Evaluating a Real-Size Man-Hill

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Abstract: "Man-hill" optimisation (a slightly different form of Ant Colony Optimisation) has been applied to the e-learning software of Paraschool (French e-learning company): instead of implementing artificial ants, students visiting the site unknowingly leave stigmergic information on the Paraschool web-site graph, in order to promote the emergence of pedagogic paths. In order to present students with exercises that match their level, it was needed to find some kind of evaluation mechanism, both for the student and for the Paraschool items. A solution was found in the Elo automatic rating process, that also provides as a side-effect a powerful audit system that can track semantic problems in exercises.

Key-Words: E-learning, Ant Colony Optimisation, Man-hill optimisation, Elo Rating.

Introduction

Paraschool (the French leading e-learning company, with 200 000 registered students) was looking for a system that could enhance web-site navigation by making it intelligent and adaptive to the user. Since their software is based on a graph traversed by students (where pedagogical items are nodes and hypertext links are arcs), Ant Colony Optimisation (ACO) techniques [6, 1, 2] can apply and show interesting properties: adaptability and robustness.

ACO (developed after the observation of ant-hills [8, 4]) uses virtual ants to find minimal paths in a graph. In the Paraschool system, the very large number of students triggered the idea to apply a similar technique using real students rather than virtual ants, with the aim of optimising pedagogical paths traversing a set of educational topics.

Real-size experimentations have shown that ant-hill optimisation techniques developed in Paraschool do not directly apply because students do not behave like artificial ants. The concept of an artificial "student-hill", or more generally "man-hill" has been introduced and analysed [13, 14, 16].

In a refinement stage, the level of items and students needs to be evaluated in order to direct students towards exercises of matching level (there is no point in suggesting an exercise that is overly difficult or simple to a particular student). The Paraschool pedagogical team could rate the different items based on their knowledge and experience, but what may seem simple for a teacher may seem difficult for a student. Moreover the level of the students must also be evaluated, which is quite difficult if the student does not have a long enough interaction with a human teacher.

A solution to this very important problem was found in the chess world, with the automatic Elo-rating computation. After a short description of the Paraschool "man-hill", the chess Elo rating is described in the second section and then applied to Paraschool system in the third section. Results on 3 years data are presented and discussed, before describing future developments.

1 The Paraschool "man-hill"

1.1 The goal

The Paraschool e-learning software is used in French schools or by individual students at home over the internet. Connected students have access to thousands of pedagogic items (know-hows, lessons, drills) that were originally deterministically related by hypertext links.

The aim of the presented work is twofold:

1. find the best succession of items to maximise learning,

2. and insert some intelligence into the system so that different students have a different view of the Paraschool software.

1.2 Differences between humans and ants

The first idea was to use Ant Colony Optimisation (ACO) since the two main features of this technique are robustness and adaptibility. Rather than using artificial ants as in ACO, the very large number of users makes it possible to use them directly to release artificial pheromones on the graph, depending on how they validated an item (success or failure). This stigmergic information can then be used by other students to choose their way on the different possible pedagogical paths.

Developing an ant colony optimisation technique using human students on the Paraschool graph has however led to the conclusion that humans do not behave as natural or artificial ants. The two main differences are the uneven students'activity over time and the need of individuality for each student. Then, the standard ACO paradigm does not work straight out of the box. The concept of "man-hill" optimisation has therefore been introduced, since what started with a couple of workarounds is now a distinct model with its own features, that can be reused in other different websites, provided that they are visited by a sufficient number of human users.

Emergent processes are still mostly unconscious in human societies: many structures have emerged over the Internet without any clear design. Studying the behaviour of our "man-hills" could allow to harness this power to optimise desired features.

1.3 Man-hill optimisation

The solution found to tackle the uneven activity during holidays, for instance, is to use an evaporation process that is not based on time, but on visits, that we call *erosion*. Erosion occurs on all arcs leaving from an item only when a user validates the item. This erosion (rather than evaporation) could also be used on ACO problems that are faced with uneven activity.

The need for individuality is dealt thanks to introduction of multiplicative pheromones, that only belong to a particular student (unlike the cumulative pheromones that bear stigmergic information accessible to all the individuals of the colony).

Standard cumulative pheromones allow optimal paths to emerge, while multiplicative pheromones applied on cumulative pheromones allow to bias the choice for a particular individual.

A further refinement allowing to tailor the system for a specific student is to take into account the level of the student, and direct him towards exercices he has a reasonable chance to solve. In order to achieve this, one must find a way to rate the drills and the students.

2 Usage of an Elo rating scheme in an interactive tutoring system

One could think of several ways to rate the respective difficulty of a drill and the proficiency of a student. The first idea that comes to mind is to ask the teachers who wrote the item to rate it on a scale going from easy to difficult, but this is error-prone because it depends on the judgement of the teacher, and on the level of the student that is faced with the drill.

A much better system would be an automatic rating process for both items and students, but such a thing is terribly difficult to calibrate. The chosen solution was to use a very refined system called the ELO rating [19], that has been used in the Chess community for the last 50 years, where individuals compete with each other on a regular basis.

This system takes into account specific difficulties, such as the fact that

1. human abilities changes over time due to learning and aging,
2. performances can fluctuate punctually (a competitor may be impaired if he is ill during the competition),
3. there is a massive turnover of participants (some people may stay in the system for a very short while only).

At the end of the fifties, a mathematician, A. E. Elo [19], developed a chess rating system, based on the Thursone Case V Model [18] which has been adopted by chess federations worldwide. His rating system was not the first one to be tried; the first rating list was published in Germany by Hösslinger, according to the Ingo system[20]. However the Elo-system was much more successful, due to the fact that rating-differences between two competitors $(s_i - s_j)$ and mutual winning chances are much more clearly related in this system than in any other.

2.1 Rating update

The equation $S_i(t+1) = S_i(t) + K(R_{ij} - R_{ij_e})$ describes how an original rating $S_i(t)$ is updated as a function of the expected outcome R_{ij_e}. If i and j are rated players, one can logically expect the stronger to win over the weaker. The expected outcome is called R_{ij_e}. However, the real outcome of the game R_{ij} may be different, for reasons quoted above.

If $R_{ij} = R_{ij_e}$, the rating of the players was accurate. If $R_{ij} \neq R_{ij_e}$, the ratings $S_i(t)$ and $S_j(t)$ need to be updated to reflect the outcome of the game.

The impact of the $R_{ij} - R_{ij_e}$ difference is tuned thanks to a variable K, which represents the maximum amount of rating points that can be won in one game. A high K-factor gives more weight to new results while a low value increases the influence of earlier performances. The K-factor fluctuates between 16 for great players (Elo-rate$>$ 2400) and 32 for weak ones (Elo-rate$<$ 2100).

According to the Bradley-Terry Model[18], if the rating difference $(S_i(t) - S_j(t))$ is known between players i and j, the expected probability of success of player i against player j can be defined as:

$$R_{ij_e} = \frac{1}{1 + 10^{\frac{S_i(t) - S_j(t)}{400}}}$$

This is the basic formula for the rating system of the United States Chess Federation.

In the Paraschool system, one can consider that students and exercises "compete" against each other, with the nice outcome that one can objectively compute their respective Elo rating, independently of any biases.

2.2 Inflation and Deflation

Since the introduction of the Elo-rating system in the world of Chess, the range of values has been expanding constantly. This is mainly caused by chess tournaments becoming increasingly popular, as well as the use of Elo ratings becoming more widespread. As the amount of players in the pool increases, the probability of some of them being extremely weak or extremely strong increases as well. The expanding range of Elo-ratings is a normal phenomenon and does not pose any problems for the system. However, other problems arise because of:

1. players entering and leaving the rating pool (turnover),
2. and the influence of subpools on ratings.

These factor question the "integrity" of the Elo system, as they can create a general inflation or deflation of the global ratings. The integrity of the system indicates to which extent a given rating s_i reflects a same level over time, and across different subpools.

2.2.1 Turnover

If no new players enter or leave the pool of rated players, then every gain in rating by one player would (ideally) result in a decrease in rating by another player by equal amount. Thus, rating points would be conserved, and the average rating of all players would remain constant over time. But, typically, players who enter the rating pool are assigned low provisional ratings, and players who leave the rating pool are experienced players who have above-average ratings. The net effect is this flux of players lowers the overall average rating. Rating deflation can be defined more specially as the result of a mechanism that causes players'ratings to decline over time when their abilities, on average, improve over time. These players will compete against underrated opponents who are improving, and will on average obtain lower ratings at the expense of the underrated players.

2.2.2 Subpools

Inflation and deflation do not only occur in the rating pool as a whole but also within subpools. A subpool is a subset of players who keep playing together over longer periods of time without much contact with players outside their group. This results in subpools with artificially low or high ratings. Within the subpool, ratings may still have a reasonable predictive value, but as soon as players from a subpool enter larger tournaments, they will start winning/loosing many points quickly, until their Elo rating is readjusted with reference to the larger pool.

Altogether, the subpool-phenomenon shows that it is important for players to periodically play against people outside of their sub-pool.

3 Elo ratings inside the Paraschool System

Since the algorithm works straigth out of the box, the equations and parameters are exactly the same in Paraschool as in Chess Tournaments. As soon as a student rating has stabilized, applications are numerous :

1. Students have a way to know their proficiency, and visualise their evolution.

2. The Paraschool pedagogical team does not have to put a subjective artificial rating on each item.

3. A very interesting side effect is that the Elo rating can tell if a drill contains a semantic or pedagogic flaw (extremely high/low rate). The Elo rating of items revealed to be an invaluable aid to the Paraschool pedagogical team if considered as an audit system.

4. Finally (and that was the primary goal of the implementation of the Elo rating), the manhill system can be refined to propose items adapted to the strength of a particular student.

3.1 Turnover and subpools in Paraschool

As in Chess, turnover in Paraschool represents students entering or leaving the Elo rating system. These cases happen more often in the beginning/end of the school year.

Normally a student should keep his account for several years. In practice, however, schools unfortunately update student lists and accounts every year leading to possible turnover and subpool concerns.

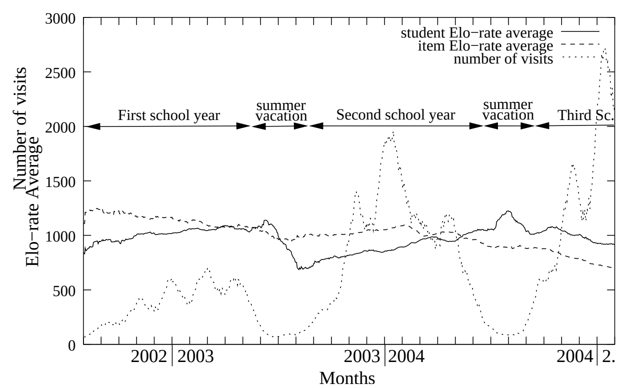

Figure 2: Average Elo Ratings and number of visits over a three years period.

3.1.1 Turnover in Paraschool

On fig. 2, the number of visits clearly shows periods of inactivity during summer vacations. In between, the Elo rate average of the students tends to increase, which is a positive result (students are getting better).

The drop in the beginning of each year comes from the fact that Paraschool increased its number of students from 50 000 to 200 000 over the three years on which data was collected (as can be seen by the increasing number of visits).

Fig. 2 also shows that the Elo rate of items tends to decrease year after year. This is because to the contrary of schools (that reset student accounts every year) Paraschool does not reset the Elo rating of items, therefore causing a constant deflation of items ratings, as students get better over the years.

3.1.2 Paraschool subpools

In Chess tournaments, a player can possibly compete with any other player, even though most competitions are held within countries.

In the paraschool system, it is much less so for several reasons:

1. An item cannot compete agains another item, and a student cannot compete against another student. This *de facto* creates two subpools of a different kind however from chess subpools where subsets of players can play exclusively within their group. The dynamics of this environment is therefore slightly different from the chess environment.

2. The Paraschool system also shows chess-like subpools, since it hosts different grades. Students in a grade will most exclusively compete with items of their grade, meaning that the rating of items of different grades may not be consistent.

A more precise analysis is necessary in order to understand the influence of these subpools.

3.2 Man-hill feedback and overall difficulty of the Paraschool e-learning software

When the Paraschool man-hill was first elaborated three years ago, the naïve conception we had of the system had us ask it to maximise success on all items, hoping that the man-hill could possibly find an optimal progression within the items allowing students to succeed all the time.

This actually worked too well, as paths emerged that found the shortest way to complete a lesson, while visiting the easiest items. This was very encouraging as it showed that the man-hill was doing its job well, even though it did not exactly correspond to what the pedagogical team had in mind.

The goal was then changed to have the system aim for items on which the students would have a 60% chance of success. The idea of the pedagogical team for this 60/40 rate was that it is necessary to fail periodically, in order to learn something. However, it was considered as encouraging if students could nevertheless succeed 60% of the times (rather than aiming for a 50% chance of success).

Of course, this 60/40 rate of success can only be attained if the students choose to follow the man-hill suggestions (indicated by a small ant on the graphic interface). Students who decide not to follow the hint are confronted with exercises of various difficulty.

A nice confirmation that things are happening according to the plans comes with the inspection of the difference in Elo between students and exercises during a confrontation, depending on the chosen navigation mode (cf. Fig 3).

This graph shows two phases. After a short unstable period (corresponding to the time needed by the man-hill to globally find paths corresponding to a 60/40 chance of success over visited items), in average, the man-hill system suggests items that have a 200 Elo difference with students. The very satisfying thing is that the Elo equation says that a 200 Elo rating difference means that the stronger of the opponents (the student in this case) has a 60% probability to win the game, which exactly corresponds to the goal set for the man-hill.

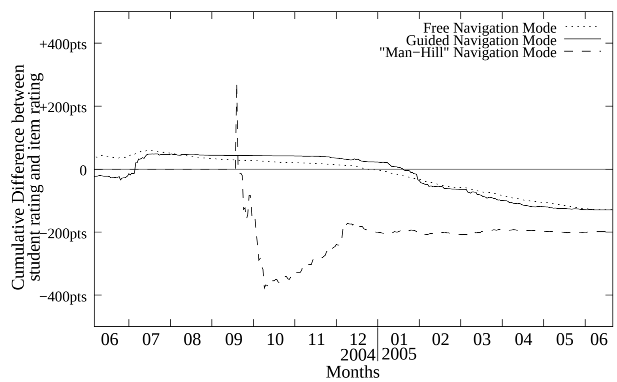

Figure 3: Cumulative difference between student rating and item rating.

4 Conclusion

The Elo rating system has been constantly used in the Chess tournament environment for the last 50 years, despite the imperfections of the method. In the Paraschool software, Elo rating of items and students provides a very interesting and useful piece of information, allowing students to have an idea of their level in the Paraschool system and follow their progression while at the same time providing the pedagogical team with a high quality feedback on the contents and relevance of proposed drills.

Moreover Elo rating helps the implemented man-hill paradigm to suggest items that are well adapted to individual students. Actually, a curve not presented in this paper for the sake of brevity shows that the Elo progression is slightly higher for students who do not follow the man-hill hints. This suggests that items proposed by the man-hill system (60% chance of success in average) are too simple for the students, not allowing them to increase their Elo rate as rapidly as if they were presented with harder drills. This observation would vote for a lesser bias (50% for instance) but this may discourage some students from using the system. This decision is therefore a strategic one, to be made by the Paraschool management and pedagogical teams.

References

[1] E.Bonabeau, M.Dorigo, G.Theraulaz, *Swarm Intelligence : From natural to Artificial systems*, Oxford University Press 1999, ISBN 0-19-513159-2.

[2] E. Bonabeau, M. Dorigo and G. Theraulaz, *Inspiration for optimization from social insect behaviour*, in Nature, vol. 406 pp 39–42, 2000.

[3] A. Colorni, M. Dorigo and V.Maniezzo, *Distributed optimization by ant-colonies*, in proceedings of European Conference on Artificial Life, Cambridge, MIT Press, pp 134–142, 1991.

[4] J.L. Deneubourg, S. Aron, S. Goss and J.M. Pasteels, *The self-organizing exploratory pattern of the argentine ant*, in Journal of Insect Behaviour, vol. 3 pp 159–168, 1990.

[5] M. Dorigo, E. Bonabeau and G. Theraulaz, *Ant algorithms and stigmergy*, in Future Generation Computer Systems, vol. 16 pp 851–871, 2000.

[6] M. Dorigo and G. Di Caro, *The ant colony optimization metaheuristic*, in New ideas in optimization, D. Corne, M. Dorigo and F. Glover (Eds), McGraw-Hill, pp 11–32, 1997.

[7] M. Dorigo, *Optimization, learning and natural algoritmhs*, PhD Thesis, politecnico di Milano, 1992.

[8] J.L. Deneubourg, J.M. Pasteels and J.C. Verhaeghe, *Probalistic behaviour in ants : a strategy of errors?*, in Theoritical Biology, vol. 105 pp 259–271, 1983.

[9] D.E. Goldberg and K. Deb, *A comparative analysis of selection schemes used in genetic algorithms*, in G. Rawlins, editor, Foundations of Genetic Algorithms, vol. 1 pp 69–93, 1991.

[10] D.E. Goldberg, *Genetic algorithms in search, optimization and machine learning*, Addison-Wesley Publishing Company Inc., Reading, MA, 1989.

[11] N. Labroche, N. Monmarch and G. Venturini, *A new clustering algorithm based on the chemical recognition system of ants*, in proceedings of the European Conference on Artificial Intelligence, IOS Press, pp 345–349, 2002.

[12] M. Resnick, *Turtles, termites and traffic jams : Explorations in massively parallel microworlds*, Complex adaptive systems series MIT Press, 1994.

[13] Y. Semet, Y. Jamont, R. Biojout, E. Lutton and P. Collet, *Artificial Ant Colony and E-Learning : An optimization of pedagogical paths*, HCI 2003.

[14] Y. Semet, E. Lutton and P. Collet, *Ant Colony Optimisation for E-Learning : Observing the emergence of pedagogic suggestions*, SIS 2003.

[15] T. Stützle, M. Dorigo, *ACO Algorithms for the travelling salesman problem*, in proceedings of the EUROGEN conference, M.Maleka, K.Miettinen, P.Neittaanmaki, J.Periaux (Eds), John Wiley & Sons, pp 163–183, 1999.

[16] G. Valigiani, Y. Jamont, R. Biojout, E. Lutton, P. Collet, "Experimenting with a Real-Size Man-Hill to Optimise Pedagogical Paths," H. Haddad et al. Eds., Symposium on Applied Computing (SAC), ACM, Santa Fe, New Mexico.

[17] W. H. Batchelder, N. J. Bershad, N. J, *The Statistical Analysis of a Thurstonian Model for Rating Chess Players*, in Journal of Mathematical Psychology, 19, 39-60, 1979.

[18] R. A. Bradley, M. E. Terry, *The Rank Analysis of Incomplete Block Designs*, The Method of Paired Comparisons, Biometrika, 39, 324-345, 1952.

[19] A. E. Elo, *The rating of chess players past and present*, New York: Arco Publishing, 1978.

[20] A. Hösslinger, *Ingo System*. Bayerischen Schachnachrichten, 1948. (From [19])