Navigation in Maps : Remembering strategies across Episodes

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Abstract

Studying how humans navigate in a map is a well studied problem with persistent research over the past 40 years however building a comprehensive system that performs similar to human reasoning still involves further research. Researches over these years have suggested lot of heuristics that humans use for the purpose of navigation - coarse to grain strategy and least decision load are few of these. Recent work [Nayak et al 2011] has further suggested that humans do not use a single heuristic but use a bunch of heuristics to navigate and they view the entire process of navigation in the form of episodes where in one episode humans use one heuristic out of the set of heuristics. They however assume that episodic navigation process is memoryless that is there is no memory of heuristics used in previous episodes and they leave it as open question to investigate whether generalizing this assumption to include memory of previously used heuristics will help or not. The present paper tries to answer the question by showing that there is a small improvement if we shift to higher order markovian models but the improvement is small and can be attributed to overfitting and further studies over large sample need to be taken to answer this. Our method focuses on coarse-to-grain and clustering method heuristics and computes feature cost for each heuristic together with biases resulting from previously used heuristic, i.e. if a strategy was used previously then probability of using the same strategy is increased. On a sample of 5 candidates who are asked 5 navigation task each with 6 targets, we find that going to higher order markovian model improves the Jaro-Winkler similarity by 0.02. The model achieves roughly the same accuracy as achieved by Nayak et. al. and uses a much simpler hill climbing method to do the same which is different from the stochastic method used by them.

Keyword : cognitive science, spatial navigation, hill climbing methods, markovian models of human reasoning, etc.

1 Introduction

Past 40 years of research has improved significantly our knowledge of how humans organize spatial information and use it to answer navigational questions. In particular we have come to appreciate the following -

- Humans organize spatial information in the form of graph like hierarchical structure [Hirtle & Jonides 1985]
- Humans do not use mere computational methods like path cost minimization to answer navigation query
- These effects are in part due to restriction of working memory
- Humans use a variety of heuristics and not just one for the entire navigational task
- Thus the navigational decision by humans can be broken down into episodes which uses a single heuristic

It is still not clear how these episodes work, for example Nayak et al. 2011 believe that the entire navigational process is a memoryless model with episodes as states and there is no memory of the previous episodes in the present episode. They however leave it as an open question to investigate whether generalizing this assumption to higher order markovian models result in better results. Trying to answer this question is the central theme of the present work. Main contribution of this work are follows -

Contributions

- to investigate if the probability of using a heuristic is increased if it was previously used.
- achieving consistent similarity index as the stochastic algorithm of Nayak et al.

There are many significance of showing that higher order markovian models perform better. Firstly it settle the question asked by Nayak et al 2011, secondly it shows that subject though a cognitive miser still has memory of previous episodes - at least to a certain extent - moreover it will show that humans are more likely to trust a heuristic if they have already used it (rigorous work can take their experience into account as well).

The rest of the paper is divided as follows - section 2 covers a brief review of various heuristics method that have been used, section 3 discusses our methodology, section 4 presents our results while section 5 summarises the work and leaves open some questions.

2 Heuristics for Spatial Reasoning

This section reviews some heuristics which are used for spatial reasoning. Nayak et al 2011 and Weiner 2009 are both excellent references for information about various heuristics and this section borrows most of it from these sources.

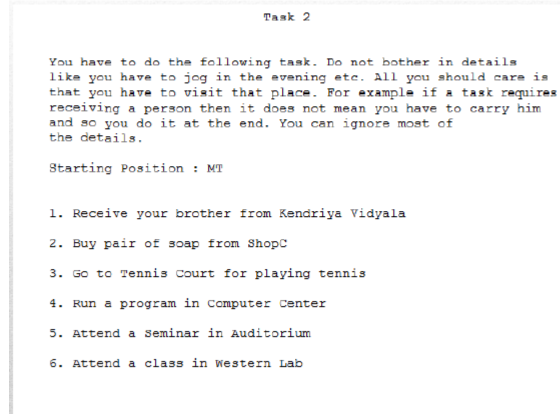
The heuristics can be divided into computational methods and cognitive methods. The computational methods consists of methods like path-cost minimization(Garling & Garling 1988; Bailenson, Shum, & Uttal 2000), Traveler (Leiser & Zilbershatz 1989), take the path with least number of turns etc. The traveler method involves going to the centroid of the present region, then going to the centroid of the target region and finally going to the target.

Examples of cognitive methods consists of coarse-to-fine strategy(Wiener & Mallot 2003), least decision load(ONeill 1992), least angle strategy (Dalton 2003), clustering method(Gallistel & Cramer 1996), road climbing principle (Bailenson, Shum, & Uttal, 1998), Initial Segment Strategy (Bailenson, Shum, & Uttal, 2000) etc. To understand these methods we have to recall that spatial understanding is represented mentally in the form of a hierarchical graph. Coarse-to-fine strategy suggests that the subject sees the details of present region while all other region are represented as points by their centroid. The candidates then finds shortest path to the next target and continues to go up the hierarchy of the graph until he sees such a region with a target. Clustering method involves going to the region with maximum number of targets and finishing them before going to the next region. The least decision method simply tries to minimize the number of decision that one has to take - this could also be equated to minimizing the number of turns for a familiar setting or for an unfamiliar setting it might translate to say following the main avenue until one sees the name of target on the direction board. The road climbing principle argues that humans try to take a path that makes them leave the present region earlier.

Certain strategies can be used to break ties in case of having multiple routes for example the Initial Segment Strategy can be used as a tie-breaker where the humans prefer the route with longest initial straight segment over other routes. Angle of turn of the road its straightness or steepness might also be taken into account.

3 Methodology

We chose 5 subjects who are fourth year students at IIT Kanpur. They were asked to remember the name of 20 landmarks of IIT Kanpur and recall them 5 times. These recalls were used to construct hierarchical structure for every subject using TIGER ordered-tree algorithm of Hirtle [Hirtle, SC. TIGER]. These subjects were then called after 5 days and were given tasks involving a starting point and a list of targets they have to visit. A sample task is given in figure 1. To make the task more natural they tasks were given in interactive story line fashion however the subjects were also asked to forget the intricate details for example if a task involves meeting a professor in faculty building then students were asked to forget details such as they have to meet professors earlier before their office hours get over. This constituted the database. Only five number of candidates were chosen because of the cost of task which involves manually feeding the tree produced by TIGER program into the program developed.


Task 2

You have to do the following task. Do not bother in details like you have to jog in the evening etc. All you should care is that you have to visit that place. For example if a task requires receiving a person then it does not mean you have to carry him and so you do it at the end. You can ignore most of the details.

Starting Position : MT

1. Receive your brother from Kendriya Vidyala
2. Buy pair of soap from ShopC
3. Go to Tennis Court for playing tennis
4. Run a program in Computer Center
5. Attend a Seminar in Auditorium
6. Attend a class in Western Lab

Figure 1: Showing a sample task that was given to 5 subjects

Next our algorithm computes a route for the same task by computing cost of using each heuristic in a given episode and using the heuristic with minimum cost. Our algorithm presently uses only coarse-to-grain and clustering method only. The cost for an episode E_i and a heuristic h is written as follows -

$$Cost(h) = a * F_{avgDistance}(h) + b * F_{targets}(h) + d_1 * \beta_1(h) \tag{1}$$

each heuristic suggests the next region to visit - using minimum distance for coarse-to-grain and maximum number of targets for clustering method and once we reach the region we finish the landmarks within that region using shortest distance method. Thus, we use a computational method once inside the region predicted by a cognitive method. This gives us a set of landmarks which will be visited in the next episode for each heuristic. Now we compute two feature for each heuristic - $F_{avgDistance}$ and $F_{targets}$ where $F_{avgDistance}$ is the average distance from one landmark to the next landmarks for the given set of landmarks to be visited while F_{target} is the reciprocal of the number of landmarks in the given region. Thus we can straightforward see that while the coarse-to-grain method tries to minimize the $F_{avgDistance}$ feature the clustering method tries to minimize the F_{target} feature. Thus increasing the value of a means favouring coarse-to-grain strategy while increasing the value of b means favouring the clustering method. The bias β_1 is the first order markovian bias which is 1 if in the previous episode a different heuristc was used and it is 0 if the same heuristic was used. For the first episode the value of β_1 is 0. The factor d_1 controls the extent of effect of the bias. This cost function can be easily generalized to k^{th} order markovian by the following equation -

$$Cost(h) = a*F_{avgDistance}(h)+b*F_{targets}(h)+\sum_{i=1}^{k} d_i*\beta_i(h) \quad (2)$$

where the bias β_i is 0 if the same heuristic was used in the last i^{th} episode else it is 1. Having defined the algorithms for the two heuristics and the cost function we need to define a metric for analyzing the closeness of our result with the data obtained from user. For this we use the measure suggested in Nayak et al. 2011, namely the Jaro-Winkler distance (Winkler 90). The output is a permutation of the set of landmarks that need to be visited. For a set of strings the Jaro-Winkler distance is defined as -

$$J(s_1, s_2) = \frac{1}{3}\left(\frac{m}{|s_1|} + \frac{m}{|s_2|} + \frac{m-t}{m}\right), 0 \text{ when } m = 0 \quad (3)$$

where m is the number of matching characters where two character are said to be matching if they are not separated by more than $\left\lfloor \frac{max(|S_1|,|S_2|)}{2} \right\rfloor - 1$. Whereas t is half the number of transpositions if the matching character of the two string are written in the order given in the string. For example for string $ABRA$ and $ARBA$ the matching characters are 4 and the number of transpositions are 2 (B to R and R to B) so $t = 1$. Hence the Jaro-Winkler distance is given by $\frac{1}{3}(\frac{4}{4} + \frac{4}{4} + \frac{3}{4}) = \frac{11}{12} = 0.9167$. Note that the maximum value of this index is 1 which implies equality also this is not a metric in true sense as it does not follow triangle inequality.

Thus for a given user and a given value of a, b and β coefficients we find the average Jaro-Winkler distance of the predicted ouput with the data for all tasks. We then use a hill climbing method to find the optimum value of a, b, c where the Jaro-Winkler distance is itself used as the hill climbing method - our aim being to maximimze its value - and the window is chosen as 40 for all coefficients. The result are then written for markovian models of order 0 to 4.

4 Results

The value of similarity index for different order of markovian is given in table 1. The plot in figure 2 reflects the same comparison of average value. The similarity index decreases from order 0 to order 1 but then goes on to increase slightly from order 1 to order 5. It is important to remember the 0.84 average similarity index of Nayak et al. for comparison purpose.

Order	average similarity index	standard deviation
0	0.81775	0.06139
1	0.81305	0.04705
2	0.82692	0.04537
3	0.83345	0.05294

Table 1: Showing average similarity index and standard deviation for different markovian models of navigation.

This increase may however be due to overfitting where we are taking too many dimensions that we are bound to

Order	Strategies for 5^{th} task and for first candidate
0	CM CM CG CM
1	CM CM CM CM
2	CM CM CM CM
3	CM CM CM CM

Table 2: Showing predicted strategies for candidate number 1 and task number 5 for different orders of model. We can see how the bias propagates. CM=Clustering Method, CG=Coarse-to-Grain Strategy.

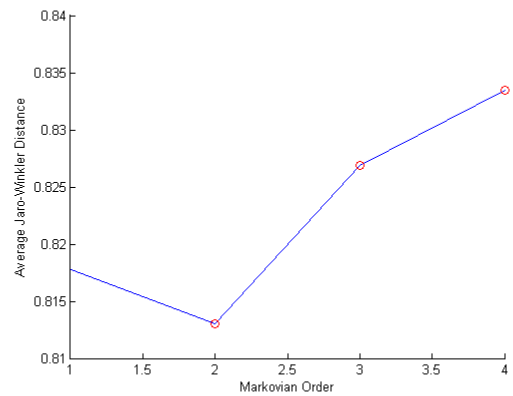


Figure 2: Plot showing the value of similarity index for different order of markovians

expect positive results. Adding regularising terms might help but then choosing the value of λ (regularizing coefficient) becomes problem. Thus, though there are hints that humans might have memory of heuristic used in previous episodes but the present work cannot claim it conclusively. Further investigation specially with respect to large sample space are needed to validate it further.

The list of strategies used for different order is given in table 2. The set of decisions for different subject was almost same showing the underline homogeneity in decision making of candidates. Another thing to note is that the bias coefficient was allowed to take negative value however the propagation of bias shows that the bias effect was positive which was expected and is further hint towards models with memory. However strangely our analysis shows that clustering method was favoured over coarse-to-grain strategy which is contradictory to previous analysis of Nayak et al 2011. This may be because the first strategy is clustering method for different orders and then due to bias the same strategy is propagated. However it might give a hint that coarse-to-grain may not be the universally favoured heuristics.

5 Conclusion

This work demonstrates that there might be evidence of remembering of strategy across episode as given by small increase in the similarity index. Moreover the similarity index of 0.834 is close enough to the value of 0.84 as given by the Nayak et al. 2011. However this increase is probably too small to give any conclusive results yet. Moreover this increase can be due to overfitting or from limitation of the sample size. Thus, we need to take this study on a further level and incorporate more heuristics before any discovery can be claimed.

Another direction will be to try more techniques of improving the similarity index. Simulated annealing can be used to do away with local maximas and different window size for different coefficient should be used as well as the starting position should be learned based on position of prior maximas along with some annealing.

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