A Framework for Automatic Selection of Indoor Landmarks using Machine Learning Algorithms and Shapley Additive Explanations

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Abstract. Landmarks are salient objects in an environment compared to their surroundings. However, a challenge of landmark-based navigation is selecting the most salient landmarks to include in route instructions. Current approaches mainly adopt weighted linear models, which assume that landmarks have absolute salience values. However, this contradicts the definition of landmarks as being salient in comparison to their surroundings. In this work-in-progress study, a probability-based soft classification approach is proposed to automatically select indoor landmarks. Specifically, we aggregated fundamental salience measures regarding visual, structural, and semantic dimensions from related studies to create an indoor landmark dataset. Then we, compared the performances of machine learning classifiers with several metrics and interpreted the local contributions of salience measures. Finally, we utilized a probability calibration technique that allows for finer-grained representations of indoor landmarks to include them in the route guidance process. According to the preliminary results of this study, boosting-based machine learning algorithms provide remarkable results, and functional uniqueness, category, and intensity measures are considered more important to select indoor landmarks. Moreover, our soft probability-based classification framework seems promising for selecting and representing landmarks in a fine-grained manner. However, the feasibility of the proposed framework should be further validated with user studies.

Keywords. Indoor navigation, landmark, machine learning, Shapley Additive Explanations

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1. Introduction

Landmarks are defined as prominent objects in an environment that are easily recognizable by their visual, structural, or semantic attributes compared to their surroundings (Sorrows and Hirtle 1999). Hence, including landmarks in the route instructions provides a more natural wayfinding experience, reducing the cognitive load of pedestrians and facilitating wayfinding by helping to organize their spatial mental representations (Hu et al. 2020; Zhou et al. 2022).

A challenge of landmark-based route communication is selecting the most salient objects along a particular route. Specifically, an object should be more salient than its surroundings regarding visual (e.g., color, size, shape), structural (e.g., location, centrality, visibility), or semantic/cognitive (e.g., function, uniqueness, socio-cultural) dimensions (Sorrows and Hirtle 1999) to be considered as a landmark candidate. Current approaches for selecting landmarks mainly emphasize weighted linear models. Typically, studies have adopted a linear model and a set of salience measures that consider visual, structural, and semantic dimensions to compute the salience value of a landmark candidate, following the work of Raubal and Winter (2002). The problem with the weighted linear model-based approaches is it assumes that landmarks have absolute salience (Zhou et al. 2022), which contradicts the definition of landmarks as being salient with respect to their surroundings (Sorrows and Hirtle 1999). Few studies adopted, machine learning (ML)-based approaches to overcome these problems for automatic landmark selection. In these studies, either only one algorithm was utilized to select salient landmark candidates or a classic binary classification pipeline was adopted, which hampers the fine-grained representation of landmarks (Zhou et al. 2022). Furthermore, they merely used global approaches to explain the importance of salience measures, which provides only an overall explanation of the contributions of salience measures. Furthermore, none of the existing studies examined the predictive performance of state-of-the-art ML models such as Random Forest, eXtreme Gradient Boosting (XGBoost), Category Boosting (CatBoost), and Natural Gradient Boosting (NGBoost).

To address the aforementioned research gaps, this study proposes a probability-based soft classification approach to automatically select landmarks from an indoor environment. Firstly, we aggregated fundamental salience measures from related studies. Secondly, we conducted an empirical study to collect ground-truth data for indoor landmark candidates. Then, we examined the salience measures regarding their interrelations and importance for the predictions. Next, we trained some ML classifiers, including some state-of-the-art ones, and evaluated their performances. Moreover, we compared the outputs of algorithms for statistically significant differences via statistical tests. We then used the SHapley Additive exPlanations (SHAP) method to investigate the local contributions of salience measures to explain their impact on the final predictions. Finally, we utilized a probability calibration technique that allows for finer-grained representations of indoor landmarks. Using this technique, we assessed the suitability levels of indoor objects to serve as landmarks in the route guidance process.

2. Methodology

2.1. Overview

This study aims to present a computational approach to automatically select indoor landmarks by using a soft binary classification pipeline. The framework of this "work in progress" study is given in Figure 1.

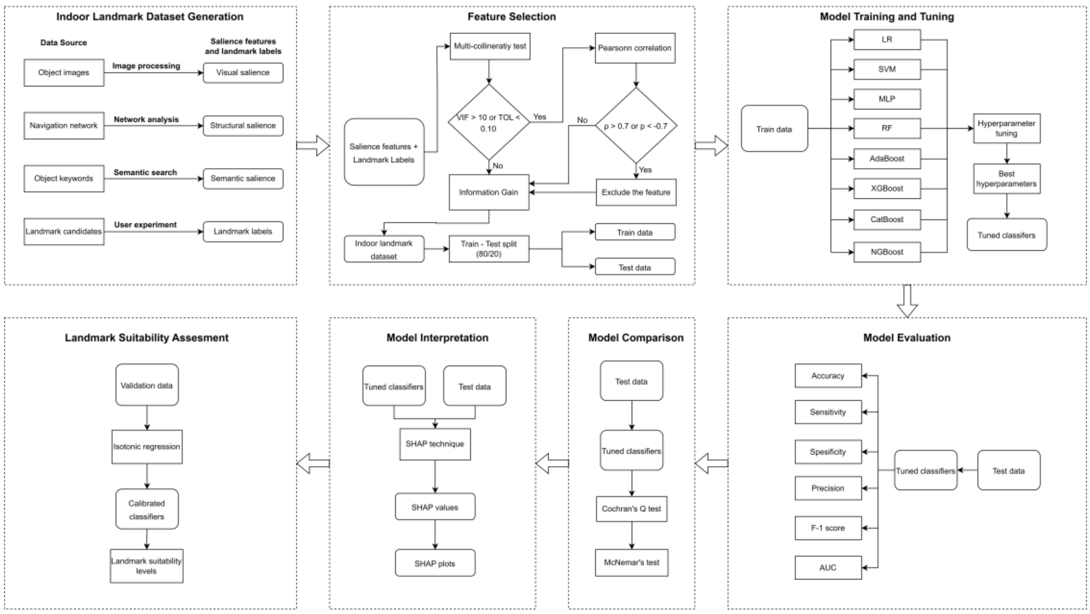

Figure 1. Framework of the study

2.2. Salience Measures

Following the conventional definition of salience dimensions (Sorrows and Hirtle 1999; Raubal and Winter 2002; Hu et al. 2020; Zhou et al. 2022), we derived the salience measures in the visual, structural, and semantic dimensions. The salience measures utilized in this study are given in Table 1.

Salience dimension	Measure	Feature name	Reference
Visual	Color	vis_color	Zhou et al. (2022)
	Intensity	vis_intensity	Zhou et al. (2022)
	Width	vis_width	Dubey et al. (2019)
	Height	vis_height	Dubey et al. (2019)
	Area	vis_area	Hu et al. (2020)
	Shape Ratio	vis_ratio	Hu et al. (2020)
	Unique Label	vis_unique_label	Fellner et al. (2017)
Structural	Visibility	str_visibility	Zhou et al. (2022)
	Permanence	str_permanence	Fellner et al. (2017)
	Distance to decision points	str_decision_point	Dubey et al. (2019)
	Proximity to floor exits	str_floor_exit	Zhou et al. (2022)
Semantic	Functional uniqueness	sem_function	Dubey et al. (2019)
	Category	sem_category	Lyu et al. (2015)
	Text	sem_text	Hu et al. (2020)
	Name prominence	sem_prominence	Hu et al. (2020)

Table 1. Salience measures used for the study (Only permanence measure for the structural category used in this work in progress study)

2.3. Indoor Landmark Dataset

A complex, multi-floor university building has been chosen as the study area to demonstrate our approach We utilized the salience measures to generate independent features for the dataset. For visual salience, the facades of landmark candidates were photographed, and Python libraries was utilized to compute them. The semantic salience measures were computed through various semantic searches. An empirical study was conducted to collect labels of landmark candidates in the study area. A survey was designed that examines the salience of a candidate in the visual, structural, and semantic dimensions. 5 participants (for this work-in-progress study) were gathered who were familiar with the study area to assess the suitability of landmark candidates.

3. Results (Preliminary)

According to the preliminary results of multicollinearity tests, none of the salience measures were found interrelated. The feature importance scores of the information gain method imply that *vis_width*, *vis_area,* and *vis_function* are the most important salience measures. The accuracy metrics of the top three ML classifiers are given in Table 2. Finally, the SHAP values for top-performing algorithms (3 out of 8) show that *sem_category*, *sem_function*, *vis_width*, and *vis_intensity* are the most important measures to select landmarks. The suitability labels provided by the tuned top-performing algorithm (NGBoost) show that approximately 42% of the candidates are “very highly” or “highly” suitable while the rest (58%) are “moderately”, “lowly” or “very lowly” suitable.

ML Algorithms	Accuracy	Precision	Recall	F-1 Score	AUC
XGBoost	91.84	88.89	88.89	88.89	91.22
CatBoost	93.88	89.47	94.44	91.89	94.00
NGBoost	95.92	94.44	94.44	94.44	95.61

Table 2. Accuracy metrics of top ML classifiers used in the study

4. Conclusion

A challenge of landmark-based navigation is selecting the most salient ones. The problem with the current approaches is they assume that landmarks have absolute salience. In this study, a probability-based soft classification approach is proposed by utilizing state-of-art ML algorithms to automatically select indoor landmarks. Specifically, an empirical study was conducted to evaluate the predictive performances of ML algorithms and to interpret the local contributions of salience measures with the SHAP method. The preliminary results of this work-in-progress study show that boosting-based ML algorithms outperform others. Category, function, width, and intensity of a landmark are the most important salience measures, and our proposed soft probability-based approach is promising for automatically selecting and presenting indoor landmarks with finer-grained representations. Thus, a finer-grained representation of landmarks can be achieved by indicating the degree of confidence that a given candidate is a suitable landmark which is the limitation of a classic binary classification pipeline.

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