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Machine Learning Techniques to Play “Where is Waldo”

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Finding Waldo, or more broadly, classifying an image as containing a pattern or not, is an interesting and difficult problem. Such pattern recognition is easy for humans, but computationally addressing this problem is much more difficult. Infinite perversions of the pattern, such as occlusion and transformed perspectives, size, and orientations, make building prediction models computationally expensive, and at best these models create many misclassification errors. This study mainly aims to evaluate the performance of various machine learning techniques and tools in solving this problem. Techniques include logistic regression, feed forward neural networks, decision trees, and support vector machines. Tools we use include Matlab, TensorFlow (python), Caffe(python), and Keras (python). We also use various methods of feature reduction - including traditional methods as well as modifying models to incorporate techniques such as the sliding window algorithm. There is little variation in the advantage of one method over the other as all methods had extremely high specificities, and significantly lower sensitivities. Many methods are augmented with modifications to the data and its preprocessing before feeding input into the machine learning algorithm or tool, which in some cases reflects better in the sensitivity and specificity measurement - however, the margin in improvement is not very large, and sensitivities are still disappointingly low. Ultimately, it seems that these results can be attributed to a weak data set with a very low proportion of positive training samples. There is still more work to be done to discover and develop good techniques and tools to find Waldo, and other patterns, computationally. For this dataset specifically, there may be few options unless more positive training samples are developed. Despite this, results from this study can be built upon to develop techniques for better general pattern image classification.

Contents

1. INTRODUCTION

Object recognition is a topic studied by many people and has many applications to different fields. A more specific subset of form recognition is human recognition and facial recognition, both of which have to a large extent been successfully solved using machine learning techniques. Narrower still is the problem of identifying whether an image contains Waldo or not, and that is the problem that we focus on in this paper. In a Wheres Waldo puzzle, a large image with lots of visual noise hides the form of Waldo, and the goal of the game is find him. While this is a problem of location discovery, we simplify the problem into one of binary classificationWaldo or Not-Waldoby using pre-cropped images and feeding them into various machine learning systems [Olson 2015b].

The sub-area of finding Waldo in images using machine learning techniques is just beginning to be explored. While not a machine learning technique, the method in [Olson 2015a] of narrowing the search space for a human to two narrow bands inspired others to apply more sophisticated methods to the problem. One such progressive used a hill climbing technique followed by a genetic algorithm to produce a close-to-optimal search path that a human could follow [Brownlee 2014]; however, pitfalls of those approaches are the reliance on preexisting Waldo locations, overfitting, running for too long, and requiring a human to manually search the programs output search space. Another progressive used template matching to find Waldo, but its flaw is in relying on searching for the exact cropped image of Waldo within the Wheres Waldo puzzle, which defeats the purpose of finding Waldo in a never-before-seen puzzle or picture. Hence, from the aforementioned methods, the problem of finding Waldo is lacking in his identification sans human support, as well as his discovery in less time that in would take a human to manually search for him.

We use a variety of machine learning techniques in order to solve these two problems. All of our techniques rely on preprocessed images; however, these images could easily be obtained as output from a facial detection program or even a brute-force method of extracting tiles from a given Wheres Waldo puzzle. Logistic regression succeeded on both accounts, but may have better results with more Waldo training samples. Feed Forward Neural Networks aimed to solve the problem, and while not having worse running time than the algorithms in [Brownlee 2014], its Waldo identification suffered due to the small Waldo samples compared to the enormous Not-Waldo samples. TensorFlow identified Waldo correctly every time, but would sometimes produce false positives; a human could comb through each returned positive and correctly ID Waldo, but this suffers from the problem of relying on a human to complete. Decision trees performed only slightly better than making a random binary classification of each cropped image, due to flawed feature extraction and a small Waldo sample set; after constructing the decision tree, the actual classification takes microseconds. SVMs revealed that Radial Kernels yield the highest proportions of specificity and the like, yet ultimately suffer on overall sensitivity due to a small Waldo sample size.

2. LOGISTIC REGRESSION

2.1 Method

According to Hofmann, Lampert and Blaschko in "Beyond Sliding Windows: Object Localization by Efficient Subwindow Search", binary classification was more effective in object recognition [Lampert et al. 2008]. To actually determine the location of an object, it is best to use binary classification in conjunction with a sliding window algorithm. The sliding window algorithm scans the original image by pixel increments to obtain smaller, overlapping sub-images which gets fed into the classifier as input. The classifier outputs the probability of the sub-image containing the object. After calculating probabilities for all the sub-images, the sub-image with the highest probability is returned as the predicted location of the object. We utilized MATLAB's `glmfit` (Generalized Linear Model Regression) to create our logistic regression classifier. Our Waldo classifier outputted a probability which we thresholded at 50%. An image contained Waldo only if the highest probability returned was greater than 50%.

We cropped Waldo's face and hat from the original images and resized those images to 27 by 20 pixels to minimize the number of features. We decided on these dimensions since we were able to reduce the number of features per sample to 72 after using histogram of oriented gradients (HOG). Not using HOG would have yielded 1620 features which is why we decided against raw RGB pixel values as features. HOG has also been shown to improve classification accuracy for human detection [Dalal and Triggs 2005]. These cropped images included different angles of Waldo's head such as his profile. To obtain the HOG features from the raw RGB values of each pixel, we used `extractHOGFeatures` in MATLAB. To increase our sample size, we added mirrored versions of these cropped images to our dataset. Since we used 27 by 20 pixel images of Waldo's head to train our classifier, we resized the original images of Waldo so his head would be as equally sized as possible in the training and testing images.

Using the previously mentioned classifier with the sliding window algorithm, we scanned the testing set images to determine Waldo's location. In addition, we cropped out Waldo's head from these images and reported our classifier's accuracy on the testing set images along with non-Waldo testing set images of the same size.

2.2 Results

Table I. : Logistic Regression Performance

Specificity	Sensitivity	Accuracy	Precision
99.96%	52.63%	99.23%	95.24%

Using the sliding window algorithm, on average, we classified 1.56% of the sub-images as containing Waldo.

2.3 Discussion

Nearly all of the samples occluded the majority of Waldo's body, so we specifically search for Waldo's face in our classifier. We decided not to include other aspects of Waldo, such as torso and legs, for multiple reasons. Firstly, those aspects of Waldo are larger, meaning the associated sub-images would require more features. Thus we would need more samples of those aspects to develop an effective classifier. Also, it would be much more difficult to integrate those multiple classifiers to find Waldo. Finally, Waldo's face is unique while other aspects of him are not and often share qualities with other objects to mislead the searcher.

Unfortunately the method employed lacks the ability to detect Waldo heads of varying size and facing directions. Furthermore, it requires that the user changes the proportions of the image so heads are of size 27 by 20. For future work, ideas and techniques mentioned in [Garg et al. 2011] can be incorporated to better locate Waldo in crowds.

3. FEED FORWARD NEURAL NETWORK

3.1 Method

[Egmont-Petersen et al. 2002] mentions using pixel values as input for an artificial neural network. As such, we decided to explore that avenue ourselves. In order to classify Waldo using Feed Forward Neural Networks, we used three methods: Black and White, RGB, and Color Mapping ([Hasnat et al. 2013] suggests that Euclidean distance can be a helpful metric for mapping similarities in two colored images of faces). Our dataset for black and white images only has one value per pixel (0 - 255), RGB has 3 values per pixel (0 - 255, 0 - 255, 0 - 255) both with 4,096 pixels each (64x64 pixel images). For Color Mapping we mapped each RGB value to it's nearest color value by using the Euclidian Distance, on a subset of 8 colors. Using Keras, “a high-level neural networks library, written in Python and capable of running on top of either TensorFlow or Theano”, we fed in pixel values as input features into our FFNN. Using a configuration of two hidden layers, each with the number of nodes equaling half the number of features, we used back propagation to train the neural network over 20 epochs. We also ran the network with configurations of up to 200 hidden nodes in each layer and achieved similar results.

3.2 Results

Feedforward neural networks suffered much more from the disproportionate set of Waldo images then Logistic Regression. The sensitivity of Feedforward neural networks is at best only 8.33%.

Table II. : FFNN Performance

Feature Space	Specificity	Sensitivity	Accuracy	Precision
Color	100%	8.33%	99.32%	100%
B & W	100%	7.14%	99.15%	100%
Color Map	100%	8.33%	99.32%	100%

3.3 Discussion

3.3.1 *Disproportionate Set and rapid convergence.* Given that there were 39 Waldo's in the entire data set of 5,378 samples (.7% positive samples), the dataset is inherently difficult to train. Furthermore, Waldo isn't statically appearing in each positive image, meaning in some images he may be missing a hat, or his glasses, or half of his face due to obstruction. In humans “the brain learns to link multiple view-specific categories of an object to view-invariant categorical representation of the object” [Chang et al. 2014]. However, within the images Waldo does appear in, he does not appear in the same place, making it difficult for the neural network to detect a trend in where Waldo might appear, which becomes problematic as our network tries to map discrete pixel locations to Waldo's appearance. Due to the dataset imbalance, and the Neural Network detecting the input as seemingly random, the model converged very quickly with the assumption that every image did not contain Waldo. This can be seen in the sensitivity of the classifier as it misclassified nearly every Waldo as not Waldo.

3.3.2 *Color mapping helped with feature reduction.* In order to retain color in the feature set without overfitting (given a 64x64 pixel image, 3 values for each pixel would lead to 12,288 features, way more than the 5,378 samples). We mapped Euclidean distance to a set of 8 prespecified colors (all the permutations of 0 and 255 of length 3). This way we are able to retain color as a distinguisher while not having to keep all three values of the color, thereby reducing our input down to 4,096 features.

3.3.3 *Why we used Keras vs. pybrain, other libs.* If you have 4096 inputs, and your first hidden layer is 2048, the network has $4096 * 2048 = 8,388,608$ edges in between the input layer and the first hidden layer, $2048 * 2048 = 4,194,304$ edges between the first hidden layer and the second hidden layer, and 4096 connections between the last hidden layer and the output layer. Considering the number of edges involved, this is a very computationally intensive task, so we wanted a library that could perform these computations in parallel. Keras offered GPU/CPU

optimization, so it was ideal for this task, as opposed to libraries such as pybrain where calculations are done in succession, only on the CPU.

3.3.4 *Difficulties.* As mentioned before, the proportion of positive samples to negative samples did bias our findings towards categorizing images as non-Waldo images. However, there were some additional issues regarding the results themselves. The results section for the feed-forward neural net indicates that the sum of the counts of true positive and false negative, which should indicate the total number of actual positive samples, are not always the same. It appears that Keras, therefore, dropped some samples in the preliminary data import so that the total number of samples used in the experiment is lower than what was available. Ideally, all samples would be used. However, given the time constraint, researchers were unable to investigate further, and we encourage other curious minds to attempt rectify these confounding errors.

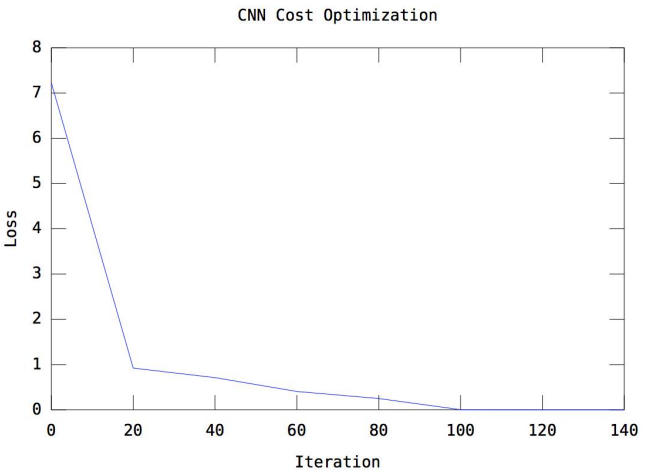
4. CONVOLUTIONAL NEURAL NETWORK (CAFFE)

4.1 Method

We utilized Caffe as our deep-learning framework. Caffe was compiled to utilize CUDA 8.051, OpenBLAS as the Basic Linear Algebra Subprogramming system, and Anaconda python 2.7 to better support high-performance computational packages. We opted for a semi-bounded-box version of input data for classifying Waldo, with each image up-scaled to 256x256. The dataset was retrieved from Jessie Salas’ DeepRed [GitHub 2015], and was augmented in order to increase the size of available data. The convolution later consisted of the following layers, as used by [Krizhevsky et al. 2012]. There are 5 convolutional layers, 6 ReLU layers, 3 pooling layers, 2 local response normalization layers, 2 dropout layers, and 3 fully connected layers. Loss was computed via softmax as per Caffe’s default. The CNN began training with a learning rate of 0.01. Every 100,000 iterations the learning rate would decrease by 10%. This strategy also stemmed from [Krizhevsky et al. 2012]. The training would use all images except 8, which would be used for testing purposes.

4.2 Results

After a significant training time and extreme heat and noise output the loss function converged to 0:

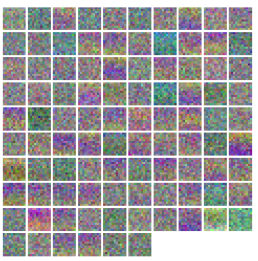


The majority of the data was used for training, so the testing set was extremely small, only 8 samples. The model scored 100% accuracy and precision, correctly marking 4 Waldos and 4 non-Waldos. The Waldo’s and non-Waldo’s were previously unseen, but had high similarity in relation to the training set, which is both critical and detrimental to the integrity of the model. Copies of the Caffe prototexts can be found in the attached files.

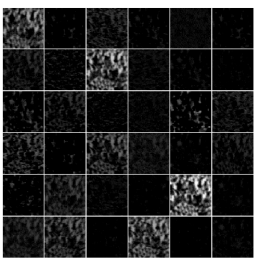
4.3 Discussion

Due to the extreme specificity of the training set, i.e. being pixelated crops of very specific full-bodied Waldos, and small scale of the data set, CNN’s translational invariance isn’t very effective and cannot account for Waldo in larger images. The variance between a normal, large-scale Where’s Waldo images and our full-bodied but miniscule crops of Waldo don’t accurately portray him in a real-world’ scenario. The only way to use the CNN as we have trained it currently would be subdividing the full image into small sections and checking each one for Waldo’s presence via a sliding window method on images of a particular size. Lack of computational power prohibits larger data sets and implementation of data augmentation.

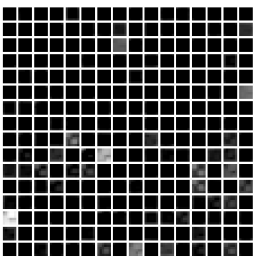
One possibility for speeding up training would be to use Transfer learning, a technique that integrates a pre-existing Convolutional Network in training over the new dataset when there is not enough data. By having a previously trained CNN that classifies similar images, it would be possible to use the values of neurons in the last layer before the output layer as a new vector of features, and train a classification method over all such vectors for the new images. Unfortunately at this moment we weren't able to find a publicly available CNN that has been trained over similar enough images (e.g. cartoon characters). As such a network is not available, it might be of use to train the new images over another existing network, which at the lower level may still be able to recognise some defining features of the images, and use the value of neurons at that layer to classify the images. The small quantity of training data prevents us from adjusting the weight of a pre-existing CNN by training it over the new images, as we might otherwise choose to do in the presence of a larger dataset.



1st Layer



5th Layer After Pooling



6th Fully Connected Layer

Fig. 2: Visualizations of various layers

5. TENSORFLOW INCEPTION MODEL METHOD

5.1 Method

Using the Google TensorFlow pre-trained Inception model, we re-trained the model to recognize waldo using the 64 by 64 pixel dataset [Google 2015]. In order to add more positive waldo images, existing waldo images were flipped horizontally (to preserve face shape) and randomly darkened and lightened. Cross-validation was used to reduce overfitting. Specifically, we are using 500 training steps, a random brightness variance of 10, and the flip-up-down flag to run the retraining on Inception.

5.2 Results

Table III. : Tensorflow results

Specificity	Sensitivity	Accuracy	Precision
79.98%	100%	80%	1.9%

5.3 Discussion

5.3.1 *About TensorFlow.* This section uses the pre-trained network for the Inception model, which was released by Google in 2015. This model, having been trained on over one hundred thousand different images in over a hundred categories has essentially trained itself on shape and edge detection.

When attempting with the raw data (no image flipping or random brightness), we were able to get an accuracy of 79.8% on the test data set. By default, TensorFlow uses 10% of the data for testing, 10% for cross-validation, and the rest (80%) for training. Whereas 100% of the positives (4 images) were correctly identified, only 80% of the negatives (426 images out of 533) were correctly identified.

By using cross-validation after every batch, we can make sure that the model is not overfitting, and will give us a better outcome in the long run. However, adding a random brightness variance of ten and random up-down flips did not seem to change the classification accuracy.

5.3.2 *Why TensorFlow’s Inception Model?.* The main reason the Inception model was picked was due to the fact that it was already trained to recognize people and objects [Mordvintsev et al. 2015]. The common denominator of the Waldo images is that his face is always visible, and TensorFlow was able to pick up on this.

5.3.3 *Overcoming Difficulties.* Like the other groups, the small ratio of positives to negatives was detrimental to the overall classification. However, given that there were nineteen total images, the neural network was able to narrow down the total number of 64 by 64 images down from one thousand (10% of the the five thousand images) to a mere 112 in the raw dataset, making Waldo much easier to find.

5.3.4 *Conclusion.* Overall, the neural network still has trouble pinpointing a specific Waldo, but it has at least learned to recognize the facial structure of Waldo and can narrow down the number of tiles needed to search through in order to actually find Waldo in the image.

6. DECISION TREES

6.1 Method

6.1.1 *Feature Extraction.* Our binary decision tree is constructed from and takes as input images with dimensions 64x64 pixels, where each pixel has a red, green, and blue component. To reduce the feature space and to give more weight to pixels that are more likely to be a part of Waldo, we apply filters to each image, and for each filter extract a new binary feature. Three filters are applied, therefore transforming the 64x64x3 feature space into one of size three. A set of training images are then used to dynamically construct the decision tree. The remaining images from the set of all 64x64 Waldo and non-Waldo images are then fed into the decision tree and classified, further yielding percent errors for Waldo detection, non-Waldo detection, and total error.

Images of Waldo are loaded and stored in an array, and likewise for non-Waldo images. For each image in each of these arrays, we apply three different filters; filters are applied independently to each original, full-color image. Each filter works the same way, which is to map each pixel's color to a new pixel color by determining which color from the set of colors

$$\{\text{Red} = (255, 0, 0), \text{White} = (255, 255, 255), \text{Black} = (0, 0, 0), \text{Blue} = (0, 0, 255), \text{Other} = (0, 255, 0)\}$$

the given pixel is closest to, where each rgb value is a nonnegative integral value out of 255.

A deep copy of the original image is created and the pixel colors in the new image are all converted to one of Red, White, or Other; this basis image will henceforth be referred to as the Red-White-Other filtered image.

A deep copy of the original image is created and the pixel colors in the new image are all converted to one of Black or Other; this basis image will henceforth be referred to as the Black-Other filtered image.

A deep copy of the original image is created and the pixel colors in the new image are all converted to one of Blue or Other; this basis image will henceforth be referred to as the Blue-Other filtered image.

For a given binary feature, the respective filtered image is used to obtain an array of regions. The filtering method used to obtain these regions is a recursive four-point stack based flood fill algorithm that iteratively moves through each pixel in the image, flags it as visited when first discovered, and, for each of the pixel's four adjacent neighbors (non-corner neighbors), makes a recursive call if that pixel is unvisited, is of the same color as the current pixel, and exists within the bounds of the image. Regions of flood-filled pixels are stored by like-color into arrays. For each feature, one of the three filtered images is used as a basis image to extract regions from.

The first feature is whether the image has any red and white stripes. To do this, an array of red regions is obtained and an array of white regions is obtained from the Red-White-Other filtered version of the image. Then, for each region, its centroid is calculated by using each pixel's position in the Euclidean plane within the image. The algorithm used to detect red and white stripes determines if there exists a pair of red and white centroids such that the distance between those two points is less than or equal to a threshold distance. We use a maximum distance of 2.0 pixels for this threshold. To speed up these calculations, the distance squared is used to compare distances because that eliminates a square root operation for each pair of centroids that are checked for close-proximity.

The second feature is detecting whether the image has at least one pair of black glasses. The basis image is the Black-Other filtered image. All black regions are obtained and their centroids calculated. For each black region, if it has a minimum number of points greater than or equal to some threshold number of pixels, and if a minimum percentage of its pixels lie within an annulus determined by the average distance of all pixels from the centroid of the current region plus or minus some constant delta radius, then this feature is set to true. We set the minimum number of points to 8, the minimum percentage of pixels with the annulus region to 70%, and the constant plus or minus delta radius to 2.0.

The third feature is whether the image contains at least one pair of blue pants. The basis image used is the Blue-Other filtered image. All blue regions are extracted from the image. By visual inspection of the sample images, there are many blue regions of varying pixel quantity, but most blue regions in the form of pants have greater than

or equal to a minimum threshold pixel count. This feature is set to true if a blue region in an image is determined to contain at least the threshold amount of pixels. We used 70 pixels for the threshold number.

6.1.2 *Decision Tree Construction.* After acquiring the three features for each image, the binary decision tree is dynamically constructed on 70% of all of the Waldo images and 70% of all of the non-Waldo images. Information gain is used as the splitting algorithm [Amro 2009]. At each node, the entropy is calculated pre-split by the equation

$$E = -P(A_P)\log_2(P(A_P)) - P(B_P)\log_2(P(B_P))$$

where A_P is the event that a given image is classified as having Waldo and where B_P is the event that a given image is classified as not having Waldo, each in the parent node. The minimum post-split entropy is then calculated. For each feature available to split upon at the current node, the post-split entropy is calculated by calculating the prospective entropy in each of the two children nodes and then summing their weighted values together, where each term is weighted by the ratio of samples at each child node:

$$E_L = -P(A_L)\log_2(P(A_L)) - P(B_L)\log_2(P(B_L))$$
$$E_R = -P(A_R)\log_2(P(A_R)) - P(B_R)\log_2(P(B_R))$$
$$E' = E_L\frac{N_L}{N_P} + E_R\frac{N_R}{N_P}$$

The information gained is

$$I = E - \min\{E'\}.$$

If the information gained is greater than a threshold value, then the current node is split upon the feature that yielded the minimum post-split entropy. We used 0.000005 for this threshold value. For a given node, if there is 100% purity of either all Waldo images or all Not-Waldo images, then that node becomes a leaf node. For a given node, if there are no more features to split on, then that node becomes a leaf node with classification determined by comparing the ratio of Waldo images at that node to total number of Waldo images with the ratio of non-Waldo images at that node to the total number of non-Waldo images, further described by the following pseudocode:

ALGORITHM 1: Leaf Node Classification

$WaldoRatio \leftarrow numWaldoImages\_currentNode$ / $numWaldoImages\_startingAmount$
$NotWaldoRatio \leftarrow numNotWaldoImages\_currentNode$ / $numNotWaldoImages\_startingAmount$
if $WaldoRatio > NotWaldoRatio$ **then**
    classification ← Waldo
end
else
    classification ← Not Waldo
end

6.2 Results

Table IV. : Decision Tree Performance

Specificity	Sensitivity	Accuracy	Precision
67.84%	74.07%	67.89%	1.64%

The percent error when detecting Waldo images is 25.9259%. The percent error when detecting Not-Waldo images is 32.1553%. The total percent error is 32.1106%.

6.3 Discussion

The number of inherent features of a single image is very large. Additionally, each pixel does not contribute equally to the discovery of Waldo. Particularly, pixels that are part of a red-white striped region, black pixels that compose a region in the shape of glasses, and blue pixels that are part of a region in the shape of pants should all have greater weight in the discovery of Waldo than any other pixels. By using the feature reduction techniques described above, images of Waldo that do not conform the 64x64 standard could be classified by our decision tree, and the classification could be performed in roughly the same amount of time as classifying a 64x64 image.

As for the classification criteria, originally we had simply compared the number of Waldo images in a given leaf node to the number of Not-Waldo images at that leaf node. However, our decision tree produced leaves that always classified as Not-Waldo because there are many more Not-Waldo samples used in the construction of the tree than Waldo images. This prompted us to compare ratios at leaf nodes instead, where these ratios are the proportion of the number of Waldo images at the given leaf node to the total number of Waldo images used to construct the tree, and similarly for Not-Waldo images. This yielded 3 nodes with the Waldo classification and 1 node with the Not-Waldo classification, where the tree had a total of 7 nodes.

In order to detect whether an image contains Waldo, we took the approach of extracting features from the image and feeding those features into a classifying binary decision tree. We were able to reduce the feature space from NxN pixels to 3 features, dynamically construct a binary decision tree and then test a set of sample images for percent error. Further improvements to our feature extraction algorithms can be done, perhaps by using more sophisticated shape detection algorithms such as Hough transforms [Solberg 2009] in order to determine whether an image has certain features. Additionally, more features can easily be extracted, such as detecting whether an image has a brown cane or a face; extracting more features would lead to a deeper decision tree with more branches, which may yield better classification results. Because our tree could only have a maximum depth of three, we did not prune the tree as that would not noticeably improve performance. However, if many more features were extracted from each image then pruning may become necessary. Additionally, other splitting algorithms may be used instead of information gain, such as impurity-based criteria, Gini index, likelihood-ratio chi-squared statistics, DKM criterion, normalized impurity based criteria, gain ratio, distance measure, binary criteria, twoing criterion, ORT criterion [Rokach and Maimon 2005]. Additionally, the benefit of using the twoing criteria as the splitting algorithm is that the decision tree can then operate on features with continuous values, becoming a regression decision tree in the vein of CART (Classification and Regression Trees) [Rokach and Maimon 2005]. The benefit of creating a regression decision tree is that a large image with a lot of noise and containing a single Waldo (a Where's Waldo image before cropping out all of the people) can be fed into the program, facial detection can be used to identify sub-images with people, feature extraction as described can be used on each of these sub-images, these images can be fed into the decision tree, and the output of the decision tree can be one or more likely coordinates of Waldo within the scene.

One last idea about improving the performance of decision trees would be to alter the splitting algorithm such that greater preference is given to classifying the image as Waldo, especially when coupled with a regression decision tree because false positives are easy to visually check on the original Where's Waldo image, whereas false negatives are equally as bad as not using the decision tree in the first place for Waldo detection.

7. SVM

7.1 Method

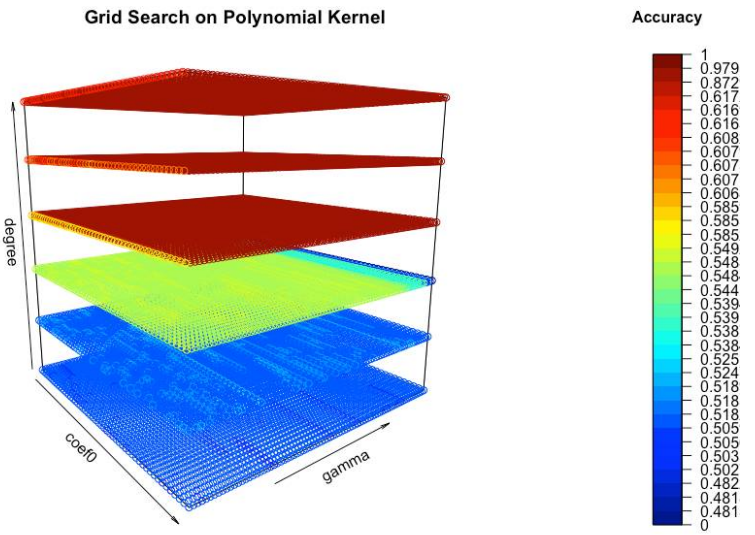
7.1.1 *Pre-Processing the Data.* The data format was in the form of pictures. In order to properly evaluate it, we needed to convert the data into features. To do this we used matlab's `imread` function. This converted each picture into it's RGB pixel values. However, since we has 64, 128, and 256 bit images we needed to find a way to combine the different sizes. Some standard compression algorithms simply merge adjacent pixels in order to compress an image. We did this for the 128 and 256 bit images in order to match the size of the 64 bit images. This allowed all available pictures to be used in a single algorithm.

7.2 Results

7.2.1 *Grid Search to Find Optimal Hyperparameters.* Since we have many Kernels to choose from with SVM, and at first glance the data looks like it is not linearly seperable, we used the grid search technique to analyze multiple Kernels. One of the Kernels was the Polynomial Kernel given by,

$$f(u,v) = (\gamma \langle u, v \rangle + c_0)^D$$

The Hyperparameters with this Kernel are γ, D, and c_0. We tuned on all three of these parameters and measured the accuracy after to determine the best values. Here is the plot containing the accuracy for each choice of these parameters.



1. Grid Search on γ, D, and c_0 for Polynomial Kernel

We see that degree has the most impact on the accuracy of the model, while extreme γ and c_0 values also lead to worse accuracy for a given choice of D. In general, a kernel with higher degree will give us better Accuracy and Specificity, but worst precision and sensitivity. Meanwhile, change in gamma will have minimal effect on the result, but coefficients appears to not contribute appreciably to the results.

We found that the Radial Kernel produced the best results overall. The following table illustrates the values of D, γ, and c_0 and the associated Accuracy, Precision, Sensitivity, and Specificity.

Table V. : Values on the optimal attributes

Optimal	D	c_0	γ
Accuracy	7.0000	4.6000	4.6001
Specificity	4.0000	4.9000	0
Sensitivity	4.0000	4.4000	7.8001
Precision	6.0000	1.5000	0.0001

7.2.2 *SVM on All Pixel Values.* Once the Kernel was decided, we began to train the data. The first run of the data was to train an SVM (using the libsvm package) on all the pixel values. Since we had RGB values for 64 bit images, this gave us $64^2 * 3 = 12288$ features. We tested many different kernels and measured the accuracy, precision, specificity, and sensitivity for each of them. These were given by

Table VI. : Accuracy Values for Different Kernels

Kernel	Specificity	Sensitivity	Accuracy	Precision
Linear	99.816%	33.929%	98.486%	79.167%
Polynomial	98.631%	33.929%	98.631%	95.000%
Radial	100%	40.00%	98.911%	100%
Sigmoid	97.43%	12.14%	97.846%	8.21%

7.2.3 *Using PCA to Reduce Dimensionality.* Next we tested dimensionality reduction by using PCA. Following singular value decomposition we found the most informative principle components by selecting the right singular vectors that corresponded to the largest 100 singular values. For X as the dataset, the singular value decomposition is given by,

$$X = USV^T$$

Then we selected the right singular vectors V corresponding to the largest singular values and reduced X into

$$\tilde{X} = X[V_1, \cdots, V_{100}]$$

We then trained SVM on $\tilde{X}$. After also transforming the testing set, we measured the accuracy, sensitivity, specificity, and precision as

Table VII. : Accuracy Values for Different Kernels

Specificity	Sensitivity	Accuracy	Precision
100%	46.939%	99.046%	100%

7.3 Discussion

Although model selection when using a SVM is a daunting task, a grid search can often easily determine the best hyper parameters. Using the best hyperparameters per the grid search, we found the Radial Kernel to be the best method according to accuracy, sensitivity, precision, and specificity. After using PCA to reduce the dimensionality, we found the same accuracy; implying that much of the information is found within a significantly smaller subset of the entire space. Future projects would require that we find more positive samples since the proportion of "Not-Waldo" pictures to "Waldo" pictures was substantially off-balance.

8. CONCLUSION

Given these findings, we have the following discoveries. Logistic regression succeeded on classifying Not-Waldo but did not provide a more efficient way of identifying Waldo than random guessing, due to its limitation in computer vision and the lack of Waldo training samples. Feed Forward Neural Networks aimed to solve the problem, and while not having worse running time than the algorithms in [Olson 2015b][Olson 2015a], its Waldo identification suffered due to the small Waldo samples compared to the enormous Not-Waldo samples. TensorFlow identified Waldo correctly every time, but would sometimes produce false positives; a human could comb through each returned positive and correctly ID Waldo, but this raises the problem of relying on a human to complete. Decision trees performed only slightly better than making a random binary classification of each cropped image, due to flawed feature extraction and a small Waldo sample set; after constructing the decision tree, the actual classification takes microseconds. SVMs revealed that Radial Kernels yield the highest proportions of specificity and the like, yet ultimately suffer on overall sensitivity due to an unbalanced data set. CNN’s were largely successful, correctly classifying Waldo and non-Waldo images most of the time. However, due to data, time, and computational limitations, the testing set used was very small. Lastly, while different approaches have various performance and they all have their own strength and weakness. For example, TensorFlow and CNN give the most impressive performances but they both require intensive computational power; SVM runs fairly fast but performs in an unsatisfactory fashion on specificity and precision due to the limitation of the data set available. However, these approaches all faces some common difficulties, such as an unbalanced data set, the limitation on computational power, and a feature space with a very large number of dimensionalities. Among these limitations, the most prominent obstacles is unbalance of the dataset. That is, a large part of the data set is of the non-waldo class, such that the punishment of classifying a true-waldo sample to a non-waldo class is weighted much less in the cost function. It, inevitably, resulted in a very low sensitivity overall in most of our teams. All in all, a more representable/useful data set will contribute appreciably in future performance.

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9. AUTHOR CONTRIBUTIONS

Table VIII. : List of Author Contributions

Author	Contribution
Pouneh Aghababazadeh	Part of FFNN subteam and writing abstract
Jason Alexander Carruthers	Introduction and decision trees
Alex Fu	Retrained Google Inception Engine to recognize Waldos
Matthew Gabor	Helped create Forward Feed Neural Network portion and assisted with discussion section of report
Shunxu Huang	Development/Writeup for SVM using Llibsvm on Matlab, writing conclusion for the report
Wei Huang	For logistic regression: For logistic regression: Helped collect more data, resized the images to reduce the number of features, wrote the code to run logistic regression and test the performance of the model, provided the calculation and assisted with the writeup
David Ibrahim	For logistic regression: Collected more data (doubled dataset), manually found waldo in the new data, cropped the images of waldo, wrote the code to run logistic regression, wrote the sliding window code, and helped with the writeup
Rachel Lee	Coordinated group meetings and task allocations and helped with Logistic Regression methods
David Lin	Development/Writeup for CNN using Caffe
Lorenzo Martinico	Development/Writeup for CNN using Caffe
Donald Pinckney	LaTeX formatting, assembling final paper, and TensorFlow subteam
Michael Romero	Development/Writeup for CNN using Caffe
Amir Sahabi	Helped write code for FFANN + derive statistics and helped write FFANN portion of methods + discussion
Doug Sherman	Development/Writeup for SVM using Llibsvm on Matlab
Christina Zhu	LaTeX formatting, assembling final paper, and TensorFlow subteam