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Understanding Safety Based on Urban Perception

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1 Introduction

Currently, there is an increasing number of methods to infer is a street is dangerous or not. In some cases, the goal is to create an application to predict criminal activities [1] or show crime maps [2]. These methods are based on crime datasets or statistical data.

Some works predict the relationship between human perception of safety and the visual appearance of the streets [3, 4]. Then, the following works make use of this human perception datasets to propose models inferring a safety score based on street photos. Some works use deep neural networks [5], linear classifiers [6, 7] or visual components [8].

In this line, we propose a method to understand machine learning models trained to predict a safety score based on street photos. For example, if an image is classified as safe, we want to know what visual features make the model predict this score.

2 Methodology

In this work, we train a neural network model to extract features from Google Street View images. These images have a safety-level score based on human perception available in the MIT Place Pulse Database Version 1.0. To make the model output explainable, we used a model-agnostic technique called LIME [9].

2.1 Image Classification

To train our model we use the MIT Place Pulse database which consists of a set of images from different cities (New York and Boston) and scores calculated using human answer comparing 2 different images and answering for "Which Image Looks Safer?"

We used a fine-tuned strategy to train our classification model (safe vs. not safe). We adapted the VGG16 [11] architecture which was trained on the ImageNet dataset, which contains millions of images across 1,000 classes. Then we fine-tune this network via back-propagation.

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2.2 Model Explanation

Model interpretation method helps us to get insights and understand our learning process. In our context, we can use them to visualize which visual features might be selected or are important to infer the model output. For instance, we want to understand why our street photos are predicted as "safe" or "not safe".

In this work, we use LIME, a local interpretable model-agnostic technique. LIME explains a black-box model by simulating local candidates close to the original prediction. Using these predictions, LIME generates a random distribution set of possible predictions based on L2 distance called "local fidelity" taken as reference the original prediction. Once, LIME defines the set of possible and better predictions than the original, proceeds to pick the best features for the explanation using its Submodular Pick Algorithm (SP-LME).

As we can see in Figure 1, this technique visualizes why our model is predicting some class (green and red pixels). This is very helpful to verify what parts of our input are being selected as "important". In this way, we can see if our model learns to associate scores with image features or not.

3 Experiments and Discussions

Our training data is made of 4,132 images grouped by city. We train two models, one for New York and one for Boston. Then, we split the data into 60%, 20% and 20% for training, testing, and validation respectively. Our hyper-parameters are the batch size=64, epochs=100, learning rate=0.0001, and stochastic gradient descent as optimizer. We obtain a 76% of testing accuracy in Boston and 69% in New York City.

To exemplify the model explainer, we selected 2 images and show the predictions and explanation with LIME. The first image has an actual safe score of 8.35 ("safe"), the second one has an actual safe score of 1.06 ("not safe"). As we can see in Figure 1, our test images were classified correctly. LIME produces two kinds of regions, the green areas called "pros" are the positive features that help our model to predict the correct class. The red areas called "cons" determine which features do not help in the prediction (See Fig.1). In Figure 1a, we have a photo from Boston with an actual score of 8.35 (very safe place). Our classifier predict this image as safe. LIME's result is shown in Figure 1c, in this example, "pros" areas correspond to trees, and "cons" correspond to asphalt. We could run more experiment and see verify is green areas are more prevalent in "safe" images. We can corroborate this hypothesis in the second example (Figure 1b-d).

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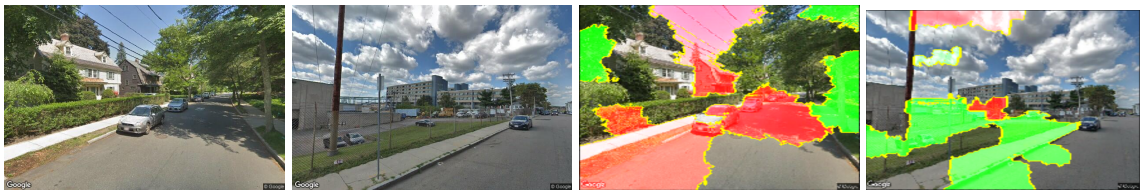

(a) Actual score: 8.35 (b) Actual score 1.06 (c) Predicted: safe (d) Prediction: not safe

Figure 1: Images from Boston (a,b) with different scores and results of LIME explainer over the Images (c, d).

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