1 Motivation
Knowing the location of the main entrance is significant in accurate navigation. Current LBS providers, such as Google Map, often guide users to a wrong location that is far away from the main entrance, as shown in Figure 1. This is an unpleasant experience especially for the mobility-impaired people. Realizing the importance of the entrance information, many buildings on OpenStreetMap (OSM) have been tagged with the entrance. However, the proportion is still small. To mitigate this gap, this work proposes using machine learning to infering the location of the main entrance of a building based on its spatial contexts (e.g., main road) and its footprint (e.g., centroid).

2 Method
2.1 Workflow

During training stage, each building is split into points (samples). Then, for each sample, the corresponding features can be extracted by measuring the relationship between the sample and the footprint and surrounding spatial contexts. To mitigate the interference of close negative samples on positive ones (true entrance), the negative ones that have a close physical or feature distance to the positive sample are removed. After collecting the samples of all the buildings, the missing value is filled out by using a strawman imputation strategy. Finally, SmoteBoost [2], Balanced Random Forest [3], and Weighted Random Forest [4] models are fitted. During tagging stage, a building is split into samples in the same way as training stage. Then, the fitted model is used to calculate the probability of assigning each sample as positive and the most likely one is chosen as estimated entrance.

2.2 Features

Figure 2. Workflow of proposed method

3 Experiment
3.1 Tagging accuracy
320 public buildings with the average perimeter at 350 meters are tested based on the five-fold cross-validation. They are collected from seven German cities. For weighted RF approach, the mean error between the true and estimated location in linear distance along the footprint and in shortest path distance are both around 20 m, and in 80% of the cases below 30 m. This can greatly reduce users’ effort to finding the entrance.

3.2 Partial tagging result

Table 1. Extrinsic feature extraction by measuring relationship between samples and spatial contexts

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<th>address</th>
<th>main</th>
<th>pedestrian</th>
<th>street</th>
<th>road</th>
<th>way</th>
<th>railway</th>
<th>parking</th>
<th>landmark</th>
<th>postbox</th>
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</tr>
</tbody>
</table>

Figure 3. Footprint split and strong negative sample selection

Figure 4. Occurrence frequency of spatial context and symmetric building

Figure 5. Importance of top 20 features

Figure 6. Linear distance error of three approaches

Figure 7. Path distance error of three approaches

References