Intersection Detection Using Vehicle Trajectories Data: Deep Neural Network Application

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Abstract

In 2021, intersection-adjacent crashes were stated to cause 7.7% of total annual road deaths in Australia [1]. Generating intersection maps is essential for future Cooperative Intelligent Transport Systems (C-ITS) deployment. Nonetheless, crowdsourced vehicle trajectories are a viable and affordable data source that can be used to generate maps. However, intersection maps are changeable, and building one map inference model for all intersection types is challenging. Therefore, we need an object detector that can detect and classify the different intersections using the 2-D scatter plot of the crowdsourced trajectories.

Consequently, each subset of trajectories data points passed to the suitable intersection map inference model. This study used two real-world vehicle trajectory datasets, T-Drive and ECML-PKDD 15, to classify the intersections by building an object detection model using Deep Neural Network (DNN). We created 2000 images to train a Single-Shot detector the initial testing results were promising.

Background

Object detection models have two tasks to perform, localization which the model tries to accurately locate the object, and classification which the model tries to classify the object. we use object detection to classify the intersections and know their locations on the map by that you can use an intersection inference map model to build an intersection map.

Method

First, we need to convert the longitude and latitude data from the chosen datasets into images, so we would be able to use them as training data for the CNN. We extracted random areas from the map within the area of interest. We then use software to create the bound box and label it for each intersection. The extracted dataset consists of less than 2000 images with 20% of it used for training. We have three classes; T-intersection, Cross-intersection, and Round-intersection. we decided to give attention to location error and reduce that error to the lowest degree we started by using Single-Shot Detection (SSD) models that could give us low location loss. Examples of training photos and testing photos are in **Error! Reference source not found.**.

The vehicle trajectories datasets

The T-drive dataset [2, 3] has a total distance of the trajectories that reaches nine million kilometers, an average sampling interval of about 177 seconds, and a distance of about 623 meters. ECML-PKDD 15 [4] dataset contains the trajectories of taxis of about 1.7 million instances and each data sampled corresponds to one complete trip. The properties of the datasets are in **Table 1**.

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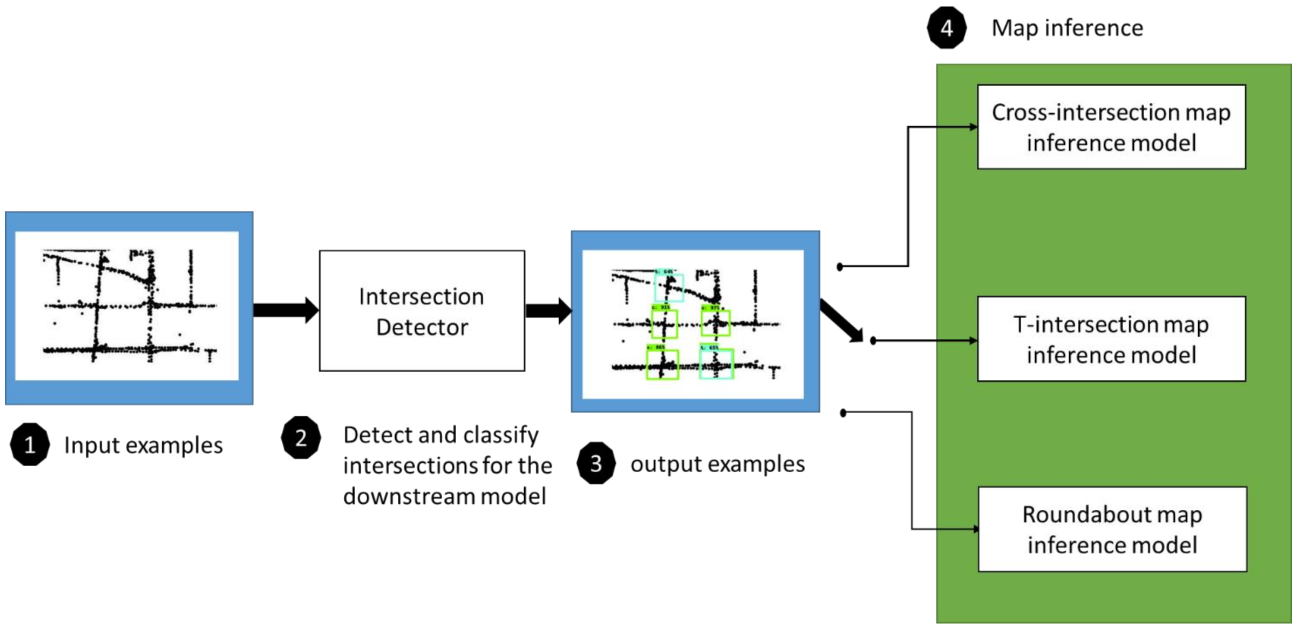

Figure 1. Illustration of the need for object detectors for intersection map inference

Table 1. Properties of the two datasets used in this study

Dataset	Location	Period	Users	Events	Reference
T-Drive	Beijing, China	1 week	10,357	15 million	[2, 3]
ECML-PKDD 15	Porto, Portugal	1 year	442	83 million	[4]

Results

The object detection model was tested on two data sets T-drive and ECML-PKDD 15. the cross intersection was more common than the other intersections in the datasets, so the numbers of intersections are slightly skewed. the confidence score ranges for the intersections were: [42-94], [51-98], and [66-94] for the T-intersection, cross-intersection, and round intersection respectively. the mean average precisions (mAP) for each class were: 15.86, 18.96, and 8.19 % for the T-intersection, cross-intersection, and round intersection respectively. The mAP results are relatively low but for a dataset of fewer than 2000 images and only tested on one type of model it's a good start.

Conclusion

The initial mAP results were: 15.86, 18.96, and 8.19 % for the T-intersection, cross-intersection, and round intersection respectively. Which is relatively low but the dataset consists of less than 2000 photos, so this is a good starting point. We believe that trying different types of models like Faster-CNN or any of the R-CNN family and expanding the dataset will result in us achieving better results.

References

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