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Label Density in Large-Scale Online Maps

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Abstract:

Large scale maps from Google, Microsoft Bing, OpenStreetMap, ESRI and Mapbox among other multi-scale panable (MSP) map providers represent an important source of information for local environments. For most map users, these services represent the only source for maps, large scale or otherwise. Evaluating these services helps to determine the quality of the underlying spatial data and the rendering process (Antoniou & Skopeliti 2015; Hecht et.al 2013; Peterson 2021; Siebritz & Sithole 2014).

Manual and automated procedures are used to compare label density between MSP map services. All approaches generate large scale maps at random locations using the associated Application Programmer Interface (API). Each representation is then evaluated for North America, Europe and Africa. In the first experiment, map pairs at the 19th zoom level for North America, Europe and Africa for Google, Bing and MapBox are visually compared. It was found that Google maps from North America had consistently higher label density than those from Microsoft Bing and Mapbox. Google Maps also held an advantage for Europe. Maps from Microsoft Bing, based on data from HERE and TomTom, were more detailed in Sub-Saharan Africa in comparison to both Google Maps and Mapbox. Relying exclusively on data from OpenStreetMap, MapBox had the lowest label density for all three continents.

In the automated experiment, a python script downloaded random tiles from Google, Bing, OSM, and ESRI. The Amazon Web Services (AWS) tool called Rekognition was used to count the number of characters on each tile. As opposed to Optical Character Recognition (OCR) that requires horizontal text with a consistent background, Rekognition uses artificial intelligence (AI) with image object recognition to recognize text. It can detect characters and words in English, Arabic, Russian, German, French, Italian, Portuguese and Spanish. This service produced a measure of map annotation for each service (see Fig. 1).

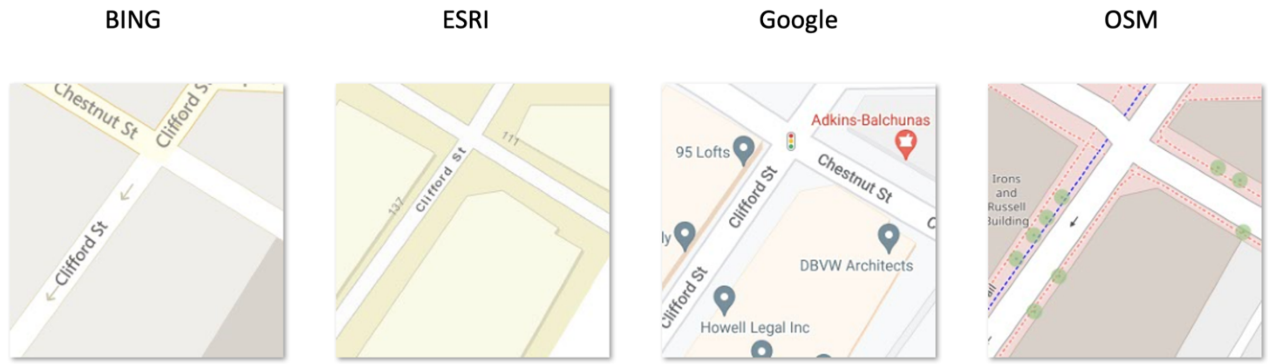

Figure 1. Randomly-selected map tiles of the identical location from Bing, ESRI, Google, and OSM. As can be seen, the tile from Google includes more features and text.

A major problem in evaluating the tiles were certain types of shadings used in OSM and ESRI maps. Shadings, depicting different types of land cover, included shapes that could be interpreted as text. An OSM symbol indicating a mix of deciduous and conifer trees was interpreted as the characters 4 and 9 (see Fig. 2). Methods were employed to identify these shadings and remove these tiles from the character count procedure.

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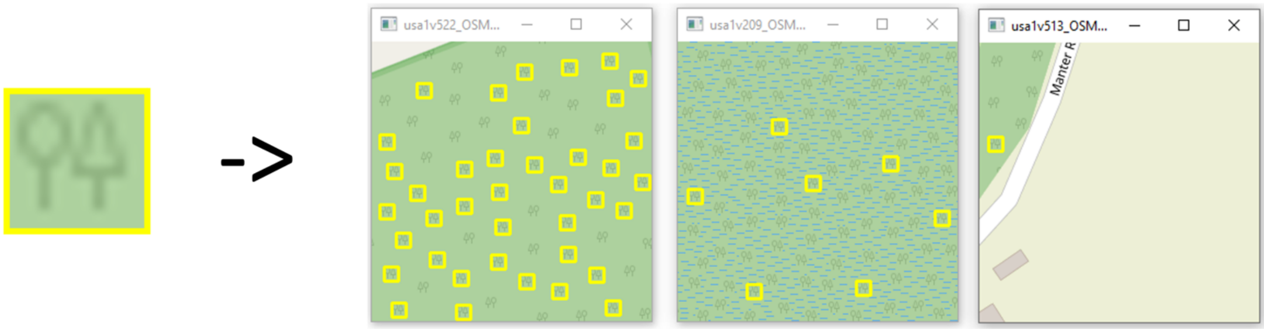

Figure 2. OSM patterns contain objects that resemble characters. In this example, an OSM tree pattern is interpreted as two numbers: 4 and 9.

Inferential statistics on the entire character count dataset from 722 random locations showed that each mean was significantly different relative to Google Maps. A pairwise t-test showed that all means were significantly different from each other at the .05 level of confidence. A Tukey Honest Significant Differences test showed that all means were different at the .05 level of confidence except one comparison between OSM and BING maps.

Overall, it was found that Google had the greatest character count in the US and Europe but trailed Bing maps in Africa. It was also observed that the method of randomly selecting tiles oriented the analysis to more rural or undeveloped areas. This favored the more commercial map providers compared to those relying on crowdsourced data.

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