reasoning (CBR) and Tabu search. Different techniques have been proposed related to course time table scheduling, each having some limitations in terms of optimality and efficiency. This paper focuses on integrating CBR with Tabu search technique to find optimal solution efficiently. Tabu search handles finding optimal solution and CBR handles satisfaction of constraints. CBR solves a new problem case by considering the previously stored cases. Tabu search keeps internal memory and do not get stuck in local maxima.

KEYWORDS: Makeup class scheduling, case-based reasoning, Tabu search, constraints.

1 INTRODUCTION

Makeup class scheduling has to be performed for every department in the university. It is a highly constrained problem similar to timetable scheduling but having different nature of hard and soft constraints. The scheduling problem involves allocating rooms for various lectures in fixed timeslots. Various clashes with regular routine lectures also have to be considered. It requires a lot of time and effort and often results in erroneous schedule due to which university faculty and students face much inconvenience. There is a need to automate the makeup class scheduling procedure to efficiently schedule makeup class schedules in less time.

This paper introduces the technique that integrates case based reasoning (CBR) approach with Tabu search approach to obtain promising result. Strengths of Tabu search are combined with CBR and utilized for precisely handling makeup class scheduling.

Rest of the paper is organized as: Section 2 contains description of work done related to timetable scheduling. Section 3 contains university makeup class scheduling characteristics and constraints. Section 4 and Section 5 contains description of weighted k-nearest neighbor approach and multiple retrieval approach using attribute graphs respectively. Section 6 contains the description of proposed technique for makeup class scheduling. Section 7 contains experiments and results. Section 8 concludes the paper. Section 9 contains future recommendations.

2 RELATED WORK

Makeup class scheduling is similar in nature to time table scheduling. A lot of work has been done related to time table scheduling. First techniques that were proposed that include linear and integer programming techniques, in which all variables are required to be integer and finds the best solution under several constraints and relationships by

(Vastrapur et al., 2000). Clustering and decomposition approaches were proposed (Amintoosi et al., 2005). These approaches grouping is done for events, constraints are handled and quality of solution is improved. Graph coloring heuristics were proposed by Burke et al, sequentially allocate events to resources (Burke, 2005). Limitation involved in this approach is that this approach suits well for small scale problems

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but fail for large problems (Tripathy, 1985) Hence, graph coloring approaches cannot be applied to large scale problems like time tabling problems. For generating high quality results evolutionary algorithms (EAs) and their hybrid versions work much better than other approaches. EAs are categorized into two categories: local search (LS) algorithms and point based algorithms. LS improve the current solution. Main techniques involved includes simulated annealing (SA), hill climbing (HC), Tabu search (TS) and others. Genetic algorithms (GAs) and other global search evolutionary algorithms maintain a population based candidate solutions. Different EAs have been applied on time tabling problem. (Burke et al., 1994) applied GA for time table scheduling. GA was implemented by (Ergul, 1996). A lot of work has been done for solving time tabling problem using TS algorithm. TS algorithm has been applied by Hertz (1992). Stochastic optimization timetabling tool is proposed by (Pongcharoena et al., 2008). A survey of meta-heuristic techniques has been done by (Lewis, 2008) .CBR has been a major point of concern for research. It is a technique that is based on notion that for solving problems humans use previous past experience and modify it for satisfying the requirements. CBR is being used in for solving timetabling problems (Burke e., 2000). Fuzzy based techniques for timetabling have been investigated by (Asmuni et al., 2005). GAs and particle swarm optimization (PSO) and their hybrid technique has been applied to timetabling problem by (Alinia et al., 2013). Similarly CBR and PSO are integrated for timetabling problem by (Ho Sheau Fen et al., 2009).All of the above mentioned approaches provides feasible solution but does not provide optimal solution efficiently. In this paper, CBR and TS are integrated and provide promising and optimal results.

3University Makeup Class Scheduling Characteristics and Constraints

University makeup class scheduling problem involves scheduling of set of lectures on the basis of given timetable’s scheduled rooms, room specification (with multimedia/without multimedia) and timeslots as input.

For scheduling makeup class, duration and room specification for makeup class is used as an input for finding the makeup class schedule.

3.1 Decomposition of problem and CBR:

Case based reasoning is an efficient technique that is used for solving a new problem case by either reusing or adapting previously stored solutions that are similar to that problem case [1]. Makeup class scheduling is highly constrained problem. These constraints are categorized into two types: hard constraints and soft constraints. Hard constraints must not be violated in any case. Soft constraints, on the other hand are commendable and they are not important to be satisfied. There are many constraints related to makeup class scheduling problem, which can be seen as constraint satisfaction problems. Hard constraints are: two makeup class schedules must not be assigned simultaneously to same timeslot and room, timeslot and room for makeup class that is scheduled must not have a clash with scheduled timetable’s classes rooms and timeslots and makeup class that is scheduled matches the required room specification (room with multimedia/without multimedia). Soft constraints are: course xyz has been assigned with time slot no. S and two makeup class schedules are consecutive with each other or not.

Makeup class scheduling is done through supervised learning technique. In this technique a data set commonly known as training data is given. There are different attributes for entries in data sets. Goal is to predict the target value or outcome for unseen example. Two methodologies for supervised learning are:

- k-nearest neighbor
- Decision trees

For investigation of data, input timetable attributes value is converted to discrete one. K-nearest neighbor will be used as classification algorithm for retrieving cases from case base in the upcoming section.

4 Weighted K-Nearest Neighbor Approach for Retrieval

In weighted K-nearest neighbor approach, if weighted sum of difference of features of a cases, which exists in the case base, with new query case is greater than other cases then that case is retrieved. In other words, a case from case base that matches k number of features with new query case will be chosen and retrieved, where $k<n$ and n is the total count of features. All of the attributes and features of case base are

not important in finding makeup class schedule. All the important features are assigned weights. This means that only relevant and important features will be considered [2]. For finding the neighbors of new query case, weighted Euclidean distance technique will be used that finds the distance between two points [3]. In makeup class scheduling, distance of between new query case that involves the duration, day and instructor name for makeup class that is to be scheduled and all the cases that are in case base is calculated. That will help to indentify which cases exactly match the new query case, yielding a zero value. If xi is new query case features and xj is a previously recorded cases features. Then, weighted Euclidean distance will be calculated as below:

d(xi,xj)=√∑Ss=1 ws(xsi-xsj)^2 (4)

ws is the weight that is assigned to features of cases in case base. Most important features are assigned greater value weights [4]. In Figure 1 the distance between query case attribute/feature x and case from data set y has to be calculated. According to Pythagoras theorem, hypotenuse2= Base2 + Altitude2. It can be seen that we have to find hypotenuse for calculating the distance between query case and stored case. Base will be found by x1-y1 and height/altitude will be found by x2-y2. This yields the formula as:

$|PQ|^2=(x_1-y_1)^2+(x_2-y_2)^2$ (5)

|PQ|2 tells how much similar or different is the query case from the cases present in the data set (case base).

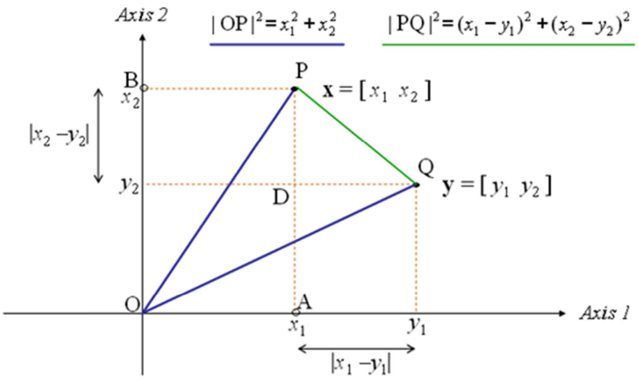

Figure 1: [4]

Figure. 1. Representation of Euclidean distance

Algorithm for weighted KNN:

Weighted K-nearest neighbor (cb:Case-base, nq: new-query, n, d:distance)

1) Assign weights to features of cases.

2) Compute weighted Euclidean distance d between new-query nq and every case in case-base cb (timetable).

3) Choose n examples in case base cb that are not nearest (exact match) to new query case nq.

The weighted kNN algorithm is very slow. Also it is sensitive to noisy data and there is a large computational overhead due to calculation and allocation of weights [5].

5 Multiple Retrieval Through Attribute Graphs And Decision Trees

Attribute graphs can be used to represent the constraints in makeup class scheduling. Edges of graph represent constraints and vertices represent courses. Notation a: b is used, where a depicts the label of attribute and b denotes the value that is assigned to that attribute [6]. Hard constraints are 3, 4 and 5. Soft constraints are 0, 1 and 2. Figure 2 contains description of hard constraints and soft constraints related to makeup class scheduling.

LABEL	VALUE	EXPLANATION
0	S (Slot No.), course xyz	Course xyz has been assigned with time slot no. S
1	N/A	Two makeup class schedules are consecutive with each other.
2	N/A	Two makeup class schedules are not consecutive with each other.
3	S (Slot No.), room R	Two makeup class schedules must not be assigned simultaneously to same timeslot S and room R,
4	S (Slot No.), room R belonging to makeup class scheduled. Rooms R_x and timeslots S_x belonging to scheduled timetable	Timeslot S and room R for makeup class that is scheduled does not have a clash with scheduled timetable's classes rooms R_x and timeslots S_x.
5	RSpec (room with multimedia (1)/without multimedia (2)).	Makeup class that is scheduled matches the required room specification RSpec.
6	RS=multimedia room(1) RS=without multimedia room(0)	Makeup class is scheduled in a RS room
7	R (Room No.)	Room R has been allocated

Figure 3 depicts the subset of graph that will be represented for makeup class scheduling.

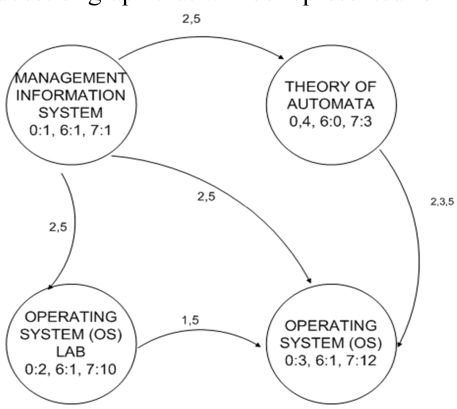

Figure. 3. Graph representation of makeup class

All of the makeup classes of courses shown by vertices match the required room specification RSpec, indicated by 5. Similarly edge between operating system and operating system lab, indicated by 1, 5 show that these two schedules are consecutive with each other and match the required room specification RSpec. For the course named Management Information System, three notations are used. In 0: 1, 0 indicates the label 0 which means that course has been assigned a time slot no. S and 1 indicate the value of slot no. which is 1 (according to discrete values assigned). In 6: 1, 6 indicates the label 6 which depicts that makeup class has been scheduled in a room with specification of RS and 1 indicates the value of room specification i.e. 1. In 7: 1, 7 indicates the label 7 which means that room RS has been allocated and 1 indicates the value of room no. depicted by 1. Similarly other constraints on courses are shown.

For retrieval, case base is constructed as a decision tree and stores the cases which are illustrated by attribute graphs like shown in figure 3. Possible permutations of the courses are gathered in a tree structure. Clustering is done on structures or substructures that have similar or same attributes under a specific node in a tree. In retrieval procedure, attribute graphs will be found and retrieved that represents the cases that are much alike to new query case. In this way, retrieved cases turned out to be the one with same constraints as the new query case. Comparison is done on the bases of values that are assigned to each of the vertices [6]

Algorithm for constructing decision tree, given a data set is given below.

Make-Decision-tree (DS: data set)

1) Identify the classes out of data set. (e.g: C may be one class)
2) If (all elements of data set DS constitutes a class C)
3) Make a leaf node and labeled it as C
4) Else
5) Construct sub-trees out of DS
6) Repeat steps 1-5 until classification gets completed

Decision tree is easy to understand. Small details that may have been skipped are considered. However, minor change in input data can result in major change in tree structure. Also it will be highly time consuming for constructing decision tree for large data set [7].

6 Proposed Solution: Integrating TS And CBR

Tabu search is an efficient optimization technique that can be applied to makeup class scheduling for attaining satisfying results. During search operation in finding a time slot for makeup class scheduling, every visited case that violates the constraints is inserted in the Tabu list. Then, this list is managed by applying a FIFO strategy. There are two controlling mechanism in Tabu search. These are categorized as diversification and intensification. Intensification concentrates on appreciating areas of search, while diversification guides the search towards unvisited search areas [8]. Case based reasoning suits well for controlling and monitoring the learning factor in Tabu search. It works best for problems where domain knowledge is represented by experience [8].

A feasible and optimal solution with minimum number of violations of constraints is found. Two operations are associated, as given below:

Case-base repair generation. When an initial solution(s) is picked then that solution violates the constraints defined in makeup class scheduling. Then repairs are generated for these violations using the case base or data sets.

Tabu list. A list is maintained that contains record of repairs that need not to be repeated. This ensures that the proposed algorithm will not get stuck in same repairs of violations that are being repeating. Case base is assumed to be well trained. The experience stored in case base will be used for generating repairs for violation of constraints in makeup class scheduling. If the repair is generated and this repair is found to be already present in Tabu list and hence needs to be forbidden. Then, next repair is generated out of retrieved case from the case base. In this way optimal solution for makeup class scheduling problem can be achieved [29]. Tabu list contains all of the makeup classes' record that is already scheduled. Thus, to avoid clashes, any newly generated schedule (case) should not match with or exists in Tabu list. Figure 4 depicts the flow chart of proposed algorithm. Following is the proposed algorithm.

Proposed Algorithm:

CBR-Tabu (CB: case base, QC: query-case, TL: Tabu list)

1) Assign weights to features of cases.

2) Compute weighted Euclidean distance d between new-query QC and every case in case-base CB.
3) For each retrieved case c1 from case base CB that does not yields a zero d.
(c1 contains violation and repair)
4) If c1 belongs to TL
Drop c1 and goto step 3 to generate repair
5) Else
Suggest the makeup schedule and store it.
6) Add chosen repair(makeup schedule) to TL

Flowchart:

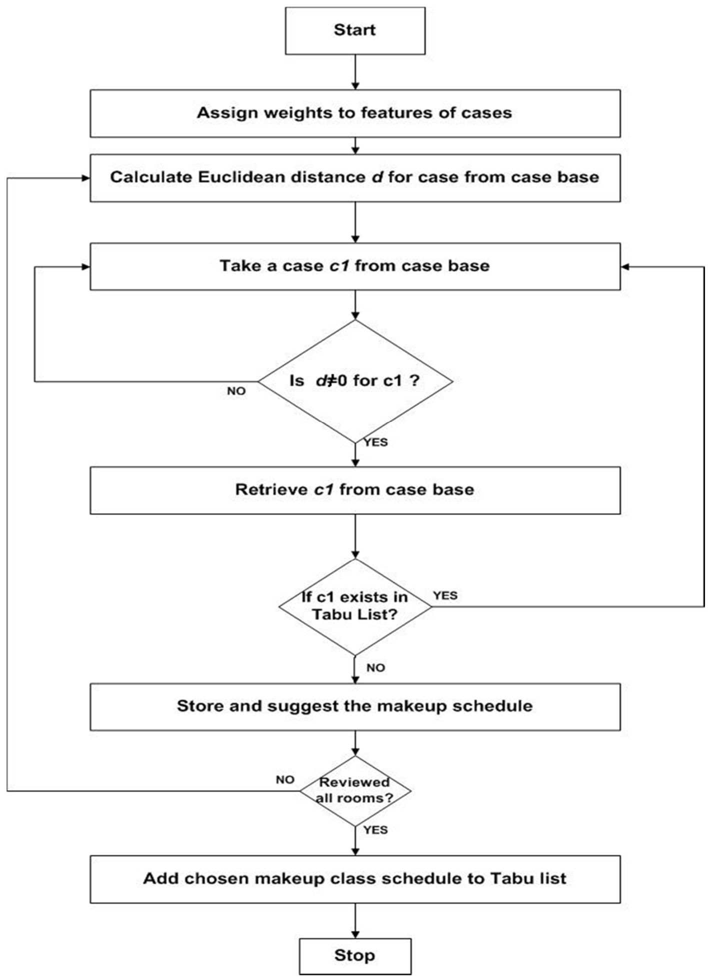

Figure 4. Flow chart of Tabu search and CBR

During searching process, Tabu search algorithm has to maintain depth and breadth in the process of searching. As Tabu search finds optimal solution during the search early, so depth will not be an issue in Tabu search. However breadth may be a crucial [30].

7 Experiments and Results

The data used in investigation of makeup class scheduling problem is obtained from timetables of five departments of Kinnaird College for Women University, Lahore, Pakistan namely Statistics, Psychology, Business Administration, English Literature and Computer Science. Integrated CBR and Tabu search algorithm has been tested on the data obtained from these departments. A makeup class schedule takes timetable as an input. Table 1 depicts the information related to this university's timetable regarding only the five departments mentioned above. Implementation is done in Java.

Table 1. Kinnaird College for Women University's timetable and makeup schedule

Resources	Count
Room	Text
Courses	Text
Scheduled makeup classes	Text
Instructors	Text

Table 2 shows the result achieved through implementation. Constraint violations are the number of times the clashes are found with existing scheduled makeup classes. Before getting results, 15 makeup classes are scheduled. Algorithm is run 10 times. As implementation involves only five departments and only 15 makeup class schedules are taken, that's why constraints are much less as compared to solutions or suggestions for makeup class schedule given by the algorithm.

Table 2. Implementation results

No. of algorithm run(iteration)	Constraint Violations	Suggestions achieved for makeup class to be scheduled
1	0	82
2	1	81
3	1	122
4	1	81
5	1	40
6	2	121
7	2	162
8	2	121
9	3	240
10	4	283

In the figure 5 graph is shown with constraint violations and suggestions for makeup class scheduling.

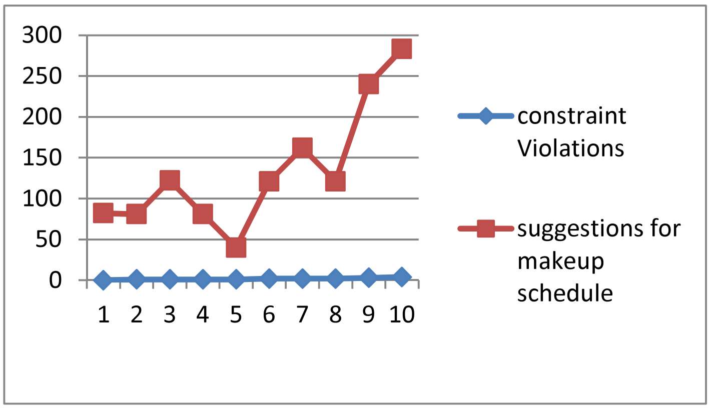

Figure 5. Graph depicting constraint violations and suggestions for makeup class scheduling.

8 Conclusion

In this paper, different classification techniques in supervised learning are presented. Limitations involved with simple CBR approach applied on makeup class scheduling are shown. Then a proposed technique involving an integration of CBR and Tabu search is demonstrated. Tabu search is a very powerful and practical approach. A case base is used for generating similar cases that have violation of constraints in them. Case base is utilized for generation of repairs. Two mechanisms were demonstrated that includes generation of case based repairs and Tabu list. Function of Tabu list is to hold in memory a list of repairs that are generated to resist repetition of usage of those repairs again. All this helps to find an optimal solution that does not involve repeating same solutions to same occurring problem.

9 Future Recommendations

In this paper, different classification techniques in supervised learning are presented. Limitations involved with simple CBR approach applied on makeup class scheduling are shown. Then a proposed technique involving an integration of CBR and Tabu search is demonstrated. Tabu search is a very powerful and practical approach. A case base is used for generating similar cases that have violation of constraints in them. Case base is utilized for generation of repairs. Two mechanisms were demonstrated that includes generation of case based repairs and Tabu list. Function of Tabu list is to hold in memory a list of repairs that are generated to resist repetition of usage of those repairs again. All this helps to find an optimal solution that does not involve repeating same solutions to same occurring problem.

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