Applying Classification Algorithms to Real World Radio Pulse Data

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Abstract

The Quail Ridge Automated Animal Tracking (QRAAT) system generates inaccurate position calculations due to the radio noise received in the radio receivers. In order to increase the accuracy, the system needs a method to distinguish a noise event from a true radio pulse event before applying the position calculation. With different variables collected by the receiver and millions of training data, one can develop a classification algorithm that classifies whether an observation is a pulse event or a noise event. The data is labeled with two different techniques. One of the techniques, Likelihood Labeling, labels the observation with a high likelihood in the expected direction as pulse and the rest as noise. Another technique, Manual Labeling, labels the observation that visually looks correct as pulse and the rest as noise. The methods implemented to classify the data are Bayes Classifier, Decision Tree, Random Forests, and Support Vector Machine. The evaluation is done with the 10-fold cross-validation to determine which method is the best to use in the QRAAT system.

1 Introduction

1.1 Background

The Quail Ridge Automated Animal Tracking (QRAAT) system provides ecological researchers with tracking data from small wild animals such as birds and rodents. This system consists of transmitters, various radio receiver towers, and a central processing server. Transmitters, which transmit radio pulses, are attached to each animal. The receiver towers, which receive the radio pulse, are stationary located throughout the Quail Ridge Reserve. The receiver towers send the received data to the central processing server. The central processing server then uses the data collected from each of the receiver towers to calculate the most likely position of the animal.

In addition, each of the radio receiver towers has a detector that captures the signal of interest. The receiver towers continuously receive radio data from the surroundings. The detector computes the sum of the signal amplitude within a time window. If this sum passes the amplitude threshold, then it is considered as a signal of interest and will be used in the position calculation. However, if there are other source such as car engine that creates high amplitude radio pulse, the detector is unable to distinguish it from a true pulse event. Althrough, the true pulse event with the signal noise can be fixed by mathematic computations, the noise event needs to be filtered.

Due to the carrying capacity of small animals, the battery of the transmitters are generally small. The researchers have to reduce the signal strength in exchange for a longer battery life. The pulse with the reduced signal strength becomes even more difficult to distinguish from the noise. Hence the resulting positions can be significantly far away from the habitats of the targeted animals. QRAAT system needs a more sophisticated algorithm to differentiate the pulse and the noise before preforming the position calculation.

1.2 Problem Description

Each observation has nine variables recorded. Band3 is the bandwidth at power 3dB. Band10 is the bandwidth at power 10dB. Frequency is the frequency of the signal. EC is the confidence of eigenvalue decomposition. TNP is the total nose power of the signal. EDSP is the eigenvalue decomposition signal power. FDSP is the Fourier decomposition signal power. EDSNR is the eigenvalue decomposition signal to noise ratio which is proportional to EDSP/TNP. FDSNR is the Fourier decomposition signal to noise ratio which is proportional to FDSP/TNP. There are a total of 7,151,826 unlabeled observations organized in different sets. The goal of the project is to use these datasets to develop a classification algorithm that will be the most suitable for the QRAAT system.

1.3 Datasets

The data is organized by different combinations of deployment and site . A single deployment refers to a specific transmitter on an animal for tracking while a single site refers to a specific radio receiver tower for collecting data. Different combinations of deployment and site are expected to experience different behaviors of the same variables and are therefore treated as separate datasets.

- Deployment 57 is a stationary wood rat transmitter (low signal strength transmitter) with a known location. The timestamp (seconds from Unix epoch) is from 1382252400 to 1385366400 (10/20/2013 - 11/25/2013). There is total of 2,222,486 observations. Site 2 has 649,060 observations. Site 3 has 881,529 observations. Site 5 has 363,391 observations. Site 6 has 328,506 observations.
- Deployment 60 is a stationary beacon (high signal strength transmitter) with a known location. The timestamp (seconds from Unix epoch) is from 1383012615 to 1384222215 (10/28/2013 - 11/11/2013). There is total of 4,874,724 observations. Site 1 has 1,224,901 observations. Site 2 has 656,838 observations. Site 3 has 762,951 observations. Site 4 has 655,953 observations. Site 5 has 398,872 observations. Site 6 has 721,619 observations. Site 8 has 453,590 observations.
- Deployment 61 and 62 are two different moving wood rat transmitters with GPS tracking. Two transmitters moved together during two periods of trackings. First tracking is from timestamp (seconds from Unix epoch) 1391276584 to 1391285374 (2/1/2014, 9:43am to 12:09pm). Deployment 61 has 11,191 total observations, deployment 62 has 22,422 total observations, and the tracking has 8,388 gps observations.
- Second tracking of deployment 61 and 62 are from timestamp (seconds from Unix epoch) 1396725597 to 1396732326 (4/5/2014, 12:19pm to 2:12pm). Deployment 61 has 11,672 total observations, deployment 62 has 9,331 total observations, and the tracking has 6,438 gps observations.

1.4 Labeling

There are two techniques to label the data. One technique is to intuitively use the GPS location to determine the label of the observation. Another technique is to use the visual recognition of the human eye to detect the pattern of the data.

1.4.1 Likelihood Labeling

The position calculation is the linear combination of the likelihoods of the data collected during a period of time. The position with the highest likelihood is chosen to be the location of the

animal. For each observation, the system can determine the likelihood of a specific angle of the observation's origin. Therefore, the direct way to label an observation is by the threshold of the likelihood at the angle of the GPS records. The observations with high likelihood from the direction of the GPS records are marked as pulse while the ones with low likelihood are marked as noise. The drawback of this method is that the likelihood threshold seems to be inconsistent throughout different combinations of deployment and site from visually viewing the labeled data. Some combinations of deployment and site may require lower threshold to separate the pulse and the noise while others can pass with higher threshold. It is not easy to set a threshold that looks good on all combinations of deployment and site. One can only choose a threshold to define the good observations. The likelihood threshold chosen to label this data is 0.7.

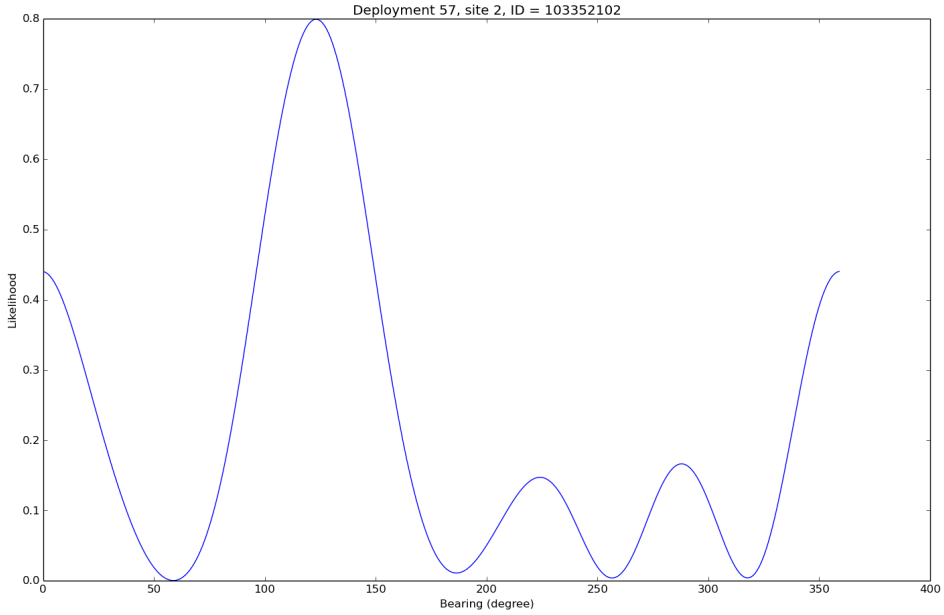
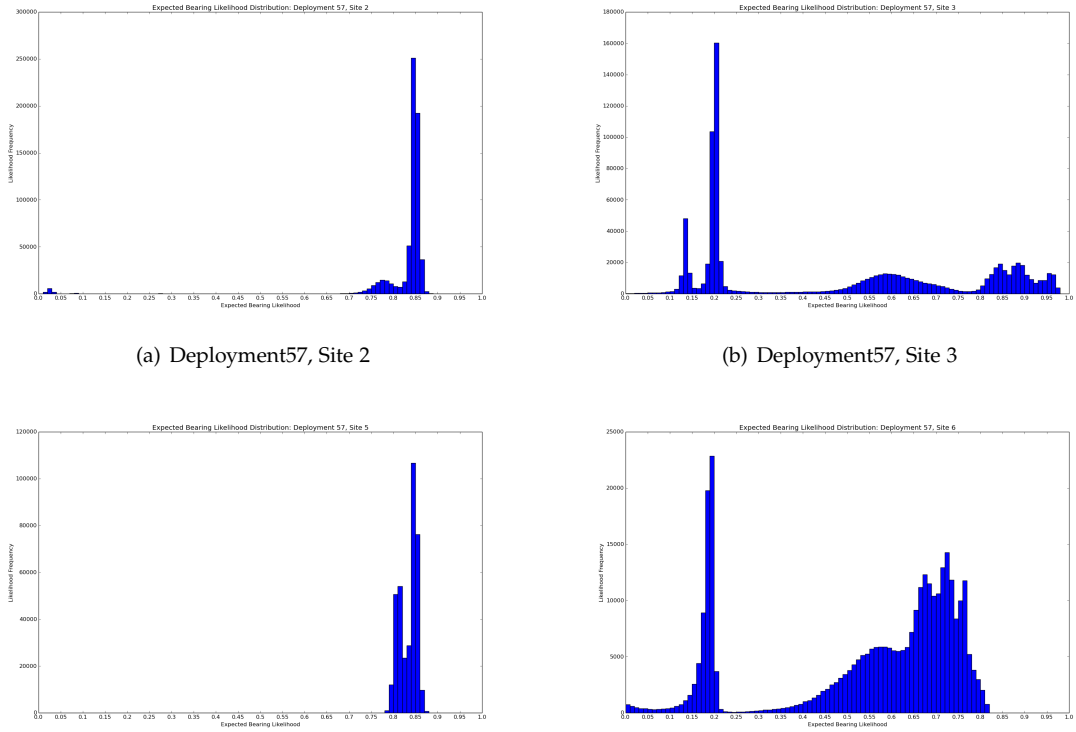


Figure 1: *A plot of bearing likelihood for an observation. There are four local maxima each near 0, 125, 225, and 290 degree. The expected angle for deployment 57 at site 2 is 124.15 degree which indicates that this is a good observation. This observation will give the expected angle (124.15 degree) the most weight (0.8) in the position calculation while giving other angles much lower weights.*

1.4.2 Manual Labeling

In the scenario with high signal strength, the pulse can be easily determined from the noise by plotting the data. From the plotted data, there are patterns to determine whether an observation is pulse or noise. The strategy is to plot each of the nine variables versus time and set a threshold to separate the pulse and the noise. The disadvantage of this technique is that one has to manually go through each combination of deployment, site, and variable to determine the thresholds. This process is not only time consuming but may include bias toward the labeling.

Both Likelihood Labeling and Manual Labeling have their advantages and disadvantages. Since one



(a) Deployment57, Site 2

(b) Deployment57, Site 3

(c) Deployment57, Site 5

(d) Deployment57, Site 6

Figure 2: *The expected bearing likelihood and its frequency distributions for each site used for deployment 57. Different sites showed different distributions of the likelihood measures. A threshold of at the expected bearing 0.7 is chosen to be the definition of a good observation in the likelihood labeling.*

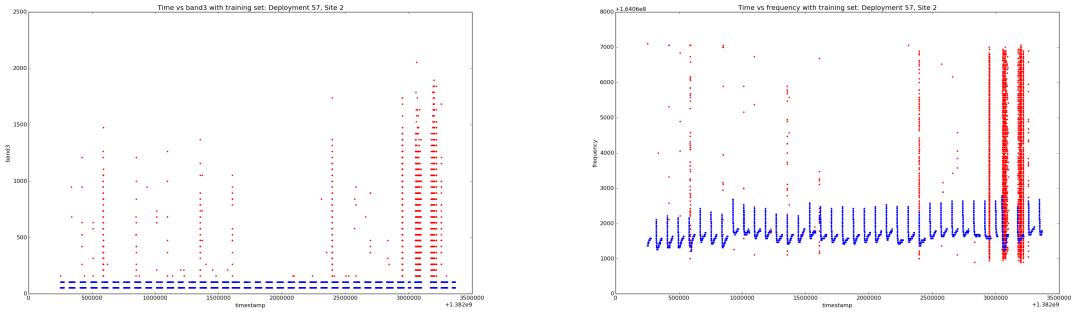
technique is not better than the other, both techniques will be used in the evaluation independently.

2 Methods

There are four classification algorithms implemented in this section: Naive Bayes Classifier, Decision Tree, Random Forests, and Support Vector Machine. Each of them have their advantages and disadvantages. This section will go through the implementation of each method in detail and troubleshoot some issues working on real world data. The pseudocodes for each method are also described after each subsection. The results will be referred in the evaluation section.

2.1 Naive Bayes Classifier

Naive Bayes Classifier is one of the simplest classifiers that one can implement. It uses Bayes' Theorem to calculate the probability of a class given an observation while assuming all variables are independent. Provided a training set, one must first determine the probability distribution of each variable given a class. All variables are assumed to be normally distributed. Hence the mean and the variance of each variable given a class are calculated and stored in the database. During



(a) Time VS Band3

(b) Time VS Frequency

Figure 3: *The plots shows labeling results for manual labeling with red as noise and blue as pulse. The manual labeling manually go through each combinations of deployment, site, and variable and determine the best thresholds on each combination to visually separate noise from pulse.*

the process of classification, one can determine the probability of each class given the data by Bayes' Theorem. The class with the highest probability will determine the class of the observation.

$$\begin{aligned} p(class_i|x) &= \frac{p(class_i)\prod_{j=1}^{9} p(x_j|class_i)}{p(x)} \\ &\propto p(class_i)\prod_{j=1}^{9} p(x_j|class_i) \end{aligned}$$

Since the denominator of the probability is constant throughout the calculation of the probability of each class, only the numerator of the probability will be considered. It is important to note that all the probabilities are small numbers, thus, repeatedly multiply the probabilities from each variable will result in a loss of floating point precision. A common way to fix this problem is to use the log probability (likelihood) instead of the original probability. By taking the log of Bayes' Theorem, the likelihood of a class becomes the sum of the log probability of each individual variables. Moreover, the exponential function can be removed when applied log probability if the distribution is assumed to be Gaussian.

$$\begin{aligned} log(p(class_i|x)) &\propto log(p(class_i)) + \sum_{j=1}^{9} log(p(x_j|class_i)) \\ &= log(p(class_i)) - \sum_{j=1}^{9}(\frac{(x_j - \mu_{class_i})^2}{2\sigma^2_{class_i}} + 0.5log(2\pi\sigma^2_{class_i})) \end{aligned}$$

Although the assumption of all variables being normally distributed works good on continuous variables, discrete variables should be treated more carefully. In the QRAAT system, band3, band10, and frequency are discrete variables with few high occurrence values. These three variables should be treated as a mixed probability distribution where high occurrence values each

has a unique probability while other values are treated as Gaussian to insure the possibility of nonzero probabilities. One should store the proportions of these unique values and normalize the overall mixed probability to 1 during the training process.

input : A labeled training set, *P* for data labeled as pulse and *N* for data labeled as noise
output: Mean and variance of data stored in database

for *i in each data type* **do**
    `// if i is discrete, remember to consider mixed probability`
    calculate mean and variance of P;
    store mean and variance in the database with pulse class and i data type;
    calculate mean and variance of N;
    store mean and variance in the database with noise class and i data type;
end

Algorithm 1: Naive Bayes Classifier trainer

input : An observation X with unknown class
output: Class determined by the model

set likelihood_P = 0 and likelihood_N = 0;
for *i in each data type* **do**
    likelihood_P += log probability of P given X_i;
    likelihood_N += log probability of N given X_i;
end
if *likelihood_P > likelihood_N* **then**
    return P;
else
    return N;
end

Algorithm 2: Naive Bayes Classifier

2.2 Decision Tree

Decision Tree algorithm is simple to visualize. It uses tree as a structure to decide which class an observation should be classified. When given a decision tree and an observation, one can traverse the tree according to the constraints at each node and determine the class at the leaf node. There are two stages of decision tree training, first is building the tree to some extend (e.g. 5 observations at each leaves), second is pruning the tree to avoid over-fitting. Given a training set, one should first hide a portion of data as the validation set for pruning purpose. The remaining training set will be used to build the tree. The algorithm will go through each parameters to find the best split by calculating entropies at each point. The split with the lowest weighted sum of entropy of children nodes will be used to create the node. The children nodes then call the algorithm recursively until one of the terminating conditions is met. The terminating conditions are the number of observations being less than 5, all records has the same class, or all records has the same variable values. If the child terminates, a leaf node will be attached with the highest occurrence class.

$$
\begin{aligned}
weightedEntropy(child_{left}, child_{right}) = & \frac{|child_{left}|}{|child_{left}| + |child_{right}|}(-\frac{|child_{left_{pulse}}|}{|child_{left}|} log(\frac{|child_{left_{pulse}}|}{|child_{left}|}) \\
& - \frac{|child_{left_{noise}}|}{|child_{left}|} log(\frac{|child_{left_{noise}}|}{|child_{left}|})) \\
& + \frac{|child_{right}|}{|child_{left}| + |child_{right}|}(-\frac{|child_{right_{pulse}}|}{|child_{right}|} log(\frac{|child_{right_{pulse}}|}{|child_{right}|}) \\
& - \frac{|child_{right_{noise}}|}{|child_{right}|} log(\frac{|child_{right_{noise}}|}{|child_{right}|}))
\end{aligned}
$$

After a tree is built, one would need to prune the tree to avoid over-fitting. Error rate of the validation set is often used as the indicator in tree pruning process. The algorithm go through each leaf node and replace the parent of the leaf node as a leaf node. It checks the error rate of the tree with the parent node assigned to each class. If new tree has a lower error rate, the original tree will be modified with the parent node as the leaf node with lower error rate. It continues this process until there are no leaves that can lower the error rate any further. This resulting tree will be the model to determine the classification.

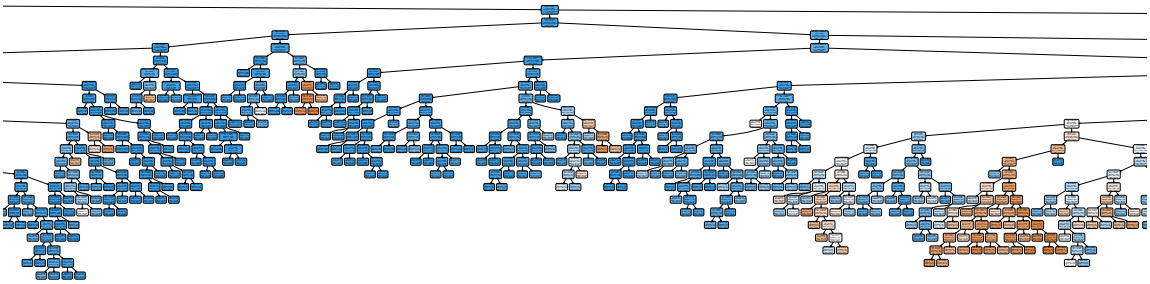


Figure 4: *A small sample of the decision tree trained with deployment 60, site 3, likelihood labeling data. The original tree contains 9659 nodes, hence only a small portion is shown in the figure.*

2.2.1 Random Forests

Since the entire Decision Tree algorithm is implemented, it is easy to extend it to Random Forests. The decision tree is suffering from high data dependence and variable dependence. When training with different subset of the same data, the resulting decision trees will have great variations. Different trees trained using different parts of the data can cause a high variance among them. To remove the effect of high data dependance, one can create multiple trees using different bootstrapped data and using majority vote of the result of the trees in classification. In addition, given a strong predictor variable, each of decision trees will have high chance of using this variable, causing each tree to correlate to each other. To remove this effect of variable dependance, one can pick a subset of parameters at each split. The random forests algorithm will build a specific amount of trees and use the majority vote as the result of the classification. Each tree is built using N bootstrapped observations from training set where N is the number of training set observations.

input : A labeled training set, S. Decision Tree, T.
output: Resulting Tree

```
// finding the best variable and value to split the data
set bestEntropy = 1, bestDataType = -1, and bestSplitValue = -1;
for i in each data type do
    if |S| > 100 then
        for j in each 100 intervals between min and max do
            calculate weighted entropy at split(S_i[j]);
            if entropy < bestEntropy then
                bestEntropy = entropy, bestDataType = i, bestSplitValue = S_i[j];
            end
        end
    else
        for j in each S_i do
            calculate weighted entropy at split(S_i[j]);
            if entropy < bestEntropy then
                bestEntropy = entropy, bestDataType = i, bestSplitValue = S_i[j];
            end
        end
    end
end
split data into SL and SR according to the bestDataType and bestSplitValue;
create a branch node in the tree with bestDataType and bestSplitValue;
// check for termination and recursive calls
if |SL| <= 5 or all SL has same class or all SL has same variables then
    create a leaf node in the tree with the class with most occurrence;
else
    recursive call with SL as training set and the current tree as the decision tree;
end
if |SR| <= 5 or all SR has same class or all SR has same variables then
    create a leaf node in the tree with the class with most occurrence;
else
    recursive call with SR as training set and the current tree as the decision tree;
end
```

Algorithm 3: Decision Tree building

input : Validation set, V. Decision tree, T
output: Pruned decision tree with the lowest error rate on V

```
leaves = array of leave nodes;
bestError = error rate of T on V;
while |leaves| > 0 do
    error_P = error rate if parent(leaves[0]) = leaf with P;
    if error_P < bestError then
        bestError = error_P;
        T = set parent(leaves[0]) to leaf node with P;
        leaves append parent(leaves[0]);
    end
    error_N = error rate if parent(leaves[0]) = leaf with N;
    if error_N < bestError then
        bestError = error_N;
        T = set parent(leaves[0]) to leaf node with N;
        leaves append parent(leaves[0]);
    end
    leaves pop index 0;
end
```

Algorithm 4: Decision Tree pruning

The decision tree algorithm then only differs in subsampling m variables at each split and building a complete tree without pruning. The number of variables used, m is typically $\sqrt{p}$ where p is the number of variables in the data. Three variables at each split and nine trees to classify is chosen to train the QRAAT datasets.

input : A labeled training set, S.
output: Resulting forests

```
set forests = empty array;
for i from 0 to 9 do
    B = Bootstrap |S| samples from S;
    /* modified decision tree building is the original decision tree
       building (algorithm 3) with sampled variables at each split and the
       terminate condition changed form 5 observations to 1 observation.
       All else stay the same.                                          */
    T_i = tree built with modified decision tree building and dataset B;
    forests append T_i;
end
```

Algorithm 5: Random Forests trainer

2.3 Support Vector Machine

Support Vector Machine (SVM) is a method that uses a hyperplane to separate two classes. The hyperplane is calculated by the finding the Lagrange multipliers that maximize the Lagrangian dual problem subject to the constraints and the KKT conditions. The simplest way to solve this optimization problem is using Platt's sequential minimal optimization (SMO). The algorithm tries

input : An observation X with unknown class
output: Class determined by the model

set class_P = 0 and class_N = 0;
for *i from 0 to 9* **do**
    class = class determined by traverse forests[i];
    if *class == P* **then**
        class_P += 1;
    else
        class_N += 1;
    end
end
if *class_P > class_N* **then**
    return P;
else
    return N;
end

Algorithm 6: Random Forests classifier

to optimize two multipliers at a time while setting all other variables constant. When optimizing two variables with the conditions, such optimization becomes a quadratic function. Hence, both multipliers can be determined in constant time. The rest of algorithm is all about finding the two best multipliers to optimize in order to converge fastest after each step. This project has used the SVC package in scikit-learn to solve the optimization problem due to its more superior than the SMO implementation in the run time with the QRAAT datasets.

Hyperplane equation:

$$f(x) = \sum_{i=1}^{l} \alpha_i y_i k(x, x_i) + \beta_0$$

Classification:

$$class(x) = sign(f(x))$$

Lagrange Dual Problem:

$$\max_{\alpha} W(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j k(x_i, x_j) \alpha_i \alpha_j,$$
$$0 \leq \alpha_i \leq C \quad \forall i,$$
$$\sum_{i=1}^{l} y_i \alpha_i = 0$$

KKT Conditions ($\forall i$):

$$\alpha_i = 0 \Rightarrow y_i f(x_i) \geq 1$$
$$0 < \alpha_i < C \Rightarrow y_i f(x_i) = 1$$
$$\alpha_i = C \Rightarrow y_i f(x_i) \leq 1$$

Despite solving the optimization problem to obtain the hyperplane, there are two parameters to tweak in SVM. One would be the constant C which determines the width of the margin. Another would be the kernel parameter, γ to determine the most suitable kernel shape (radial basis functoin kernel is used in this project). The standard way to find the best C and γ values is to do a coarse grid search on different values of C and γ combinations, then do a fine grid search to narrow down the neighborhood of the values. When calculating with one set of parameters, one would typically do a 3-fold cross-validation to acquire the error rate for this set of parameters. After all combinations of parameters are trained, one would pick the C and γ with the lowest error rate and use these parameters to train the entire dataset to obtain the final model. Due to the computation complexity from the amount of data, this project only did a coarse search with C $\in \{2^{-5}, 2^{-2}, ..., 2^{13}\}$ and $\gamma \in \{2^{-15}, 2^{-12}, ..., 2^{3}\}$. In addition, the error rate of a hold out method with 20% of data is used instead of the error rate from a 3-fold cross-validation.

Notice that the amount of Lagrange multipliers needed to optimize the Lagrangian dual problem is linearly dependent to the amount of training observations. A big dataset with more than few thousands of observations will be computationally infeasible to train with SVM. This is even more so if cooperate with 10-fold cross-validation for final error rate and grid search for the best parameters. To reduce the training time, one should only feed the smallest amount of data that can represent the entire dataset. One way to solve this problem is to do a k-means clustering and use these k-means as the training set for SVM. Another way with much less computational effort is to use the technique of bagging from implementing random forests. The main idea is to bootstrap enough training data to represent the dataset while keeping the training set small. A bootstrap of one thousand observations is used to train the SVM in the implementation.

3 Evaluation

After each algorithm is implemented, the next step is to determine the best model to use in the QRAAT system. In order to fairly access the error rate throughout different methods, one should use k-fold cross-validation to evaluate. In this section, 10-fold cross-validation is chosen as the evaluation method and each dataset is split into ten nearly equally sized blocks in advance. Provided a dataset, the i^{th} block is used as the validation set and the rest 9 blocks as the training set. The training set is used to train the model and then the model is evaluated against validation set. During evaluation, each of false positive rate, false negative rate, and overall error rate of the model will be recorded. After repeating this procedure ten times, the calculated mean and standard deviation of each false positive rate, false negative rate, and overall error rate will be used to determine the performance of the method.

The result is organized into eight separate tables. Tables 1 to 4 are Manual Labeling with deployments 57, 60, 61, and 62 respectively. Tables 5 to 8 are Likelihood Labeling with deployments 57, 60, 61, and 62 respectively. Each tables has columns of method, mean and standard deviation of false positive rate, mean and standard deviation of false negative rate, and mean and standard deviation of overall error rate.

There are 7 methods being evaluated in each table. Bandwidth filter is the current deployed method in the QRAAT system to filter out the noise. It is hard coded to filter out observations with band3 > 450 or band10 > 900. EST score filter calculates a score for each observation and filter observations by a score threshold. It uses the bandwidth filter as the first layer to do a locally weighted regression on each of the variables. It then denote a score as the distance from this regression in local standard deviation to each variable. The sum of the scores from all variables are then used to determined the class of the observation. NBC is naive bayes classifier with the

input : A labeled training set, S.
output: Lagrangian multiplers, α's. Model constant, b. RBF parmeter, γ.

```
// finding the best C and gamma using grid search
set bestC = 0, bestGamma = 0, and bestErrorRate = 1;
set C = [2^-5, 2^-2, ..., 2^13] and gamma = [2^-15, 2^-12, ..., 2^3];
for i in C do
    for j in gamma do
        validationSet = 20% of S;
        trainingSet = the rest 80% of S;
        if |trainingSet| > 1000 then
            trainingSet = bootstrap 1000 observations;
        end
        model = SVM trained with trainingSet as data, i as C, and j as gamma;
        errorRate = error rate of model applied to validationSet;
        if errorRate < bestErrorRate then
            bestC = i;
            bestGamma = j;
            bestErrorRate = errorRate;
        end
    end
end
// train the model with best C and gamma
if |S| > 1000 then
    S = bootstrap 1000 observations;
end
model = SVM trained with S as data, bestC as C, and bestGamma as gamma;
return α's and b from model and bestGamma;
```

Algorithm 7: Support Vector Machine trainer

input : An observation X with unknown class
output: Class determined by the model

```
set f = b;
for i in α do
    K = rbf kernel calculated using data corresponds to i, X, and bestGamma;
    f += i*y[i]*K;
end
if f > 0 then
    return P;
else
    return N;
end
```

Algorithm 8: Support Vector Machine classifier

assumption of all variables are gaussian. However, after careful examination of the distribution of each variable, discrete variables such as band3, band10, and frequency can be improved with mixed distribution to calculate the probabilities. Modified NBC is the model assuming band3, band10, and frequency are mixed distribution while keeping all other variables gaussian. Decision Tree, Random Forests, and SVM are standard algorithms with descriptions in the method section.

Table 1: *Manual Labeling: Deployment 57*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.04925	0.00067	0.00001	0.00001	0.01128	0.00015
EST Score Filter	0.29542	0.00174	0.00006	0.00002	0.06766	0.00048
NBC	0.04218	0.00076	0.00178	0.00028	0.01103	0.00021
Modified NBC	0.04446	0.00085	0.00030	0.00006	0.01041	0.00018
Decision Tree	0.00873	0.00075	0.32312	0.23560	0.25116	0.18156
Random Forests	0.00940	0.00078	0.00123	0.00007	0.00310	0.00008
SVM	0.06633	0.01269	0.06153	0.08859	0.06265	0.06568

Table 2: *Manual Labeling: Deployment 60*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.25081	0.00279	0.00000	0.00000	0.00785	0.00009
EST Score Filter	0.17012	0.00204	0.00050	0.00002	0.00580	0.00005
NBC	0.16115	0.02116	0.00747	0.00908	0.01228	0.00813
Modified NBC	0.17066	0.00206	0.00033	0.00005	0.00566	0.00006
Decision Tree	0.14406	0.00708	0.42270	0.14028	0.41400	0.13590
Random Forests	0.15113	0.00171	0.00064	0.00004	0.00535	0.00006
SVM	1.00000	0.00000	0.00000	0.00000	0.03128	0.00022

Table 3: *Manual Labeling: Deployment 61*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.29954	0.01224	0.00000	0.00000	0.13223	0.00526
EST Score Filter	0.92182	0.00679	0.00243	0.00143	0.40834	0.00658
NBC	0.14974	0.00909	0.13115	0.01862	0.13940	0.00987
Modified NBC	0.28355	0.01183	0.00235	0.00103	0.12650	0.00556
Decision Tree	0.09597	0.01542	0.65953	0.09608	0.41059	0.05007
Random Forests	0.14561	0.00873	0.06876	0.00664	0.10270	0.00506
SVM	0.37152	0.00910	0.03955	0.02912	0.18625	0.01692

Table 4: *Manual Labeling: Deployment 62*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.39254	0.00604	0.00000	0.00000	0.22867	0.00414
EST Score Filter	0.98687	0.00188	0.00060	0.00057	0.57516	0.00626
NBC	0.04305	0.00519	0.08417	0.01214	0.06018	0.00562
Modified NBC	0.07441	0.00611	0.00344	0.00525	0.04475	0.00424
Decision Tree	0.02704	0.00941	0.59759	0.18252	0.26545	0.07728
Random Forests	0.04079	0.00500	0.03350	0.00269	0.03776	0.00298
SVM	0.17537	0.07043	0.05139	0.02368	0.12347	0.03699

Table 5: *Likelihood Labeling: Deployment 57*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.45021	0.00220	0.00000	0.00000	0.17820	0.00091
EST Score Filter	0.59276	0.00124	0.00019	0.00003	0.23475	0.00071
NBC	0.43427	0.00219	0.00333	0.00023	0.17390	0.00089
Modified NBC	0.44659	0.00217	0.00091	0.00008	0.17732	0.00091
Decision Tree	0.03101	0.00067	0.45433	0.27024	0.28681	0.16340
Random Forests	0.01982	0.00066	0.02081	0.00031	0.02042	0.00036
SVM	0.35620	0.10955	0.05207	0.06065	0.17245	0.01601

Table 6: *Likelihood Labeling: Deployment 60*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.85769	0.00108	0.00006	0.00001	0.14098	0.00012
EST Score Filter	0.84252	0.00098	0.00068	0.00003	0.13900	0.00013
NBC	0.03302	0.00234	0.03235	0.00944	0.03246	0.00791
Modified NBC	0.08985	0.00356	0.00343	0.00041	0.01763	0.00067
Decision Tree	0.00540	0.00064	0.27986	0.07012	0.23476	0.05855
Random Forests	0.00653	0.00028	0.00083	0.00004	0.00177	0.00006
SVM	0.18109	0.00146	0.00000	0.00000	0.02976	0.00029

Table 7: *Likelihood Labeling: Deployment 61*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.35446	0.01603	0.00042	0.00042	0.17001	0.00904
EST Score Filter	0.92793	0.00633	0.00268	0.00153	0.44579	0.00945
NBC	0.20108	0.01541	0.18337	0.01662	0.19180	0.00939
Modified NBC	0.34285	0.01726	0.00344	0.00249	0.16603	0.00907
Decision Tree	0.09007	0.01366	0.44294	0.08030	0.27398	0.04140
Random Forests	0.15348	0.01141	0.10311	0.00928	0.12728	0.00870
SVM	0.37109	0.01147	0.03150	0.01137	0.19407	0.00850

Table 8: *Likelihood Labeling: Deployment 62*

	FP Rate		FN Rate		Overall Error Rate	
Method	Mean	SD	Mean	SD	Mean	SD
Bandwidth Filter	0.54189	0.00513	0.00561	0.00331	0.41839	0.00553
EST Score Filter	0.99046	0.00169	0.00248	0.00172	0.76292	0.00782
NBC	0.07243	0.00778	0.19488	0.01750	0.10065	0.00847
Modified NBC	0.13276	0.00789	0.00426	0.00337	0.10320	0.00688
Decision Tree	0.03000	0.00483	0.55081	0.10170	0.15010	0.02336
Random Forests	0.04694	0.00587	0.13700	0.01033	0.06771	0.00478
SVM	0.11067	0.01521	0.10279	0.04786	0.10891	0.00531

4 Conclusion

There are new findings after each method is evaluated. As the results of NBC come out, it shows the performance slightly better than the bandwidth filter in the system. With more research on the probability distribution of each variable, modified NBC reduced error rate even further. While Decision Tree shows the worst result of all implemented methods, Random Forests does significantly better than any of the other methods. Lastly, since SVM shows a similar error rate as NBC, Random Forests showed as the best method to use in the QRAAT system.

This paper first introduces the QRAAT system and the need of classification algorithm to improve the performance of the system. It labels data with two techniques. Likelihood labeling, which gives a solid definition of a pulse and a noise. Manual labeling, which determines a pulse by visually recognizing the data. Both techniques have its advantages and disadvantages, so all methods are trained and evaluated with both sets of labelings. Naive Bayes Classifier is the first attempt to solve this classification problem as it is one of the easiest algorithm to implement, train, and evaluate while giving respectably good accuracies. After further investigation, Naive Bayes Classifier was improved by associating mixed distributions with discrete variables. The next algorithm this paper describes is Decision Tree learning, which contains the detail of building and pruning the tree. While Decision Tree does not generate great accuracies, its extension to the Random Forests is the best method to be used in the QRAAT system. With bootstrapped data and variable sampling, classification with multiple trees greatly improves the accuracy of the model. The last algorithm attempted to solve this classification problem is the Support Vector Machine.

SVM uses hyperplane to separate one class from the other. The hyperplane is obtained by solving an optimization problem subject to multiple conditions and KKT conditions. SVM has issues with the run time to train huge amounts of data and the requirement of choosing training parameters. The first problem can be solved by bootstrapping small amounts of data as the training set, while the latter problem can be fixed by the grid search. Lastly, the paper describes evaluation method of 10-fold cross-validation and presents the result of each classification method. In conclusion, Random Forests is the best method to be used in the QRAAT system.

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