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RESEARCH ARTICLE

Computationally determining the salience of decision points for real-time wayfinding support

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Abstract: This study introduces the concept of computational salience to explain the discriminatory efficacy of decision points, which in turn may have applications to providing real-time assistance to users of navigational aids. This research compared algorithms for calculating the computational salience of decision points and validated the results via three methods: high-salience decision points were used to classify wayfinders; salience scores were used to weight a conditional probabilistic scoring function for real-time wayfinder performance classification; and salience scores were correlated with wayfinding-performance metrics. As an exploratory step to linking computational and cognitive salience, a photograph-recognition experiment was conducted. Results reveal a distinction between algorithms useful for determining computational and cognitive saliences. For computational salience, information about the structural integration of decision points is effective, while information about the probability of decision-point traversal shows promise for determining cognitive salience. Limitations from only using structural information and motivations for future work that include non-structural information are elicited.

Keywords: navigational aids, wayfinding, geospatial information, human spatial cognition, real-time applications, salience, PageRank, information entropy

1 Introduction

Imagine stepping off a plane into a typical Japanese city. There are no street signs, as here the streets have no names. You must navigate to your destination using only your GPSequipped cellphone and spatial reasoning abilities. After inputting the requisite information, you get some directions and start out on your way. However, you fail to reconcile the information on the phone's map with the environment that you are traversing and you miss an important turn. If only your cellphone's software had known that this turn was important and provided some additional information to help with navigation! But how could it have known that a particular point in space was especially important to a wayfinding task? To help with situations like this, the present work explores the problem of calculating the importance of intersections in an environment.

Through design or accident, spatial environments often pose navigational difficulties for humans. Due to bounds on human rationality [42], people engaged in wayfinding tasks, to navigate environments from a starting to a goal location, often require assistance. Paper maps, and more recently, electronic navigational aids based on mobile GPS devices, provide externalized ways to access spatial representations that can augment human spatial reasoning. Despite the potential to help wayfinding by augmenting human memory, however, GPS devices have been shown to increase travel time, while decreasing configurational knowledge of routes traveled [18], when compared with using paper maps. Technology is obviously not being utilized optimally.

One way to improve electronic wayfinding devices may be to increase the ability of devices to adapt to an individual wayfinder's needs and desires, so that they can provide personalized assistance. Ishikawa and Montello [19] showed that significant individual differences exist in the configurational understanding of routes, which may also suggest differences in individual spatial abilities (see also [14]). People who have different abilities tend to employ different strategies when navigating [23]. Men [10] and older people [3] tend to prefer cardinal coordinate systems. Baldwin [3, 4] has shown that some people respond better to spatially provided information, while others may prefer information to be presented aurally. It has also been demonstrated that people with cognitive difficulties may require information to be displayed differently [30]. Ishikawa and Yamazaki [20] showed that people with a lower mental-rotation ability had a harder time orienting themselves in space using maps at subway exits, than with pictures that graphically showed where to go. These examples demonstrate that different people have different needs and abilities and hence may make different mistakes. Therefore, they may benefit from personalized wayfinding assistance.

A variety of psychometric tests have been developed to determine spatial abilities (e.g., [15]), but these tests must be answered before wayfinding activities take place, thus limiting practical use for assessing a user's ability online. Furthermore, Takemiya and Ishikawa [44] showed that wayfinding performance is related to the structure of the environment, so even if spatial abilities could be determined a priori, they may or may not be relevant to the current task. Additionally, Hölscher, Tenbrink, and Wiener [17] studied routes planned by participants who were familiar with an environment. They found that the routes planned by individuals for themselves to follow, the routes planned for others, and the routes actually traversed through the environment were significantly different from each other. Thus, cogitation about wayfinding tasks is vitally linked to the context of the activity being carried out. Ideally, the kind of assistance that a wayfinder needs would be automatically determined from online wayfinding performance, without directly asking the wayfinder, because the assistance required may change over time.

In previous work [44], we developed a novel approach for classifying the performance of wayfinders in real-time, thus opening up possibilities for providing personalized wayfinding assistance based on observed performance. By "real-time" we mean that not only is the method computationally efficient and results can be calculated within timescales that are useful to humans while they are navigating, but also that the calculation can be done using only information available up to the point in time when the calculation is performed. In that work we conceptualized space as a graph of decision points (i.e., points where roads connect to form intersections, thus causing a wayfinder to make a decision about which path to take) connected by roads, and showed that wayfinders can be classified into groups of "good" and "poor" wayfinders using only existential information about traversed decision points. This is a "bag of words" approach to classifying routes traveled, because each decision point is considered independent of the contextual relationship to other points.

In this research, we aim to explore the salience of decision points to classifying wayfinders in real-time and verify our methods by analyzing data from two empirical wayfinding trials. Although the distinction between many different types of saliences can be made, we consider two types of saliences:

1. Computational salience: the importance of a decision point for classifying wayfinders with respect to their abilities.
2. Cognitive salience: the importance of decision points to humans undertaking a wayfinding task.

Cognitive salience has been previously studied in relation to landmarks. Sorrows and Hirtle [43] explored visual, cognitive, and structural qualities that contribute to the importance, or salience, of a landmark to humans in an environment (roughly what makes a landmark or object in a spatial environment cognitively salient). Raubal and Winter [37] explored automatically extracting and calculating the salience of landmarks to humans (cognitive salience) with the aim of supporting route directions. Nothegger, Winter, and Raubal [34] developed automatic methods for calculating the cognitive salience of buildings as landmarks, using visual and semantic properties of building facades, with the aim of supporting the generation of route directions. Empirical validation using human participants showed that their approach can automatically extract landmarks important to people, although visual and semantic information about buildings are required for their approach to work.

This approach was expanded to also account for structural features, such as *advance visibility* [46] and relation of landmarks to decision points [27]. The cognitive salience of the structure of intersections was also studied [25] with respect to the theory of wayfinding choremes [24, 26]. Claramunt and Winter [9] explored calculating the structural salience of landmarks, using metrics from space syntax and graph theory. In a similar vein, Tomko, Winter, and Claramunt [45] applied graph-theoretic centrality measures to determining the relationship between the structure of a graph and the importance of streets to wayfinders and proposed a new measure, "experiential ranking," to quantify the relationship between the structural and functional (with respect to partitioning a city) properties of a street.

All the above approaches for determining the salience of landmarks focused on cognitive salience with respect to humans. Though not completely neglecting cognitive salience, this research instead focuses primarily on calculating what we call the *computational salience* of decision-points; we are interested in automatically determining points useful to discriminate classes of wayfinders. We theorize that computationally salient points, although not necessarily cognitively salient to wayfinders (though, conversely, not necessarily independent of cognitive salience), are important to wayfinding because these points reveal an underlying statistical structure about where wayfinders of different performance classes are likely to go and thus at what points assistance may be particularly helpful.

Furthermore, our method is distinguished in that to enable practical implementation, we do not rely on visual or semantic features of an environment. Rather, we present a method that can produce results using only information available while a wayfinder navigates an environment in real-time. The computational efficiency of the method is such that it can produce results within seconds, thus enabling its use while humans are engaged in a wayfinding task.

First we summarize our previous work on classifying wayfinders in real-time in Section 2, which we then expand to calculate the computational salience of decision points with respect to the classifications (Section 4). Section 5 presents results of our work, the implications of which are discussed in detail in Section 6. We then conclude with a summary of our findings and an outlook for future work (Section 7).

2 Classifying wayfinders in real-time

2.1 Synthetic route generation

Our previous work [44] was grounded in exploring feasible ways to improve electronic navigational aids. We focused on classifying wayfinding performance in real-time using synthetically generated routes to train our classifier, rather than data collected from human participants. The use of a probabilistic classifier allowed us to calculate the probabilities of each decision point being in either a class of "good" or "poor" routes, based on our generated training data.

We generated training data using our method from [44], where a modified implementation of the A* heuristic search algorithm [13] was used, with distance from the current decision point to the goal as the heuristic cost of decision points. Our modification to A* was to add a 10% random chance that each outlink from a decision point would be made untraversable, which caused the algorithm to generate a large variety of good routes. By inverting the heuristic function, we generated poor routes. In total we generated 250 good and 500 poor routes, which we then used to classify the wayfinding performance of human participants in our empirical study. Our method of route generation only considered route length, but future work may consider additional features, such as route complexity [6, 12, 40], points used for "coarse" route directions [38], or routing through regions that have similar complexities [39].

2.2 Probabilistic classification

In [44], to classify wayfinders, we used a probabilistic scoring function to determine whether a wayfinder was good or poor. The scoring function is shown in the following equations, adapted from [11, 31]:

$$\mathit{class}(r_i) = \begin{cases} C & \mathit{eval}(r_i) > 0 \\ C' & \mathit{otherwise} \end{cases} \tag{1}$$

$$eval(r_i) = \sum_j score(d_j) \tag{2}$$

$$score(d_j) = \frac{P(d_j|C) - P(d_j|C')}{P(d_j|C) + P(d_j|C')} \tag{3}$$

where d_j is the jth decision point in route r_i. A route is classified as good (class C) if the sum of the scores of all individual decision points is greater than 0; otherwise it is poor (C'). Decision-point conditional probability scores were calculated from Equation 3. $P(d_j|C)$ is a probability function that calculates the probability of decision point d_j given a class C. A decision point's probability score was calculated by taking the frequency of a decision point d_j in routes of a given class and dividing it by the total number of decision points in the given class, multiplied by the respective frequencies. Thus, an individual decision point's probability score will always be in the range [-1, 1]. The scoring function is resistant to missing information, because it can make a classification given as few as one decision point, albeit accuracy will suffer when not enough data are available. Additionally, as in [44], a decision point is automatically given a score of -1 if it does not occur in the training data, because it is assumed that points that are not included in the generated data are in traversals that lead away from the direction of the goal and should thus be associated with poor wayfinding performance.

To calculate the probabilities for the probabilistic classification, our generated route traversals were used. The route generation and classification can be accomplished very quickly. Our implementation, which was not optimized for speed, can generate routes and classify a wayfinder within 10s on a desktop computer with a 2.93 GHz processor. This makes our approach applicable to real-time systems, because results can be obtained within a timescale useful to humans navigating an environment.

3 Empirical studies

3.1 Empirical wayfinding study

To study classification of wayfinding performance, we previously [44] conducted a wayfinding study featuring 30 participants (15 female) traversing two routes in unfamiliar environments, while using only provided paper maps. Goal locations were explained to participants at each starting location, but a route to the goal was not explicated; participants had to plan their routes on their own. After traversal, participants were divided into two performance classes—good and poor—and labeled as poor if they met the following criteria:

1. failed to reach the goal; or
2. took a route traversing less than half of the decision points located along the shortest route.

Traversals from all participants are shown in Figure 1. Since this empirical study tested the wayfinding performance of people traveling through unfamiliar environments, the traversal data collected in the study were used to validate the present work (Section 5).

Our goal in the previous work was to explore the relationship between spatial ability and performance, so we had participants take two spatial-ability tests: the Santa Barbara

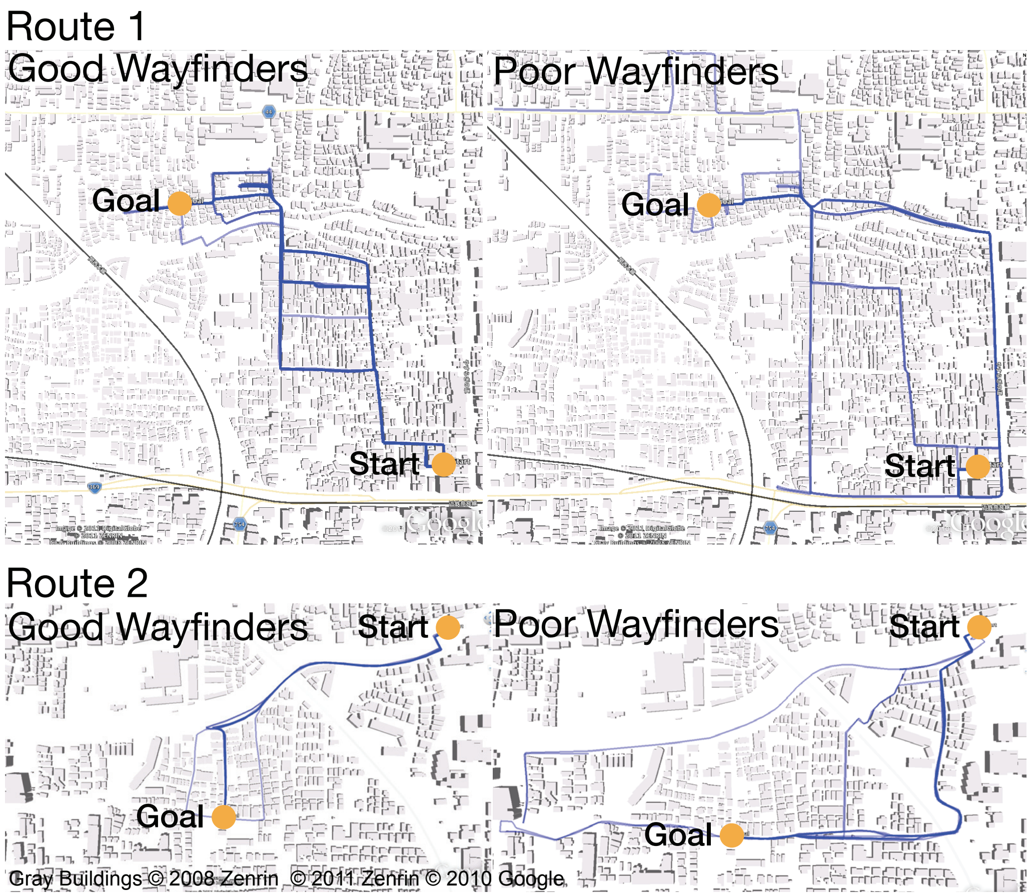


Figure 1: Route traversals for all participants. Good and poor labels were calculated according to similarity with the shortest path from start to goal, as described in [44]. Darker (thicker) lines show traversals taken by a larger number of participants. Generally, good wayfinders took more direct routes to the goal than poor wayfinders, who either got lost or took routes to the goal location that were indirect and thus were much longer than optimal. Good and poor wayfinders for the first route had average traversal lengths of 1168m and 1396m, respectively. For the second route, good wayfinders traveled an average of 577m, while poor wayfinders traveled 722m.

Sense-of-Direction (SBSOD) scale and the mental rotation test. The SBSOD scale consists of 15 Likert-type statements with a 7-point scale, and it has been demonstrated that people who scored highly on this test were good at updating their orientation and location in space when traversing an environment, making this a reasonable metric to try to correlate spatial ability and wayfinding performance [15]. The mental rotation test consisted of 21 questions involving the mental rotation and identification of line drawings, and is often used in studies of map use [29]. We used the scores from these tests as a part of the validation for this present work (Section 5.5).

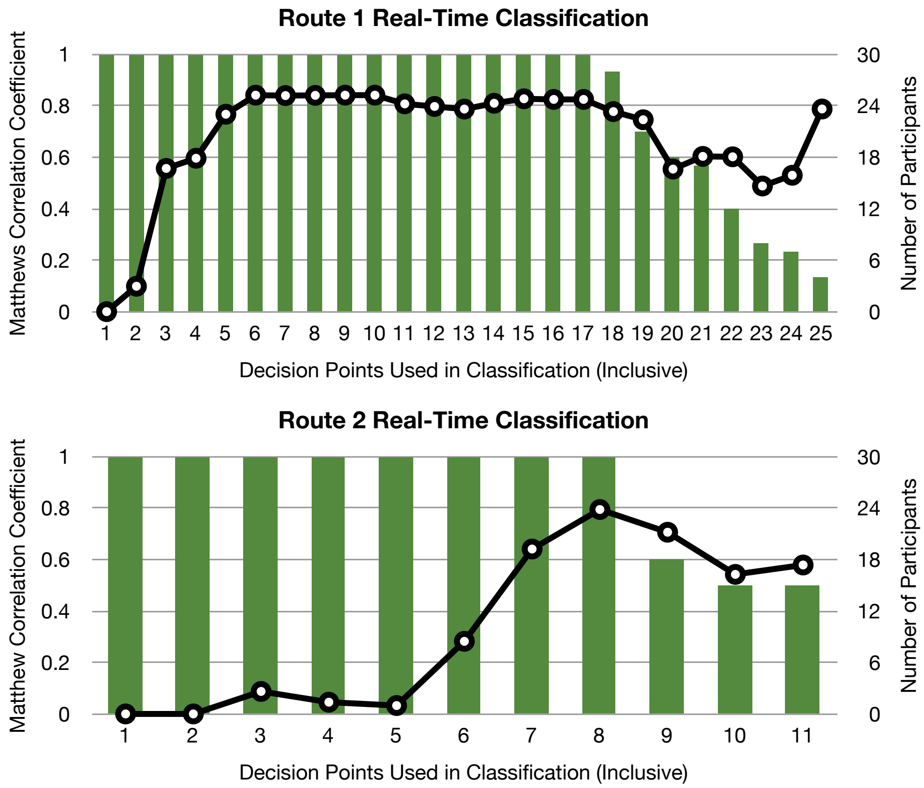


Figure 2: Real-time route classification results, where the x-axis numbers the nth decision point and only decision points 1 to n are used to classify wayfinders. Bars show the number of participants classified at each iteration.

Figure 2 shows the real-time classification results for the first and second routes used in [44], along with bars representing the number of participants classified at each iteration, from the first decision point, up until the remaining wayfinders were all from the same performance class. The number of participants being classified gradually declined over time as participants reached the goal and were no longer classified. Since different participants took routes of different lengths, containing varying numbers of decision points, the number of points required to reach the goal was varied across participants. The sharp rise in classification efficacy after some decision points were traversed, shows that some points were very important for discriminating between classes of wayfinders. Thus, it appears that not all decision points are created equal; different decision points have different saliences to a wayfinding task.

3.2 Photograph recognition experiment

Approximately six months after traveling the routes, we showed participants photographs taken at decision points for each of the two routes in the empirical study. This experiment was not performed in our previously published work and was designed to test if participants could recall higher-salience decision points better than points with lower computational salience scores. In addition to the binary question of whether participants remembered the area shown in a photograph, participants were asked to rate the subjective “strength” of their memory, on a scale of 1 (weakest) to 5 (most vivid).

For each route we selected decision points that were commonly traveled by many participants in our previously-performed empirical wayfinding study; 10 points were chosen for route 1 and 8 for route 2, with 17 and 14 of the 30 total participants traveling the selected decision points in routes 1 and route 2, respectively. 13 participants took part in the photograph recognition experiment for route 1, and 10 participants for route 2. All photographs were taken in the direction of travel at head level, with approximately the focal length of human vision, to replicate what participants might have visually experienced when traversing the route. Half the photos shown were from the area around where we performed our empirical study, but they were of decision points that were not traversed by the participants; the other half were of the decision points that participants traversed. The order of presentation was randomized and the photos were presented in the same order to all participants. For the presentation of photographs, there was no time limit, however once a participant had advanced to the next photograph, they were not allowed to go back and view previous photographs or change any answers

4 Calculating decision-point salience

The results of real-time classification in previous research showed that including certain decision points greatly increased the efficacy of classification (see Figure 2); that is, some decision points were more important than others for discriminating classes of wayfinders. Thus, determining a viable method for calculating the computational salience of decision points is the main objective of this current work. To examine important aspects of decision-point salience, we used a variety of algorithms to calculate the salience of decision points. Each algorithm was chosen based on its relation to either previous wayfinding literature or connections to graph theory.

4.1 Conditional probability scores

Decision points that are strongly associated with one wayfinding performance class over another can discriminate between groups of wayfinders and thus may be important in a spatial environment. The most obvious way to find important points is using Equation 3 to calculate the conditional probability that a decision point belongs in one class or the other. For this method, points with higher absolute-valued scores were considered more important.

4.2 Probability

The Pearson correlation between the probabilities of decision points appearing in the generated and empirical data from our wayfinding study was 0.93 and 0.83 for the first and second routes, respectively. These high correlations make it reasonable to use the probability of a decision point being traversed in the generated data as the salience of a decision point. Probability is calculated from the synthetically generated data as the number of routes containing a decision point $|R_D|$, divided by the total number of routes $|R|$.

$$P(D) = \frac{|R_D|}{|R|} \tag{4}$$

Decision points with higher probabilities are considered more salient. As this is a measure of where wayfinders tend to go in an environment, decision points that are often traversed are likely to be highly salient.

4.3 PageRank

PageRank is an algorithm for calculating the stationary probability distribution of an ergodic Markov chain [28]. It was developed originally for ranking web pages in Google search results, but has also been successfully applied to word-sense disambiguation [1], citation analysis [32], and ranking popular locations in a spatial environment [21].

In PageRank, the importance of a node in a graph is related to the importance of nodes that point to it [36]. Thus, the algorithm uses direction information about which nodes point to each other. In the context of wayfinding, nodes are decision points and the edges connecting nodes are streets, with the direction of the edges being determined by movement from a starting decision point to a goal decision point. In iterative implementations of PageRank, all nodes are first initialized with the probability that a node is randomly chosen; that is, 1 divided by the number of decision points in the graph, $|G|$:

$$\mathit{PageRank}^0(i) = \frac{1}{|G|} \forall i \in G \tag{5}$$

After initializing all decision points, the algorithm assigns a score for the current iteration (r) based on the score from the previous iteration ($r-1$). We used a weight (d) of 0.99, which corresponds to a 1% chance of randomly jumping to another node. For many applications a weight of 0.85 is used, corresponding to a 15% chance of randomly jumping to another node from the current node, in a random traversal of the graph. However, as shown by Jiang [21], because wayfinders cannot physically jump to a random node when traversing a spatial environment, results are usually better with larger weights (unlike [21], we still used a weight less than 1.0 to guarantee mathematical convergence of the algorithm). This is shown in the following equation:

$$\mathit{PageRank}^r(i) = (1-d) \times \frac{1}{|G|} + d \times \sum_{k=1}^{s} \frac{1}{|O_{jk}|} \times \mathit{PageRank}^{r-1}(j_k) \tag{6}$$

where $|O_{jk}|$ is the number of outlinks from the current node to other nodes.

Finally, the algorithm continues until the change in page ranks between iterations is less than some specified ε:

$$\left(\sum_{i \epsilon G} (\mathit{PageRank}^r(i) - \mathit{PageRank}^{r-1}(i)) \right) < \varepsilon \tag{7}$$

The transition probability matrix between decision points is stochastic, irreducible, and primitive, so the algorithm is guaranteed to converge. For more details on the mathematical theory of PageRank, see [8].

4.4 Information gain

Shannon first introduced the concept of information entropy [41] to quantify the statistical "surprise" of data. With respect to analyzing route traversals, information gain measures the amount by which a decision point decreases entropy (i.e., increases the homogeneity) of good and poor sets of routes, bounded by whether or not they contain the decision point being considered. Our approach of computationally generating routes as a prior for classifying wayfinders allows us to compute the entropy of each decision point with respect to performance classes, which is an original contribution of this work.

To calculate the information gain, first the entropy of the entire data set of routes is calculated as follows:

$$\textit{entropy}(R) = -\sum_{i=1}^{k} P(C = c_i) \times \log_2(P(C = c_i)) \tag{8}$$

where $P(C = c_i)$ is calculated by dividing the number of routes in class C by all the routes in the set R, for both good and poor performance classes:

$$P(C = c_i) = \frac{|R_i|}{|R|} \tag{9}$$

To calculate the information gain for a single decision point, we split the set of all routes into two subsets, s: those that contain the current decision point and those that do not. The entropies of these two subsets (D_i) are then calculated and summed, while being normalized by the size of the current (jth) subset divided by the size of the entire set of routes:

$$\textit{entropy}_{D_i}(R) = \sum_{j=1}^{s} \frac{|R_j|}{|R|} \times \textit{entropy}(R_j) \tag{10}$$

where R_j is the set of routes for the current subset.

Once the entropy of the two subsets of routes, split on existence of a decision point, has been calculated, we can then calculate the information gain of the splitting decision point as the reduction in entropy by dividing the set of routes into two subsets, relative to the entropy of the unsplit set of routes:

$$\textit{Gain}(R, D_i) = \textit{entropy}(R) - \textit{entropy}_{D_i}(R) \tag{11}$$

Intuitively, the information gain measures the decrease in class heterogeneity for sets of routes, as split by the existence of a decision point. Thus, decision points with high information gains are important for discriminating between classes of wayfinders and therefore may have high salience in an environment.

4.5 Local and global integration

The structure of space can greatly influence human navigation. The field of space syntax has studied the effects of the structure of space on humans [16]. From space syntax, many measures of graph-theoretic connectivity and integration have been developed that attempt to quantify how streets relate to each other. Although originally developed to focus on streets, more recent work has applied metrics such as local and global integration to studying characteristic points in space that are either decision points or that mark significant changes in orientation [22]. Taking this approach, integration measures how many points are connected s steps away from the current point, where s is the shortest-path length from the current decision point to other points. Integration is thus a way to quantify the relation that decision points have to other points in an environment. As an exploratory effort, we apply local and global integration measures to the present work. These metrics are shown in the following equation, adapted from [21]. We used a k_i of 2 for local integration, similar to [21].

$$\sum_{s=1}^{k} s \times N_s = \begin{cases} \textit{local integration} & \iff 2 \leq s \leq k_i \\ \textit{global integration} & \iff s = k \end{cases} \tag{12}$$

where N_s corresponds to the number of decision points with a shortest distance of s steps away from the current point and k is the number of steps in the longest shortest path in the graph. Since local and global integrations quantify how well integrated a point is into the, respectively, local and overall graph structure, these metrics can show how the graph-theoretic connectivity of decision points may contribute to where humans travel. Other metrics, such as centrality measures [45] and relative adjacency [5], should also be considered in future work.

4.6 Outflux scores

The outflux scores are considered as meta-algorithms that take as input salience scores calculated via one of the other algorithms to calculate decision-point salience. This methodology is original to this work.

By plotting decision points' salience scores on a map, we observed that regions of similar scores appeared. We hypothesized that decision points bordering these regions may be important to wayfinding, as they provide a chance to get from one fairly homogeneous region of values to another. Our generated routes allow calculating the net direction of travel along edges in our graph, so we used the following equation for computing the salience of a decision point based on scores calculated by one of the other algorithms:

$$\textit{outflux} = \left| \left(\sum_{out} \omega_{out} \right) - \omega_{curr} \right| \tag{13}$$

where ω_{out} is the score for an outlink decision point and ω_{curr} is the score for the current decision point. The heuristic sums up all the scores for the decision points pointed to by the current decision point via its outlinks, and calculates the salience of the current decision point as the absolute value of the difference between the summed scores and the current score, where scores are calculated by the current algorithm under consideration. The outflux values for each algorithm are marked with the word "outflux" in front of the algorithm name in the following results and discussion. As an example, the salience value of "outflux probability" is the absolute value of the difference between the sum of the probabilities of decision points pointed to by the current point, and the probability of the current decision point.

5 Results

One of the problems of verifying the efficacy of computing the salience of decision points is the lack of a "ground truth" to compare the results to. It is not possible for a human to sit down and go through more than 100 decision points and rank them all in order of salience, not only due to reasons of combinatorics, but also because definite criteria do not exist for determining that one decision point is more salient than another in an absolute way. To get around this, we analyzed the performance of each algorithm for calculating computational salience from three different perspectives: classifying overall routes of wayfinders using only high-salience decision points; real-time classification of wayfinders weighted by salience scores; and correlations between salience scores and observed wayfinding performance. The photograph recognition experiment was performed as an exploratory work to study the relationship between computational and cognitive saliences.

5.1 Validation

In the validation of our classification results, we used the Matthews correlation coefficient (MCC) [33] to analyze classification performance. This was calculated from the confusion matrix using the following equation from [2]:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FN)(TP + FP)(TN + FP)(TN + FN)}} \tag{14}$$

where TP, FP, TN, and FN are the quantities of true positives, false positives, true negatives, and false negatives, respectively, calculated from each applicable classifier's results.

5.2 High-salience decision point classification results

We first verified the salience scores calculated by each algorithm by examining how well participants' wayfinding performance could be classified using only high-salience decision points (called overall classification, in comparison to the real-time classification that is explained in Section 5.3). We used the same probabilistic classifier as discussed in Section 2, only this time limiting the decision points available for classification based on the computed salience scores. Our classification procedure was as follows:

1. Sort all decision points based on computed scores.
2. Remove points that were not in any of the participants' traversals.
3. Cumulatively add one point at a time in order of salience score, iterating over the set of points traversed by human participants; classify all participants using only the currently added points.

To evenly compare classification performance across all algorithms, we left out any classification results that did not classify all 30 participants. This would happen, for example, if the first few highly scored points were only traversed by some, but not all, of the wayfinders. Thus, we continued adding points in order of the computed score, one per iteration, until we had a set of points where all 30 wayfinders traversed at least one of the points in the set. After achieving this minimum level of points, we left out the first classification result, because it was poor across all algorithms and thus uninformative. The MCC values

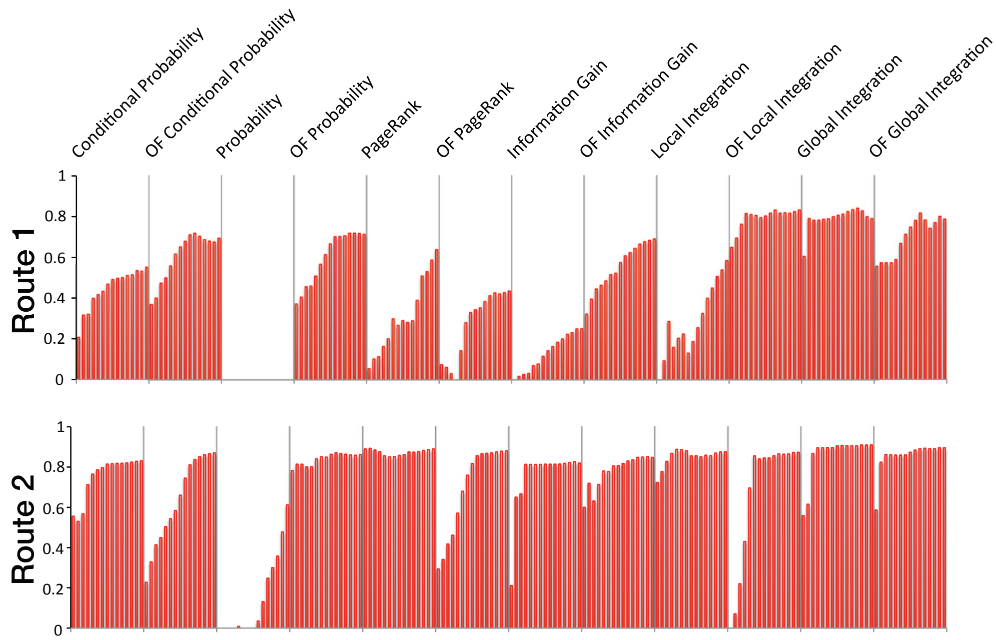


Figure 3: Matthews correlation coefficients for classification results for routes 1 and 2. Each columnar bin corresponds to the results for one algorithm. The 15 columns within each bin show the classification performance obtained using up to the nth iteration that met the criteria defined in Section 5.2. Outflux is abbreviated as "OF."

for each algorithm from the first 15 iterations that met these criteria are shown in Figure 3, where higher values indicate better performance. The results show that classification performance was better for all algorithms on the second route than on the first route.

5.3 Real-time classification results

When classifying wayfinders in real-time, given only information about decision points traversed up to the current point in time, knowledge about the traversal of some decision points can greatly improve classification, compared to other decision points. Thus, it is hypothesized that some decision points have more information-theoretic salience than others with respect to both computational and cognitive saliences.

To incorporate the calculated salience scores to improve real-time classification, we modified the scoring function in Equation 3 to use the calculated salience scores. This was accomplished as follows:

1. Normalize the salience values calculated by each algorithm to be within the range [0, 1]. This makes the salience scores directly comparable to the absolute values of the probabilistic classification scores, because they are within the same range.
2. For the probabilistic classification function, use the class as calculated by the scoring function (the sign of the score in Equation 3). The magnitude of the calculated score is mapped to the exponential function and then added to the salience score, mapped to

the exponential function $\exp(2\varsigma)$. This is shown in Equation 15, below, where *score*(d_j) is as defined in Equation 3 and ς is the salience score. If any point is not in the training data, assign it a score of -1; this follows the methodology from [44], where points that do not appear in the training data are given an automatic score of -1 (the largest-magnitude poor value).

$$score(d_j, \varsigma) = \begin{cases} \exp\left(|score(d_j)|\right) + \exp(2\varsigma) & score(d_j) > 0 \\ -\exp\left(|score(d_j)|\right) - \exp(2\varsigma) & score(d_j) \leq 0 \\ -1 & \textit{point not in data} \end{cases} \quad (15)$$

It was empirically observed that mapping the conditional probability and salience scores to the exponential function improved the classification results across a majority of the algorithms, compared with simply using the calculated scores. The distribution of salience scores seemed to follow a power distribution, where only a few points had very high scores and the majority of points had low scores. Mapping the values into an exponential space increased the spread between the points, thus causing the few important points to play a larger role in classifying wayfinders. Additionally, it was found that adding together the exponentially mapped conditional probability and salience scores produced better results than multiplying them together.

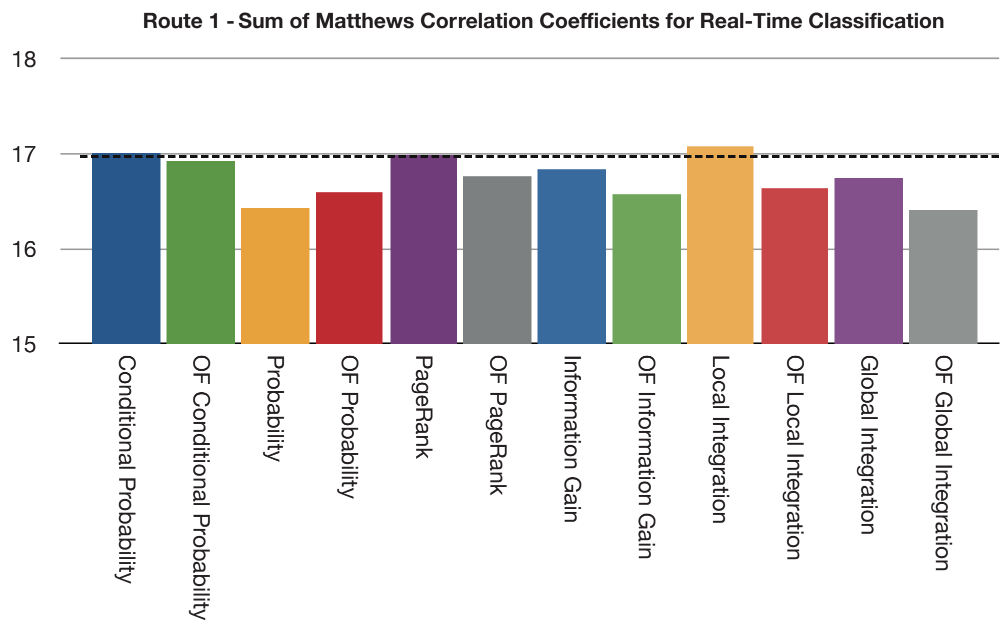
Real-time classification results are shown in Figures 4 and 5. Figure 4 shows cumulative MCC values for both routes for each algorithm. Cumulative values were calculated by summing the MCC values that were calculated at each iteration, from the starting decision point to the last decision point that still had a MCC above 0. As with Figure 2, as wayfinders reached the goal and finished traversing their routes, the MCC suddenly became zero when the remaining wayfinders were all members of the same performance class. Figures 4 and 5 use classifications from decision points up until right before this happens; that is, the first 25 decision points for route 1 and the first 11 points for route 2. Numbers of participants classified at each iteration are the same as the bars in Figure 2.

Figure 5 shows the MCC values for each iteration. Each point on the horizontal axis represents the nth point traversed from the starting point. Individual wayfinders took different routes, so the nth point for one route is not necessarily the same as the nth point in another route. However, limiting the classification to using only up until the nth point simulates real-time classification, where complete traversal information is not available. For computing the Matthews correlation coefficient, all participants were classified until they reached the goal and stopped traversing. As with Figure 4, numbers of participants classified at each iteration are the same as the bars shown in Figure 2.

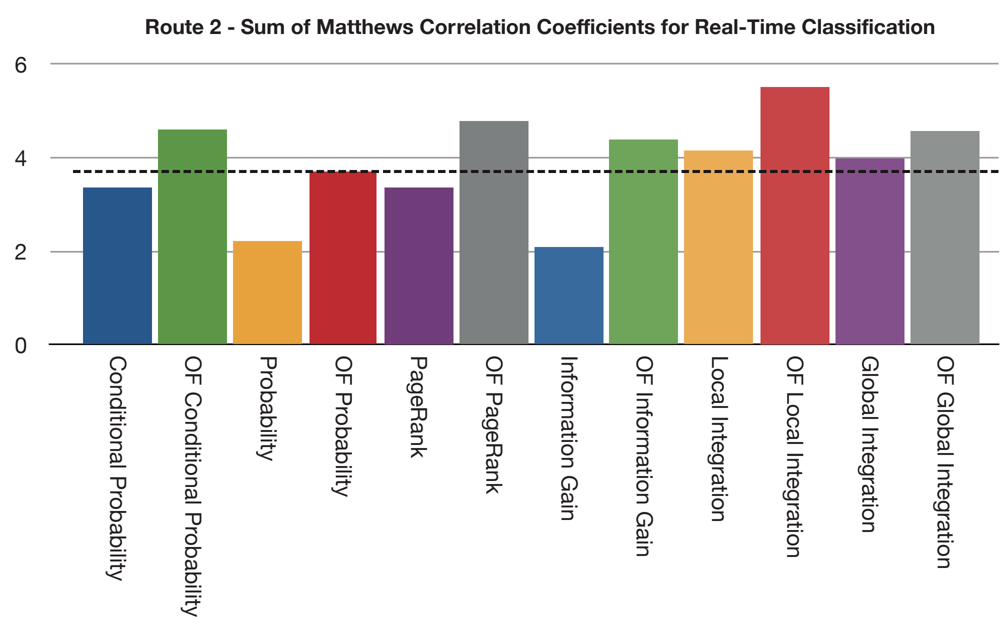
5.4 Photograph recognition experiment results

In addition to examining the importance of decision points from the computational perspective of analyzing the topological graph structure of the environments, we also conducted a photograph recognition experiment to analyze participants' memory for decision points and the relation to computationally determined decision-point salience. The rationale is that higher-salience decision points should be remembered better.

We calculated the accuracy of photograph recognition and the average memory-strength score for each decision point for which a photograph was shown to the participants. Correlations between the correct recognition rate and the memory strength and

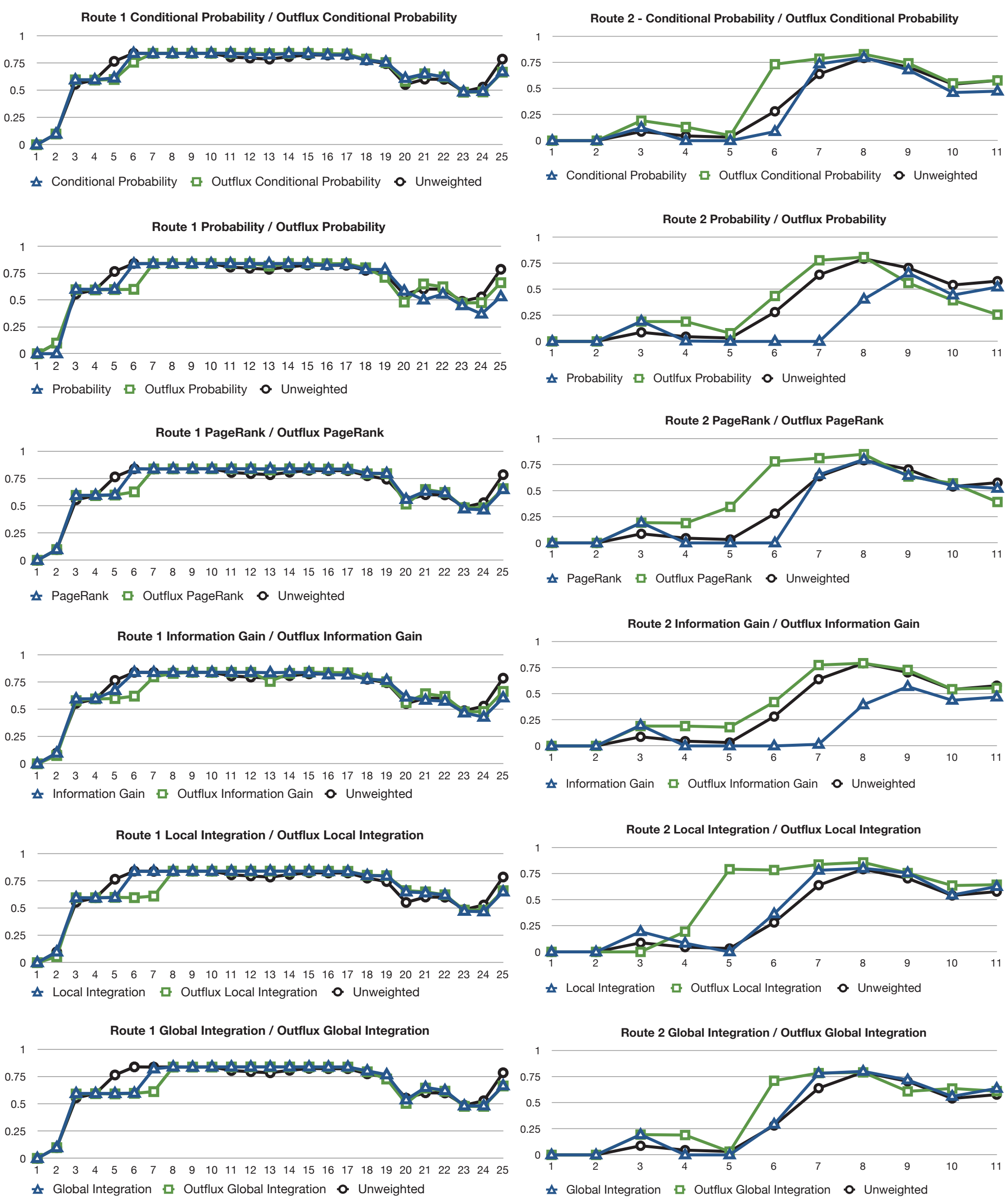


(a)



(b)

Figure 4: Cumulative real-time Matthews correlation coefficient scores for (a) route 1 and (b) route 2. The dashed line indicates results of the unweighted classifications. OF stands for "outflux" in the above labels.



(a) (b)

Figure 5: Iterative Matthews correlation coefficient results for real-time classification of wayfinders for each algorithm (shown in blue, with its outflux shown in green) for (a) route 1 and (b) route 2, compared to the unweighted baselines (shown in black). Each point on the x-axis represents the nth decision point traveled from the start to goal.

	Condtional Probability	OF Condtional Probability	Probability	OF Probability	PageRank	OF PageRank	Information Gain	OF Information Gain	Local Integration	OF Local Integration	Global Integration	OF Global Integration
Correct Rate R1	0.33	0.14	-0.09	0.5	0.31	0.52	0.35	0.19	0.43	0.15	-0.26	-0.4
Memory Strength R1	0.01	-0.08	-0.1	0.51	0.47	0.39	-0.03	0.23	0.4	-0.06	-0.07	-0.47
Correct Rate R2	0.65	-0.47	-0.63	0.11	0.28	-0.31	0.33	-0.11	0.02	-0.62	0.49	-0.47
Memory Strength R2	-0.11	0.15	0.1	-0.69	-0.73	-0.3	0.08	0.3	-0.06	0.21	-0.07	0.02

Figure 6: Results from the photograph recognition experiment. Colored squares are significant, $p < .05$, with red indicating positive correlations and gray being negative correlations (also shown as positive and negative numbers).

decision-point salience scores are shown in Figure 6. Even though the photograph recognition experiment was conducted six months after route traversal, the average correct recognition rate for route 1 was 60% and 78% for route 2, indicating that participants did indeed remember some features of their previous traversal.

Overall, there were few significant correlations between the photograph recognition rate and the salience scores. As discussed later (Section 6.2), this implies that using only structural information for calculating decision-point salience may not be a good correlate for recognition memory.

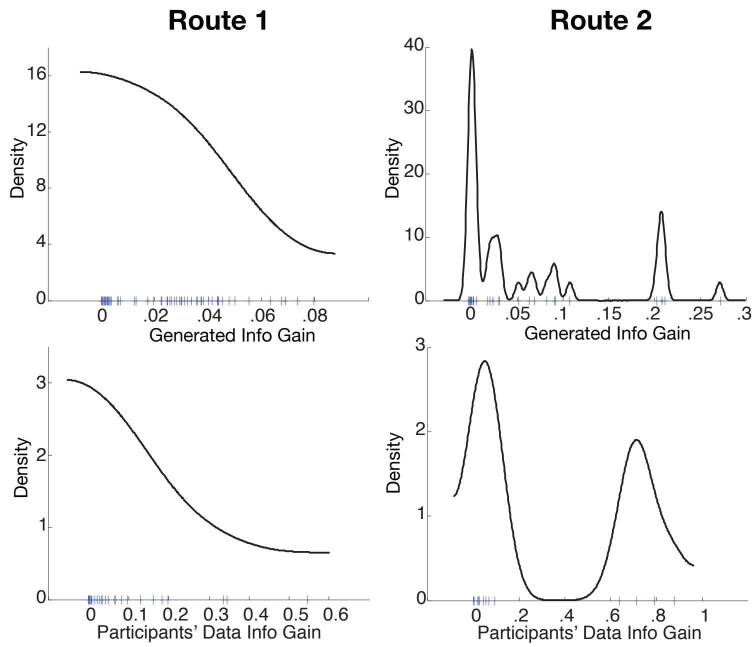
5.5 Correlations to wayfinding performance and ability tests

To analyze the salience scores computed by each algorithm from another perspective, we correlated the scores with wayfinding performance metrics. This was accomplished by summing up the scores for all decision points in each route for each wayfinder. The Pearson correlation between the sum of the scores and the performance and ability metrics (wayfinding performance [good or poor], SBSOD scores, mental-rotation scores, traversal time, and traversal length) were then calculated. The results are shown in Figure 7.

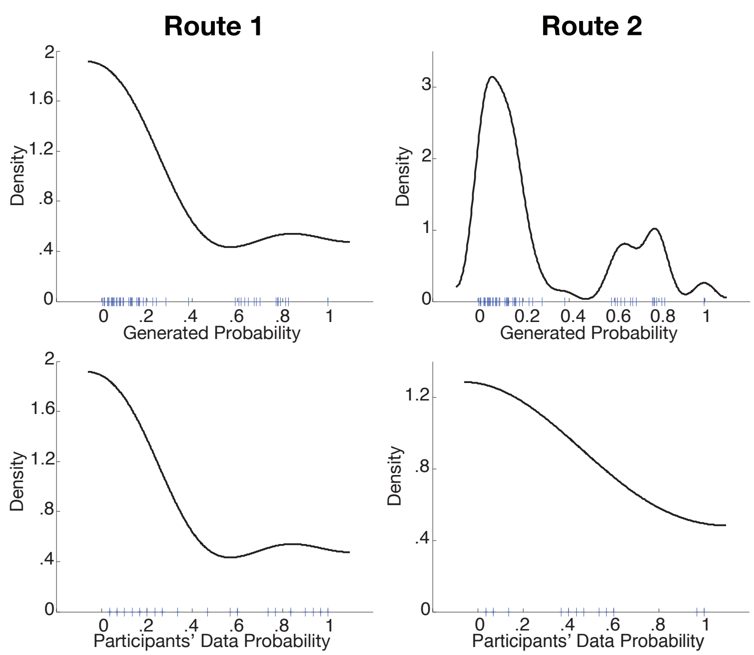
As with previous work [44], there were few significant correlations with the SBSOD scores and the mental-rotation scores, suggesting that the spatial abilities covered by these written tests are not related to wayfinding performance or structural aspects of routes. However, most of the algorithms showed positive correlations with the performance and negative correlations with time and length, showing that route traversals that included higher-salience scores, for many of the algorithms, were associated with better wayfinding performance. This provides good evidence for the efficacy of using the calculated scores for improving classification of wayfinders.

	Route 1					Route 2				
	Wayfinding Performance	SBSOD	Mental Rotation	Traversal Time	Traversal Length	Wayfinding Performance	SBSOD	Mental Rotation	Traversal Time	Traversal Length
Conditional Probability	0.87	0.21	0.09	-0.58	-0.36	0.92	0.23	-0.28	-0.27	-0.4
OF Conditional Probability	-0.3	-0.08	-0.4	0.19	-0.14	-0.61	-0.13	0.34	-0.29	-0.06
Probability	0.86	0.19	0.13	-0.72	-0.68	0.97	0.26	-0.26	-0.4	-0.5
OF Probability	-0.27	0.01	-0.19	0.09	-0.33	0.91	0.17	-0.13	-0.46	-0.42
PageRank	0.57	0.04	-0.06	-0.58	-0.79	0.09	0.04	0.12	-0.68	-0.55
OF PageRank	0.36	0.06	-0.1	-0.4	-0.72	0.97	0.28	-0.18	-0.55	-0.57
Information Gain	0.79	0.24	0.12	-0.65	-0.65	-0.18	-0.02	0.14	-0.19	-0.1
OF Information Gain	0.59	0.04	-0.06	-0.53	-0.72	0.82	0.21	-0.12	-0.53	-0.61
Local Integration	0.56	0.06	-0.03	-0.56	-0.8	0.9	0.24	-0.11	-0.7	-0.71
OF Local Integration	0.39	0.11	0.13	-0.55	-0.79	0.98	0.25	-0.21	-0.43	-0.53
Global Integration	0.07	0.05	0.14	-0.22	-0.56	-0.77	-0.19	0.3	-0.13	0.02
OF Global Integration	-0.04	-0.13	0.05	-0.18	-0.54	0.21	-0.12	0.08	-0.48	-0.51

Figure 7: Correlations to wayfinding performance. Colored squares are significant, $p < .05$. Red indicates positive correlations and gray shows negative correlations (also shown as positive and negative numbers).



(a)



(b)

Figure 8: (a) Kernel density estimation plots for information gains for route 1 (left panels) and route 2 (right panels). (b) Kernel density estimation plots for decision point traversal probabilities for routes 1 and 2.

5.6 Quantifying differences between the two routes

For some of the algorithms used to calculate decision-point salience, performance improved dramatically from routes 1 to 2 (see Figures 3, 4, and 5). To analyze structural reasons for these differences, we used a kernel density estimation function [7] (Figure 8a). For both the generated and empirical data, the distributions of information gains across the decision points in each environment differed both in magnitude and in relative distributions. Decision points on route 1 had a fairly even distribution of information gains that gradually tapered off to only a few decision points with high gains. Route 2 included many points with very low information gains and only a few decision points that had very high information gains, relative to the magnitude of the gains in route 1.

To analyze where wayfinders went in the environment, we graphed the probability density distributions for the probabilities of decision points being traversed for routes 1 and 2 (Figure 8b). Despite changes in the distributions of information gains between routes 1 and 2 and the similarities between generated and empirical data (see Figure 8a), the distributions of probabilities that decision points were traversed did not show any large differences between the routes for the generated data, but rather for the empirical data only.

Next, we analyzed structural differences between the graph topology for routes 1 and 2 by calculating the percent difference in average local and global integrations, as shown in Table 1. Since the average local and global integration values for both routes are almost the same, it can be inferred that the graphical structure of the environments were very similar.

	Route 1	Route 2	Difference
Avg. Local Integration	20.8	21.7	4.9%
Avg. Global Integration	30510	31040	1.7%

Table 1: Differences in local and global integration values.

6 Discussion

Our results show that it is not only possible to classify wayfinders exclusively using information about decision points in an environment, but that the relative importance of decision points to this classification can also be elucidated. The calculated salience of decision points with respect to discriminatory efficacy of classifying wayfinders confirms that not all decision points in an environment have equal computational salience and that the relative salience of these points can be effectively determined. The implications of this are that key decision points can be automatically calculated and used to provide assistance at important points in an environment. This may be used to improve wayfinding performance for users of real-time navigational aids.

6.1 Incorporating computational salience for real-time classification

Incorporating salience information greatly increased the efficacy of real-time wayfinding classification for the second route. This is related in part to the cumulative nature of the real-time classification—the classification at the current point in space is based on a summation of the scores of all the points from the starting to the current point. For the second route, the first four points were traversed by 29 of the 30 participants, restricting their usefulness for discriminating wayfinding performance classes. Since the unweighted baseline classified wayfinders by simply summing the scores of points in a wayfinder's traversal, the baseline did not start to improve until the sixth point in route 2 had been traversed. The classifications weighted by the salience scores, by contrast, began improving as soon as decision points were able to discriminate between classes of wayfinders. Many of the outflux algorithms, such as outflux PageRank, were able to achieve good Matthews correlation coefficient values even at the fifth decision point, due to the salience-based weighting of decision points. This type of effect was not observed for the first route, because wayfinders from the good and poor performance classes could be reliably differentiated as soon as the third decision point in their traversals.

As shown in Figures 4 and 5, incorporating salience information into the real-time classification caused some algorithms to do worse. On the first route, incorporating salience information caused many classifications to be worse overall than the unweighted baseline. On the second route, conditional probability score, probability, outflux probability, PageRank, and information gain performed worse than when not using the salience information, while the other algorithms, in many cases, greatly improved classification performance. One reason for this worse performance is that the salient points in an environment are often traversed by both good and poor wayfinders, thus reducing the ability of those points to discriminate between performance classes. These points are often important intersections that are frequently used across a diversity of route traversals. This can help explain the efficacy of the outflux algorithms in cases where the standard algorithms did not perform well, because the outflux algorithms were designed to assign high scores to the points leading to key decision points in an environment.

6.2 Structural and non-structural effects on wayfinding activities

Knowledge about connections between decision points and their frequency in the generated routes enabled us to classify the performance of wayfinders reliably, using relatively few decision points. Using only the decision points with the highest salience scores as calculated by outflux probability, outflux local integration, global integration, and outflux global integration, we obtained MCC values of greater than 0.8 for classifying the overall traversals of wayfinders for both routes 1 and 2 (see Figure 3). Similarly, for real-time wayfinder classification, reliable classification performance was achieved using only information about the first seven, and for some algorithms even fewer, decision points for routes 1 and 2. This importantly shows that good classification results can be obtained using only information about environmental structure, without including complex cognitive models or spatial ontologies about objects in the environment. The limits imposed on movement by the structure of space alone seem to have a large effect on wayfinding tasks. However, the average values for local and global integrations were not very different between the two routes (see Table 1). Therefore, differences in algorithm performance cannot be attributed only to differences in the connectivity of space. Thus, non-structural effects may also have played a large role in the traversal choice of decision points by wayfinders in our empirical study.

Information gain as a metric performed much better on route 2 than on route 1 for overall route classification. This difference may have been caused by some decision points containing much more information in route 2 than in route 1. However, differences in information gain distribution alone may not be enough for explaining classification performance differences between routes 1 and 2. From Figure 7, the correlations between information gain and the wayfinding performance metrics weakened and became statistically nonsignificant for route 2, compared with route 1, although both overall and real-time classification performance increased and the distributions of decision-point information gains were different in that route 2 included points with larger information gains.

Difference between the distributions of probabilities that decision points were traversed by our participants (Figure 8b) for routes 1 and 2 may have been influenced by factors such as landmarks and scenery, which were very different between the two routes. Route 2 had a meandering river surrounded by trees and several bridges and a rail line crossed the area, which make good landmarks. In fact, several participants remarked that the area of the second route was "beautiful" during the empirical study. In contrast, the area for route 1 had a very homogeneous structure of buildings, with very few notable landmarks. Differences in the cognitive salience of landmarks and individual preferences for natural scenery may have played a large role in the efficacy with which some algorithms were able to weight important points to classify wayfinders.

The results of the photograph recognition experiment (Figure 6) showed that the information gain did not significantly correlate with the photograph recognition results and the correlations did not significantly differ between routes 1 and 2, although information gain performed much better for overall classification of wayfinders for route 2 than for route 1. Thus, the relationship between cognitive salience of landmarks, route choice, and computational salience of decision points to wayfinding tasks merits further investigation. The photograph recognition experiment covered only a small amount of the graph, so future work will have to explore the relationship between recognition memory, route choice, and salience of decision points to wayfinding tasks.

6.3 Implications for navigational aids

Algorithms that exhibited good classification results should work well for many practical applications. For determining computational salience, outflux local integration is recommended based on the efficacy exhibited for overall and real-time classifications.

Calculating the computational salience of decision points can help navigational aids to detect where users are likely to make mistakes, because these points are good at discriminating between performance classes of wayfinders, allowing greater assistance to be offered. Computationally salient points could thus be useful for improving a user's configurational knowledge of routes traveled, because these points or the points leading up to decision points with high computational-salience may be where wayfinders need to make important decisions. For example, a pop-up display could show first-person perspective photographs for important points, which may help with recognition (and later, recall) of the important points, and possibly increase understanding of an environment. Showing photographs at important points could also help with orientation in space for users that need help (cf. [20]).

Outflux probability is recommended for calculating the cognitive salience of decision points, due to the significant correlations with scores in the photograph recognition experiment for route 1, although future work will have to confirm this. Theoretically, outflux probability is a reasonable algorithm for cognitive salience, in that if there is a large change in probability between the current decision point and the points connected via outlinks from the current point, then the current point may represent a "chance" in the environment, as you can go from an area that is often visited to an area that is seldom visited, or vice versa. This is similar to Ohsawa's "chance discovery" [35] methodology, in that decision points that are not necessarily frequent themselves offer access to frequently visited decision points and thus become important based on network topology. These points may represent key decisions that wayfinders must make when traversing an environment.

Finally, while wayfinding context is certainly important for many applications, the efficacy of our "bag of words" classification approach, using only the information about existence and not the order of decision points, shows that reliable classification of wayfinders can be obtained using very limited existential information about where people traveled. This has important implications for real-world classification of wayfinders where reasoning under incomplete or erroneous information must be performed.

7 Conclusions and future work

Previous work has focused on studying points in space that are cognitively salient to humans, either based on visual, semantic, or structural features, or combinations thereof. In this work we introduced the concept of *computational salience* of decision points to wayfinding tasks and explored how to quantify this value using only the structure of an environment. Computational salience is the efficacy that decision points can discriminate between different classes of wayfinders. This information can be useful for implementing navigational aids because the decision points leading up to points with high computational salience may be key locations where users can decide on different paths to take that will have a large outcome on their wayfinding efficiency. Our method makes this information computationally accessible, thus opening up possibilities for providing real-time support to wayfinders via navigational aids.

Using only information about the graph topology of decision points and connecting roads, we confirmed that not all decision points have an equal computational salience to wayfinding; some decision points have a higher salience for discriminating between wayfinders of varying performances than others. We also confirmed the importance of the structure of environments to wayfinding tasks, because the performance of human wayfinders can be classified with a Matthews correlation coefficient of greater than 0.80, based only on decision points with high computational salience values.

Using computational salience scores to weight decision points to classify wayfinders, we were able to improve real-time classification from previous work [44]. Our classification method uses computationally generated training data to classify human wayfinders, enabling us to calculate the salience of decision points using only information available while humans are traversing an environment. This is a novel contribution that allows our approach to be practically implemented in real-time navigational aids, without requiring a priori training data from humans or semantic or visual information about the environment.

However, despite the importance of environmental structure on human wayfinders, our results also suggest that non-structural or environmental factors unrelated to decision point topology, such as landmarks and aesthetic aspects, may also influence wayfinders. Future work should also consider these non-structural aspects in determining salience of decision points in environments. An approach considering a hierarchy of points and landmarks, similar to [37], and incorporating computational salience into the framework of visual, semantic, and structural features for determining cognitive salience proposed in [34], is a logical continuation for future work. Future studies should also explore functional roles of decision points with different salience values.

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