CS 461 – ARTIFICIAL INTELLIGENCE

Term Project Proposal

Group Nick

YAINDU

Members

Umer Shamaan (CONTACT)
Taha Khurram
Muhammad Ali Khaqan
Hassan Raza Waraich

Project Description

In this project, we'll write a program called YAINDU. We'll use the Python programming language. Our program will input the clues of a 5x5 New York Times mini-puzzle (by Joel Fagliano, see this link https://www.nytimes.com/crosswords/game/mini) and its official solution. To achieve this objective, we will first try to extract relevant information such as clues from the New York Times Website. Using these clues, the program will look for the appropriate words through the online lexical database called WordNet. By iterating the process, the program will be able to find and fill all the words of the crossword. We will also implement a clue filtering functionality to identify clues that would be simpler. In case of the word not being found within a given time the application will start searching for the next word and then refer to the former word later (the increased constraints will make the search process shorter).

Literature

OUR REVIEW: This paper not only studies semantic information such as clues and orthographic patterns to examine differences between novice and expert crossword solvers but also gives a computational model based on a Biologically-Inspired Artificial Intelligence approach, incorporating assumptions about lexical access routes and solution strategies of skillful crossword players to draw visual distinctions. The semantic route searches for possible answers using clue-word associations, and the orthographic route obtains candidate answers using letter-word associations and combinations. These two routes are implemented independently in this paper. The results reveal that experts rely on strategies for a quick memory search and retrieval in a similar fashion as the computer-based model.

OUR RESOURCE: Thanasuan, Kejkaew, and Shane T. Mueller. “Crossword Expertise as Recognitional Decision Making: An Artificial Intelligence Approach.” Frontiers in Psychology, vol. 5, 11 Sept. 2014, 10.3389/fpsyg.2014.01018.

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Crossword expertise as recognitional decision making: an artificial intelligence approach

Kejkaew Thanasuan and Shane T. Mueller*

Department of Cognitive and Learning Sciences, Michigan Technological University, Houghton, MI, USA

Edited by:
Eddy J. Davelaar, Birkbeck College, UK

Reviewed by:
Adam Sanborn, University of Warwick, UK
Raymond Stephen Nickerson, Tufts University, USA (retired)

****Correspondence:***
Shane T. Mueller, Department of Cognitive and Learning Sciences, Michigan Technological University, 1400 Townsend Drive, Houghton, MI 49931, USA
e-mail: shanem@mtu.edu

The skills required to solve crossword puzzles involve two important aspects of lexical memory: semantic information in the form of clues that indicate the meaning of the answer, and orthographic patterns that constrain the possibilities but may also provide hints to possible answers. Mueller and Thanasuan (2013) proposed a model accounting for the simple memory access processes involved in solving individual crossword clues, but expert solvers also bring additional skills and strategies to bear on solving complete puzzles. In this paper, we developed an computational model of crossword solving that incorporates strategic and other factors, and is capable of solving crossword puzzles in a human-like fashion, in order to understand the complete set of skills needed to solve a crossword puzzle. We compare our models to human expert and novice solvers to investigate how different strategic and structural factors in crossword play impact overall performance. Results reveal that expert crossword solving relies heavily on fluent semantic memory search and retrieval, which appear to allow experts to take better advantage of orthographic-route solutions, and experts employ strategies that enable them to use orthographic information. Furthermore, other processes central to traditional AI models (error correction and backtracking) appear to be of less importance for human players.

Keywords: crossword puzzles, recognitional decision making, AI, expertise, lexical memory search

1. INTRODUCTION

Crossword puzzles were first introduced in 1913, and have become both a popular pastime, mental training aid, and a domain of study for psychological researchers (e.g., Nickerson, 2011), who have long acknowledged the role of memory access in puzzle solving. Previously, Mueller and Thanasuan (2014) we proposed a model of the basic memory search processes involved in solving individual crossword clues, and suggest that the joint access and constraint provided by cues in crossword puzzles make it similar to expert decision making in many domains.

For many of the same reasons that make them engaging puzzles for humans, crossword puzzles also pose an interesting problem for Artificial Intelligence (AI) systems, as solving them requires using many of the fundamental aspects of modern AI: search, heuristics, constraint satisfaction, knowledge representation, optimization, and data mining. Because crossword solving requires searching simultaneously within two distinct spaces (i.e., semantic and orthographic), and easily permits backtracking and recursion, it is also a useful problem for learning and teaching AI (e.g., Ginsberg et al., 1990; Harris et al., 1993; Shazeer et al., 1999; Littman et al., 2002). "Dr. Fill" (Ginsberg, 2011) is currently the best-known and most advanced AI crossword solver, and it typically performs perfectly on nearly all "straight" puzzles, only making mistakes on puzzles with complex or unusual themes or letter arrangements (Lohr, 2012). For example, when competing at the 2012 American Crossword Puzzle Tournament (ACPT), Dr. Fill failed on a puzzle in which many of the answers were required to be filled in backward, a twist that also challenged many human solvers. Dr. Fill finished the 2012 ACPT 141st of approximately 600 contestants and improved to 92nd place in 2013, and 67th place in 2014. The improvement over time is related not only to broader knowledge corpora being used, but also the incorporation of more rules for handling tricky puzzle themes, which often include puns, rebuses (i.e., letter substitutions), and other wordplay devices.

Although Dr. Fill illustrates that AI can be competitive with the best human players, AI systems typically use very non-human strategies to accomplish this. In arriving at a final answer, they may end up solving a puzzle dozens or hundreds of times, selecting the solution that best fits many constraints. In contrast, human solvers use a different combination of skills, including decision making, pattern recognition (Grady, 2010), lexical memory access (Nickerson, 1977) and motor skills such as typing or moving in a grid. Speed-solvers develop these skills to challenge themselves, to enable solving more puzzles per day (often five or six), and to compete in competitions. They tend not to use backtracking or error correction extensively (at least to the extent that computerized systems do), and they are minimally impacted by difficulty (see Mueller and Thanasuan, 2013). Moreover, they still outperform AI solutions on puzzles that are moderately challenging.

Although AI crossword solvers can complete many puzzles almost perfectly, these systems tend not to be based on human strategies or known human memory structure. In this paper, we