Color Classification and Recycling Bin Detection

Huafeng mai
University of Sandiego
La Jolla, CA 92122
Email: humai@ucsd.edu

***Abstract*—In the field of robotics, it is very important to enable the robot to accurately identify the target. Therefore, it is necessary to establish a model with strong generalization ability, mean model has high accuracy on unseen pictures. This report proposes a color recognition classifier model based on logistic regression, and uses this model to identify blue trash cans.**

I. Introduction

It is important for robots to accurately identify specific objects, such as rescue robots, food delivery robots etc. These tasks often do not need the model have high multi-target detection ability, but need to have a high recognition rate on finite objects. Because training to recognize multiple objects is often time-consuming and requires strong hardware support, and in some tasks, it does not require strong multi-object recognition capabilities. In this report, I propose a lightweight high accuracy logistic regression based classifier, the technique can be extended to situations involving outcome variables with 3 or more categories [1]. make the model to recognize objects with a certain color. For this report, is detect blue trash cans. The one challenge of solving this problem is how to correctly segment the ROI image. Need to extract features that enable the model to learn effective, Object detection is an important computer vision problem, where the goal is to report both the location in terms of a bounding box, and the category of objects in an image [2]. So the second challenge is use what method to further segment the correct target. For the first part, This project is based on the traditional combination of softmax with logistic regression model to realize multi color classification, and the second part uses the sigmoid combined with logistic regression to implement a binary classification model to realize the identification of blue trash cans.

II. Problem Formulation

Given a Obseration x predict which one of the multiple prediction categories y should be assign. $y = \{y1, y2, y3...yn\}$, So For all n possible classification outcomes, we run $n - 1$ independent binary logistic regression models, So for any one of the logistic model, corresponds to one of the features yi. Assume x is positive sample, each sample is a vector, W is the coefficients of the model.

$$f(z) = \frac{1}{1+e^{-z}}, z = W^T x \tag{1}$$

Need to Find W, which can maximize the f(z), similarity if x is negative sample, Find W, which can minimize the f(z) function.

III. Technical Approach

For color classification, suppose we have n samples, and each sample has m features, which forms an n*m matrix X, then, dot product a coefficient matrix C get matrix Z, each row on the Z matrix corresponds to each sample, and each column corresponds to the probability of each sample under the feature, such as Zij (represents the i-th sample under the jth feature probability output , and finally normalizes each row to a probability by softmax function S, and only retains the largest output result, and discards the rest and obtain an n*1 y matrix Y

$$\begin{gathered} X_{n\times m} \times C_{n\times m} = Z_{n\times m} \\ S_{ij} = \frac{zij}{\sum_{k=0}^{m} zik} \\ Y_i = max(S_{i1}, S_{i2}, S_{i3}....S_{in}) \end{gathered} \tag{2}$$

At the same time, we transpose y and perform one hot encoding, which is convenient for our model to process discrete data. Each row represent the feature and each column represent the one hot encoder column. Combining the probability output of positive and negative samples get the following probability product form.

$$p(y|w,x) = (\frac{1}{1+e^{-w^T x}})^y \times (1-(\frac{1}{1+e^{w^T x}}))^{1-y} \tag{3}$$

Taking the logarithm of it and accumulating the results yields the following loss function.

$$J_{log}(w) = \frac{1}{m}\sum_{i=1}^{n}(-(1-y_i)log(1-p(x_i;w)) - y_i log(p(x_{i;W}))) \tag{4}$$

Which yi is the value that model predict y=1,0, p(xi;w) stand for the probability that a xi is positive sample. Compared with the multi-class problem using softmax for output. for part2, the sigmoid function (1) is used as the output of positive and negative binary samples. Therefore, on the basis of the first part, the normalization with softmax is omitted and the sigmoid is used for binary classification(1).

Here W is the parameter updated in the process of gradient descent. We map the data input to (0,1) as the probability output.

A. Parameter update

The goal is to find an optimal parameter that minimizes the loss function.

$$\underset{w}{min} J_{log}(w) \tag{5}$$

m features have m parameters for the w vector. Minimize our cost function, need to run the gradient descent on each parameter wj

$$w_j \leftarrow w_j - \alpha \frac{\partial}{\partial w_j} J_{log}(w) \tag{6}$$

B. Part1 formula Derive

$$p(y_i|x_i, W_i) = \prod_{i=1}^{n}) \frac{exp(-x_i w_{k=y_i})}{\sum_{k=0}^{c} exp(-x_i w_{k=y_i})}$$

$$= \frac{1}{N}\left(X^T(Y-P)\right) + 2\mu W$$

$$= \frac{1}{N}\sum_{i=1}^{N}\left(X_i^T I_{[Y_i=k]} - X_i^T \frac{\exp(-X_i W_k)}{\sum_{k=0}^{C}\exp(-X_i W_k)}\right) + 2\mu W$$

$$= \frac{1}{N}\left(X^T(Y-P)\right) + 2\mu W$$

C. Part2 formula Derive

The goal is to find an optimal parameter that minimizes the loss function.

$$\mathrm{J}(\theta) = -\frac{1}{m}\sum_{s=1}^{m}\left[v_l \log h_e(x_t) + (1-v_l)\log(1-h_e(x_t))\right]$$

$$= -\frac{1}{m}\sum_{i=1}^{m}\left[y_i \frac{1}{g(\theta^\tau x_i)} - (1-y_i)\frac{1}{1-g(\theta^\top x_l)}\right]\frac{\partial}{\partial\theta_j} g(\theta^\tau x_i)$$

$$= -\frac{1}{m}\sum_{i=2}^{m}\left[y_i\left(1-g\left(\theta^T x_i\right)\right) - (1-y_i) g\left(\theta^T x_i\right)\right] x_l$$

D. Improvement method

When selecting the ROI area of the image, I used hard sample, which means that I will add negative sample is blue color, but not from blue trash, such as extract blue area from sky, blue flags etc. After using this method, the performance of the validation set of the model is better than before. For each image in the verification set, first corrode and expand each segmented image, and then use CV2.findcontour function obtains the outer contour of each segmentation blob, and then obtains the bounding box of each segmentation blob. Filter out the bounding box with small area, and filter out the box does not conform to the shape of the trash can, the final blue bin boxes are obtained

IV. EVALUATION

A. Color classification

Color classification model parameter is

$$-1.99021036, 0.9888991, 1.00131126$$

$$0.95215365, -1.90982654, 0.9576729$$

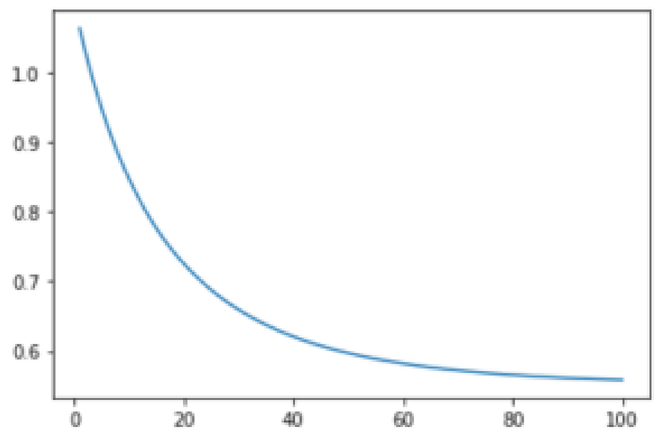
$$0.92080558, 0.94986447, -1.87067005$$

The training and testing accuracy of the color classification model is

$$Trainscore: 0.9423111163867292$$

$$Valscore: 0.9434981304528459$$

Iteration 100 times, step size is 0.1,The accuracy of the validation set is 95.1807



The graph of cost value during the iterations between 0 to 100

	Red	Green	Blue
Red	82	0	0
Green	1	67	0
Blue	4	0	49

The confusion matrix

	precision	recall	f1-score	support
red	0.94	1.00	0.97	82
green	1.00	0.99	0.99	68
blue	1.00	0.95	0.98	83
accuracy			0.98	233
macro avg	0.98	0.98	0.98	233
weighted avg	0.98	0.98	0.98	233

Four data indicators

Demonstrates high accuracy in blue and greenA small part of blue is regarded as red by the model, show it have lowest recall at blue color, The effect of the classifier combined with other colors will be improved, such as the classifier that recognizes red.

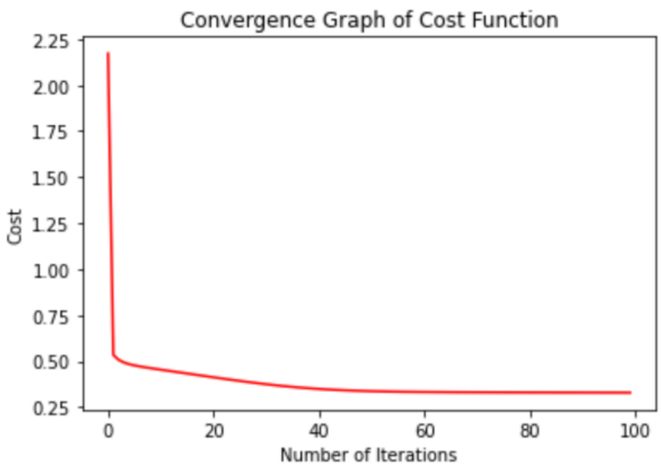
B. Blue bin detection

Bin trash detection model parameter is

$$0.02903287, -0.0415715, -0.06720769, 0.06795101$$

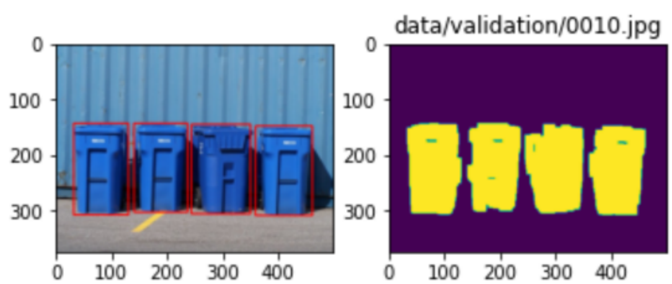
$$Trainscore : 0.9280092674472074$$

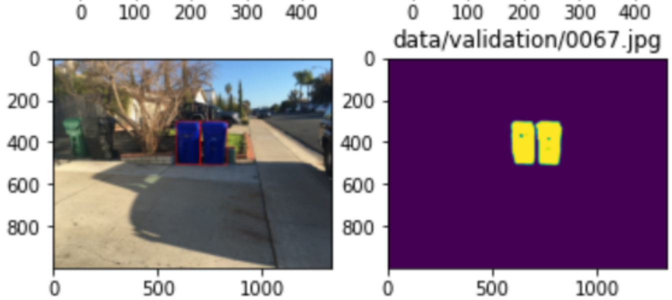
$$Valscore : 0.9257004910659019$$

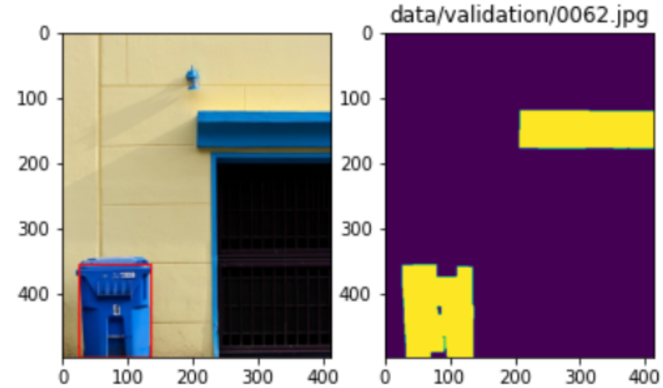


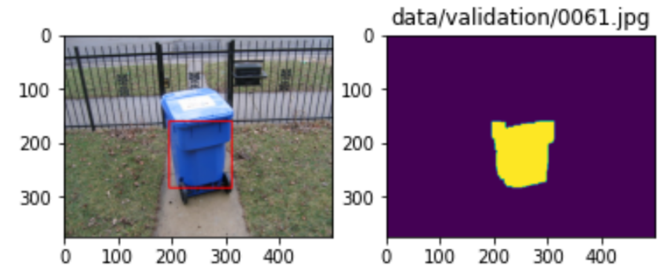
The graph of cost value during the iterations between 0 to 100 iterations = 100 learning rate = 0.001 The loss function drops nicely to a small value, Combining the results of the validation set and training set, there is no overfitting and underfitting phenomenon.

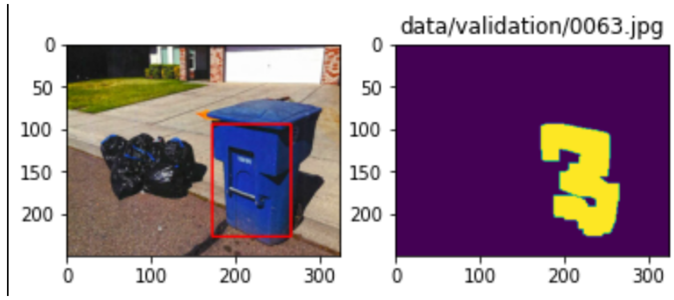
C. Some validation set renderings

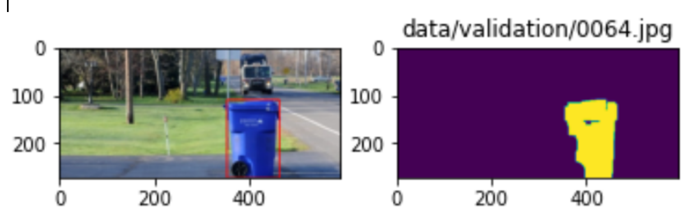


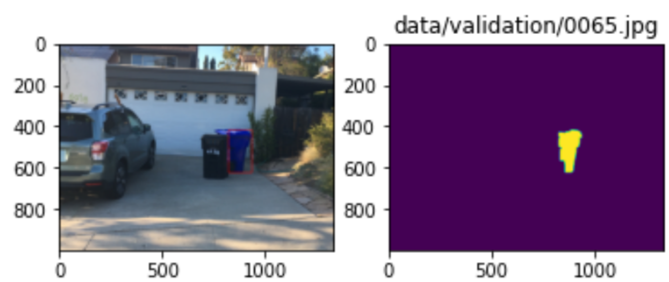


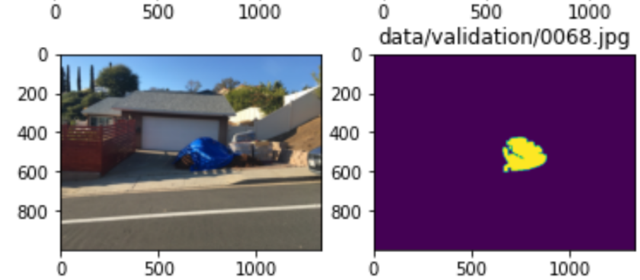


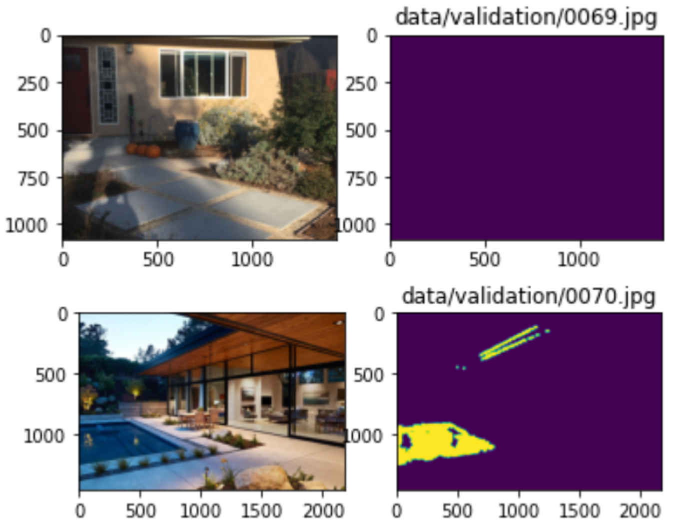












It can be seen that the use of corrosion and expansion operations can well select pictures containing multiple trash cans and can distinguish the blue parts actually belonging to trash cans instead of blue sky which befit from using hard sample.

D. weakness of logistic model

Logistic regression cannot be used to solve nonlinear problems, because Logistic is more like a linear classifier, so the classification effect is not so good, and it is difficult to fit the real distribution of the data.many logistic regression analyses assume that the effect of one predictor is not influenced by the value of another predictor. When this is not true and the value of one predictor alters the effect of another, there is said to be an "interaction" between the 2 predictors. Such interactions need to be explicitly included in the analysis to ensure the estimated associations are valid. [3]

References

[1] GWright, R.E., 1995. Logistic regression.
[2] Gould, S., Gao, T. and Koller, D., 2009, December. Region-based Segmentation and Object Detection. In NIPS (Vol. 1, p. 2).
[3] Tolles, J. and Meurer, W.J., 2016. Logistic regression: relating patient characteristics to outcomes. Jama, 316(5), pp.533-534.