MATCHMAKERS: CROWD-SOURCING SOLUTIONS TO AN NP-HARD PROBLEM



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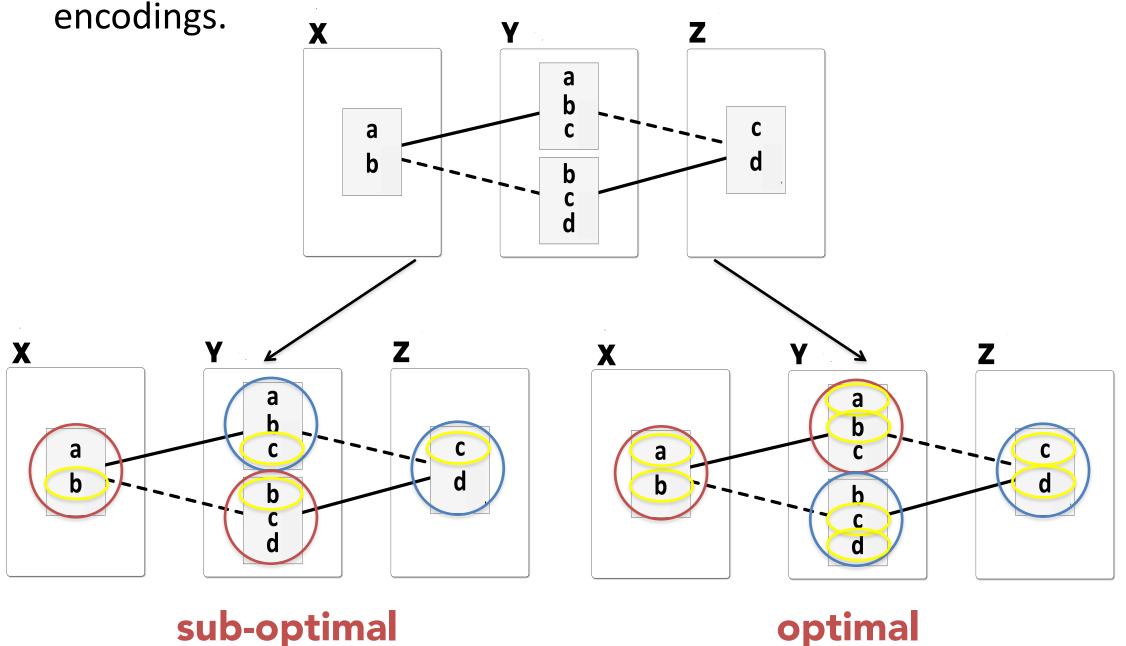


Overview

- N-way matching consists of finding correspondences between elements of input models [1].
- Useful for software engineering practices such as merging branches of a software configuration management system [2].
- N-way matching is NP-hard [1].
- Approximating solutions don't scale, heuristic solutions lack approximating factor of optimal solution.
- Our approach: Encode problem in an engaging game where players try to improve solutions of best heuristic algorithm.
- Among first to look at applicability of *serious games* to solve computationally-intensive problems [1].

Problem: N-way Matching

- Create n-way match by identifying elements from distinct inputs that share common properties [1].
- Input represented as models containing elements with properties.
- Representation is high-level so solution can apply to many



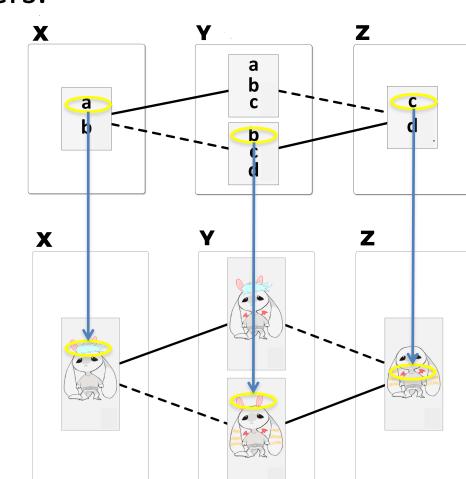
- Figure shows example of matching options.
- "Optimal" is better because matched elements share more properties.
- Optimal since no solution where matches share more properties.
- NP-hard with more than two input models [1].
- Table below lists approximating and heuristic solutions.

Algorithm	Description	Approximation Factor	Feasible	Matching score (on real case)
Greedy	Pick best match over all models greedily.	•	*	N/A
Greedy + Local Search	Greedy with local search.		*	N/A
NwM*	Apply bipartite graph algorithm over all elements, repeat.	*	•	+1.80 %
Greedy (by chunk)	Apply greedy to a subset of models.	*	•	+1.15 %
Pairwise	Apply bipartite graph algorithm to 2 models. combine into one, repeat.	*	✓ (state of practice)	+0.00 %

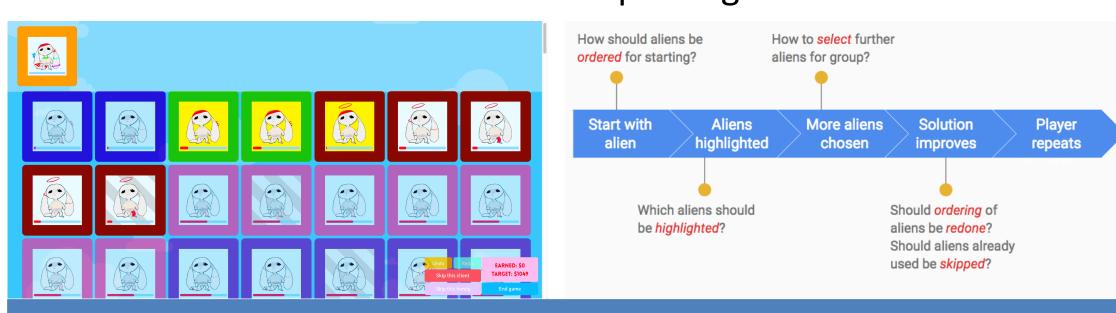
* Best heuristic solution thus far

Solution: The Game

- Our game, MATCHMAKERS encodes input elements as characters.
- Characters "visualize" properties.
- Goal: match visually similar characters.
- Game played in iterative manner.
- Player starts from best solution computed by NwM or another player.
- Player modifies solution by recombining groups.
- If player improves score, solution gets saved.



- Success through game achieved in two ways
- Many players improving on each other's results.
- 2. Human ability to make snap judgments about visual scenes.
- Tested many configurations to ensure good player support.
- By observing the way humans pay earlier versions of the game, built simulator to speed up evaluation of configurations.
- Simulator identified feasibility of players improving heuristic solution.
- Simulator itself was effective in improving the solution.



Results

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- Players played game over three real world cases.
- In all cases, players improved the score of NwM.
- Players improved on simulator score in one case.

simulator score in one case

Significance

- Provided two new ways of producing better matches than NwM.
- Validated use of serious games for computational problems.
- Showed power of crowdsourced solutions.

Simulator	MM (game)	
+10.30 %	+10.16 %	
+0.36 %	+0.61 %	
+32.79 %	+24.86%	
	+10.30 % +0.36 %	

Future

- Run longer user study to see if improvement still possible.
- Implement machine learning algorithm that learns from players.

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References

[1]. J. Rubin and M. Chechik, "N-Way Model Merging," in *Proc. ESEC/FSE*, 2013, pp. 301–311.

[2]. M.Hess, J.Wiemeyer, K.Hamacher, and M.Goesele, "Serious Games for Solving Protein Sequence Alignments - Combining Citizen Science and Gaming," in Proc. of the International Conference on Serious Games (GameDays'14), 2014.