Deep learning for anchor detection in multi-scale maps

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Abstract:

Landmarks, in physical space, are salient elements in the environment that allow people to orientate themselves and to find their way in the landscape. The concept of landmark has been extended to non-physical spaces as well (Sorrows and Hirtle, 1999). In a map, a landmark can be any noticeable object or distinct pattern such as a building, a river, or even a space where there is an absence of features. When grouped, they allow people to make sense of maps (Figure 1). Automatic landmark detection in maps is a well-studied field (Figure 2), where applications range from map generalization to GPS guidance. It combines numerous research fields from machine learning, pattern recognition, statistics and data visualization (Elias, 2003).

Multi-scale anchors are a specific kind of landmark in multi-scale maps that are salient in different maps at consecutive scales (Touya et al., 2020). The presence of multi-scale anchors allows a human to maintain a sense of location when zooming in and out of an interactive map. Our research explores how we can detect potential multi-scale anchors in order to make them more distinct and memorable in maps with different levels of detail, and thus make the zooming process more fluid and intuitive.

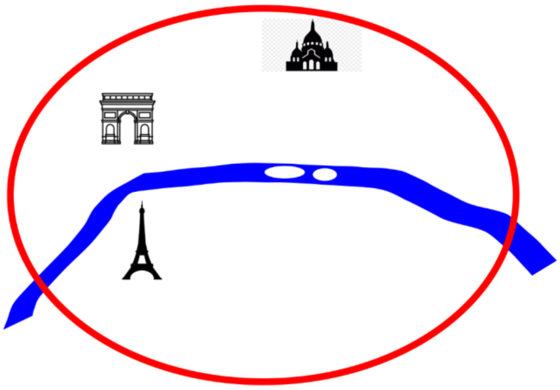

Figure 1. A naive cartography of Paris based on anchors, (Touya et al., 2020).

Figure 2. Detection of buildings as potential landmarks, (Elias, 2003)

Deep learning techniques can help with the detection of multi-scale anchors. To demonstrate this potential we trained, in a first experiment, a U-Net segmentation model to detect cities in maps. As input we gave the model tiles cut from an IGN map. The training set was automatically generated from a vector multi-scale database. We trained two different models at two different scales. Figure 3 shows that the model prediction matched well the mask (the expected answer). Although specific to our data, these results were encouraging.

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In our future experiments we propose to adjust our protocol to better take into account the two mains properties of multi-scale anchors which are i) that they should be considered as ‘noticeable’ from a human map reader perspective, – ii) that they must be considered so at different scales.

First, we want to produce a new manually generated training dataset that captures all types of landmarks perceived by map readers (in addition to cities). This approach will better capture the cognitive aspects of landmarks. In order to create this dataset, we will use a newly developed tool, which allows people to interactively “tint” a map on a web application to mark up what they consider are landmarks (Figure 4).

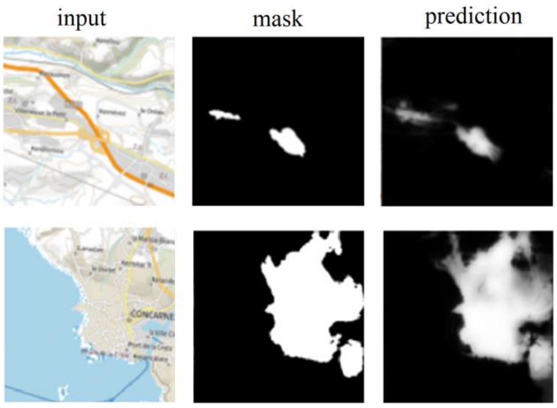

Figure 3. City delimitation with U-Net model, zoom level 13, i=120

Figure 4. Landmarks heatmap produced with data issued from our drawing tool, Paris

Then we want to distinguish multi-scale anchors from simple landmarks by highlighting their multi-scale properties. The first approach will be to create one model for each scale and then try to match their results using data-matching techniques. The aim is to verify if two detected objects at different scales correspond to the same real-life object or not. An alternative approach is to give data from different scales to a single model and allow it to make the correspondence between scales.

While the multi-scale anchors remain a human-specific concept, we hope to be able to detect them within multi-scale maps via these experiments. Will our model get better results with one large training dataset that includes all kind of multi-scale anchors, or will it be more successful if we segment multi-scale anchors type by type? How will text, which can be considered as a potential specific anchor, be processed by our model? Are certain anchors better for zooming in and others for zooming out? Our research will try to answer as many of these questions as possible.

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