My Support Vector Machine Algorithm

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1 Selection

With the sheer amount of Machine Learning algorithms these days, it is a daunting thing to even decide upon one to pursue to its' core. Some appear to be complete black boxes when it comes to simply understanding the basics of them, whereas some can be easily comprehended but when it comes to the implementation can become very complex. An example of the latter, which I decided to focus on is the Support Vector Machine Learning Algorithm. At its' simplest form it aims to separate objects into two different classes by drawing a line between their feature space. For 2 features we can use the word line, however for 3 features we use the word plane and for objects with more than 3 features we use the term hyper-plane , for the remainder of the text I will use these words interchangeably. The Support Vector Machine receives its name from how the plane is formulated. The algorithm aims to bisect the data into the two classes as optimally as possible, support vectors refer to the closest points (vectors) to the plane separating the two classes. The plane is aimed to be placed between the two vectors of different classes such that the perpendicular distance between the support vectors and the plane is maximised, this distance is called the margin giving us the ideal plane called the large-margin hyper-plane [1].

2 How does the SVM work

The challenging part in formulating an SVM is finding this large-margin hyper-plane, it is an optimisation problem which is quite mathematically intense. From algebra we know any hyper-plane can be represented in the form $\mathbf{w} \cdot \mathbf{x} + b$ where $x = \{x_1, x_2....x_n\}$ for n features of the data and where $w = \{w_1, w_2....w_n\}$ for the weights assigned to each x variable. For a vector $\mathbf{X}$ we know $\mathbf{w} \cdot \mathbf{X} + b = 0$ if $\mathbf{X}$ lies on the plane ($\mathbf{w} \cdot \mathbf{X} + b \neq 0$ if X is not on the plane). In order to setup our formulation of this problem we must relabel our target classes as 1 and -1 respectively and so can define the hypothesis function where if $\mathbf{w} \cdot \mathbf{X} + b \geq 0$ label the point +1 and if $\mathbf{w} \cdot \mathbf{X} + b < 0$ label the point -1 (graphically, if point i lies on or above/right of the plane it will be classed as +1, else classed as -1) Taken as given that we have a hyper-plane which separates our classes, then in order to find the optimal hyper-plane , we define the geometric Margin of the data-set as $M = \min_{i=1...n} y_i(\frac{\mathbf{w}}{\|w\|} \cdot \mathbf{X} + \frac{b}{\|w\|})$ [2] where $y_i \in \{-1, 1\}$ This formula represents finding a training point which has the minimum distance from our hyper-plane. The formula in brackets represents the perpendicular distance from the hyper-plane which is divided by the norm of w which ensures scale in-variance for each feature, this equation is then multiplied by the class of each point which ensure the resulting value to be always positive (if class -1 then $y_i(\frac{\mathbf{w}}{\|w\|} \cdot \mathbf{X} + \frac{b}{\|w\|})$ will go to -(-) = + and vice versa for +1). The formula is computed for all training points and the minimum is chosen as our support vector. If we consider s unique hyper-planes h each with their own value of M, then the large-margin hyper-plane is defined as the hyper-plane with the maximum value of M. By finding the minimum distance from the support vector to the plane and maximise this distance, the idea is that it should give more leverage for future points to be predicted which would fall in around the hyper-plane. The problem is now how to select the optimal hyper-plane, or at least a decent initial guess in order to apply the optimisation criterion, else the value for the number of hyper-planes s could be incredibly large. Finding b and $\mathbf{w}$ for our hyper-plane is the difficult task which requires a lot of mathematical manipulation involving Lagrangian optimisation, Karush-Kuhn-tucker multipliers and the Wolfe duel problem. For this I refer the reader to the incredibly helpful article by Written by Shuzhan Fan on May 7, 2018 [2] which deals with this heavy task. For my implementation of the algorithm I utilised some important results from Fan's derivation . Once the optimal hyper-plane is found , new points can now be predicted using the aforementioned hypothesis function. This algorithm can also be extended to a multi-class algorithm by utilising multiple binary SVM's and a one-vs-all / one-vs-rest [3] approach implemented to complete the multi-class classification (more on this in implementation). With the overall structure of the algorithm in place we can now move on to my approach of implementing this powerful machine learning technique.

3 Implementation

3.1 Binary Class

I choose to utilise Python for the task of implementing this machine learning algorithm making use of the built in class function to define my SVM, the algorithm would work on both python and java with minimal conversion, however I choose python over the latter to avoid constant declaration of variable type and make use of Python's pandas library to visualise the data easily. I include all of my code in the appendix attached with this text however here I go over my overall approach and design choice. I made two python classes, one for the main SVM algorithm and another to extend this class to a multi-class classification SVM. As with many learning algorithms, the SVM contains a number of hyper parameters which are user tuned to each individual problem, These hyper parameters are included in the initialisation of the class , which include {regularization parameter ,number of iterations, kernel, c , d, gamma} with the addition of one extra parameter in the multi-class SVM class , namely comparison method. Most of these hyper parameters include a default, which have been chosen to usually perform well (for in depth overview on these parameters see code comments). The SVM class has a train method which takes a list of vectors of features X and a list of the classes of each point y where $y \in \{-1, 1\}$. This method finds the optimal hyper-plane by first finding the maximum margin by solving $\max_\alpha \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i \cdot x_j)$ where $0 \leq \alpha_i \leq C$ and $\sum_{i=1}^{n} \alpha_i y_i = 0$. [2] In the implementation, the α values are chosen at random in the given range where C refers to the user specified Regularisation parameter and where K is the user-defined Kernel. This maximisation is run over the user defined number of iterations to find the maximum possible margin (note I was unsuccessful in implementing the second boundary condition on alpha into my code. I considered the alpha values to take on the span of y, but could not find a suitable method to implement this). After the number of iterations the alpha vector which yields the largest margin is stored and used to calculate w s.t. $w = \sum_{i=1}^{n} \alpha_i y_i x_i$. We can then in turn solve $b = \frac{1}{S} \sum_{i=1}^{S} (y_i - w \cdot x)$. where S is the number of points in the training set which lie in the range of the maximum margin of the hyper-plane (not taking its intercept value b into account). Once solved we have our large-margin hyper-plane and can now predict future points using the aforementioned prediction hypothesis.

3.2 Multi-Class

The multi-class SVM python class , when initiated also initiates the made binary class SVM , where the user specifies whether a one-vs-one or one-vs-rest approach is to be utilised to compare these binary classes. The training method for Multi-Class algorithm accepts the same list of vectors of features X as the Binary but now the target variable y can be in any format (not just 1,-1) e.g. String, Double etc. . The algorithm takes each class and maps it to an integer class, where if there are m classes, there will now be a list of classes 1 through to m. Depending on which comparison method is chosen the algorithm learns on a "one vs rest" or "one vs one" basis. In one verses rest, the selected class is assigned a value of +1 and the the rest grouped into the -1 category, this is repeated for each class. The one vs one method can take substantially longer as each class is compared against every other class, omitting the points of the training set which are any other class than the two being compared, requiring more data manipulation and SVM computations than the former method. Specifically the "one vs rest" does m calculations and $\frac{m(m-1)}{2}$ for the "one vs one" method. For both methods , the hyper planes for each binary comparison are stored for predictive use. When a new point is to be predicted, the point is passed through each binary SVM and based on what each binary SVM predicts, a vote is tallied up and the class which receives the most votes is what the point is predicted as. This method is defined as the max wins voting strategy [4].

4 Evaluation

Firstly the data must be pre-processed, and one thing that the SVM algorithm benefits from is scaling the data, of which I included a method in my SVM class to do so, with an option for scaling the data between 0 and 1 or using z-normalisation to give the data a mean of 0 and standard deviation of 1. Using the data-set beer.txt the entries are divided into $\frac{2}{3}$ for training and $\frac{1}{3}$ for testing purposes. Using the well known library scikit-learn I implemented their SVC learning algorithm for comparison purposes with my own, also using their built in scaler function to have a separate prepossessing step as well. I compared both the linear and RBF kernel approaches between both mine and the scikit-learn program, having done a small amount of tuning of my hyper parameters. Performing a 10-fold cross validation on the small available data set I can now produce the results of the evaluation seen in the appendix.

Achieving an average accuracy of 90% for the linear classifier and a mere 35% for the multi class classifier, my SVM performed significantly worse than the developed one, which was to be expected as the Scikit-learn SVC was most likely worked on over many hours through many people and iterations. One flaw with my implementation is the choice of α being randomly chosen between a range, this leads the performance of the algorithm very much up to chance. One other condition which I could not ensure satisfaction for was $\sum_{i=1}^{n} \alpha_i y_i = 0$ which may have hindered the performance of my algorithm further. As the multi class SVM is highly faulted, possible improvements could be made to the voting system, perhaps including a weighted / probabilistic voting strategy [4].

In summary, the algorithm is quite robust and user friendly for specifying user defined hyper parameters. The binary classifier performs rather well however the multi-class algorithm could use tweaking, such possibilities I already suggested above.

References

[1] Nikita Sharma: Jan 31 : Understanding the Mathematics behind Support Vector Machines https://heartbeat.fritz.ai/understanding-the-mathematics-behind-support-vector-machines-5e20243d64d5

[2] Shuzhan Fan: May 7, 2018: Understanding the mathematics behind Support Vector Machines https://shuzhanfan.github.io/2018/05/understanding-mathematics-behind-support-vector-machines/

[3] Paul G. Allen School course CSE446: Machine Learning Week 7: Multiclass Support Vector Machines

https://courses.cs.washington.edu/courses/cse446/16sp/svm_3.pdf

[4] DEHUI WU*, CHAO LI, JUN CHEN, DEHAI YOU and XIAOHAO XIA: International Journal of Performability Engineering, Vol. 10, No. 2, March 2014 : A Novel Multi-class Support Vector Machines Using Probability Voting Strategy and Its Application on Fault Diagnosis of Gearbox

https://paris.utdallas.edu/IJPE/Vol10/Issue02/pp.173-186%20Paper%206%20IJPE%20471.13%20Wu.pdf

5 Appendix

LukeMurphy_Assignment2

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Support Vector Machine

[1]:
```
import numpy as np
from collections import Counter # used to count number of occurrences of each␣
↪class in training set.


#First Define a class where we can store all functions for the Binary␣
↪SupportVectorMachine.
class SupportVectorMachine:
    #Specify all variables required to initialise the class, some of which have␣
↪default values

    #regularization_parameter, controls how hard or soft the margin calulation␣
↪is. The higher the value the more hard
    #  the margin calculation is which doesn't tolerate outliers and will only␣
↪work with linearly seperable data.
    #  small values makes the margin wider allowing for more noisy data.

    #number_iterations, speficies how many times the algorithm is run to␣
↪maximise the margin, the higher means higher accuracy,
    #  but longer computation time.


    #Kernel, takes values "linear", "polynomial" and "RBF" where RBF is the␣
↪default
    # This controls the activation function in the margin calculation, where␣
↪the formulae can be viewed below.
    # specifies what the plane will resemble , a line for linear, a polynomal,␣
↪etc.


    #c and d which specify parameters in polynomial kernel, d is the degree of␣
↪the polynomial and c is the contant to be added.

    #gamma which relates to RBF kernel
```

```
    def __init__(self,regularization_parameter ,number_iterations,Kernel =␣
↪None, c= 1,d=2,gamma = 1):
        #Using the self keyword so the variables can be used in different␣
↪methods in the class
        self.num_iter = number_iterations
        self.C = regularization_parameter
        self.c = c
        self.d = d
        self.gamma = gamma

        if Kernel == "linear":
            self.K = self.linear_kernel
        elif Kernel == "polynomial":
            self.K = self.polynomial_kernel
        else:
            self.K = self.RBF_Kernel

    #The different Kernels avaiable

    def linear_kernel(self,x,y):
        return sum([x[i]*y[i] for i in range(self.number_of_features)])

    def polynomial_kernel(self,x,y):
        c = self.c
        d = self.d
        return sum([(x[i]*y[i]+c)**d for i in range(self.number_of_features)])

    def RBF_Kernel(self,x,y):
        gamma = self.gamma
        return np.exp(-gamma*sum([(x[i]-y[i])**2 for i in range(self.
↪number_of_features)]))

    #A self contained normalisation function to scale the data to either [0,1]␣
↪range or zero mean 1 variance.

    def normalise(self,data,method = "z-normalisation"):
        normalised_data =[point for point in data]

        number_of_points = len(data)
        number_of_features = len(data[0])

        if method == "zero-to-one":
            for i in range(number_of_features):
                min_feature_value = np.min([data[j][i] for j in␣
↪range(number_of_points)])
                max_feature_value = np.max([data[j][i] for j in␣
↪range(number_of_points)])
```

```
            for j in range(number_of_points):
                normalised_data[j][i] = (data[j][i] - min_feature_value)/
↪(max_feature_value-min_feature_value)
        else:
            for i in range(number_of_features):
                mean_of_feature = np.mean([data[j][i] for j in␣
↪range(number_of_points)])
                stdev_of_feature = np.std([data[j][i] for j in␣
↪range(number_of_points)])
                for j in range(number_of_points):
                    normalised_data[j][i] = (data[j][i] - mean_of_feature)/
↪stdev_of_feature


        return normalised_data

    def train(self,data,target_var):
        #data is a nested list corresponding to the features of each point
        #target_var must have only two classes and be represented as 1 and -1␣
↪respectively

        #store these values locally
        number_of_points = len(data)
        number_of_features = len(data[0])
        #..and globally (within the class)
        self.number_of_points = number_of_points
        self.number_of_features = number_of_features

        #We wish to maximise the margin, so we initialise a margin of 0 which␣
↪will be overwritten through iteration.
        max_margin = -99999

        #Here the user specified variable number_iterations is utilised to␣
↪train the model over however many iterations.
        for n in range(self.num_iter):
            #alpha known as a "slack" variable is a random float value between␣
↪0 and the user specified value Regularization Parameter
            #This generally specifies how the SVM will handle errors
            alpha = [rand.uniform(0,self.C) for i in range(number_of_points)]
            margin = 0   #initilse the current margin

            #Calculating the max margin iteratively
            for i in range(number_of_points):
                for j in range(number_of_points):
                    margin += alpha[i] - (1/
↪2)*alpha[i]*alpha[j]*target_var[i]*target_var[j]*self.K(data[i],data[j])
```

```
            if margin> max_margin:
            #if the new margin has exceeded the previous max, we store it and the alpha vectore
                max_margin = margin
                alpha_star = alpha

        #Now solve for w vector
        w = np.sum([[alpha_star[i]*target_var[i]*x for x in data[i]] for i in range(len(data))], axis = 0)

        #x_star which is the list of points which qualify as support vectors to the hyperplane
        x_star = [data.index(x) for x in data for i in range(number_of_features) if sum([x[i]*w[i]]) <= max_margin]
        S = len(x_star)
        #Now calculate the intercept b
        b = sum([target_var[x_star[i]] -sum([w[j]*data[x_star[i]][j] for j in range(number_of_features) ]) for i in range(S)])/S

        self.b = b
        self.w = w


    def predict(self,point):

        hypothesis = sum([point[i]*self.w[i] for i in range(self.number_of_features)]) + self.b
        if hypothesis >= 0:
            return 1
        else:
            return -1

    #method to return the plane of the SVM
    def get_plane(self):
        plane = [self.w,self.b]
        return plane


class MCSupportVectorMachine:
    #Multi-class SupportVectorMachine
    def __init__(self,regularization_parameter ,number_iterations,Kernel = None, c= 1,d=2,gamma = 1,comparison_method = None):
        #Same input parameters as binary class SVM with one addition
        #Comparison_method takes values "one_v_one" and "one_v_all" with one_v_all being the default
        #Import binary SVM with given parameters
```

```
        self.mySVM = SupportVectorMachine(regularization_parameter␣
↪,number_iterations, Kernel, c,d,gamma)
        self.compare = comparison_method

    def normalise(self,data,method = "zero-to-one"):
        return self.mySVM.normalise(data,method)


    def train(self,data,target_var):
        #data is a nested list corresponding to the features of each point
        #target_var can have any amount of classes and be represented by any␣
↪type e.g. String, Double etc.

        classes = list(set(target_var))  #get list of unique classes in␣
↪training set
        num_classes = len(classes)  #number of classes there are
        num_points = len(data) #number of data points
        #Here we take each class any map it to an integer starting from 1
        classes_translated = [i for i in range(1,num_classes+1)]
        #With a corresponding integer for every class, we now map all of the␣
↪target variables to their respective integer values
        target_var_translated = [classes_translated[j] for j in␣
↪range(num_classes) for i in range(num_points) if target_var[i] == classes[j]]

        mySVM = self.mySVM #import initialized SVM from _init_

        planes = []    #To store each plane for binary classification to use␣
↪for multi-classification
        tries = [i for i in classes_translated]  #Creat a copy of the list of␣
↪integer classes called tries
        if self.compare == "one_v_one":
            while len(tries)>1:
            # this will iterate through s.t. every class with be compared with␣
↪every other class
                for itr1 in range(len(tries)):
                    current_class = tries.pop(0) #Remove and store the class to␣
↪be compared against every other
                    for itr2 in range(len(tries)): #loop through the remaining␣
↪classes in tries
                        class_to_compare = [current_class,tries[itr2]] #the two␣
↪classes being compared
                        #Remove all data point which are not of the current two␣
↪classes
                        sub_data = [data[i] for i in range(num_points) if␣
↪target_var_translated[i] in class_to_compare]
```

```
                        sub_target = [target_var_translated[i] for i in range(num_points) if target_var_translated[i] in class_to_compare ]
                        new_target = [1 if sub_target[i] == current_class else -1 for i in range(len(sub_target))]
                        #train a binary SVM on these two classes
                        mySVM.train(sub_data, new_target)

                        class_to_compare[1] = [class_to_compare[1]]  #Storing this as a list to be consistent with the
            #one_vs_rest approach which has the second elt of class to compare as a list. noted by **
                        class_to_compare.append(mySVM.get_plane())

                        planes.append(class_to_compare) #Store the two classes compared and the plane dividing each


        else:   #One_vs_rest approach
            for itr in range(len(tries)):
                current_class = tries[itr]
                other_classes = [otherClass for otherClass in classes_translated if otherClass != current_class]

                class_to_compare = [current_class,other_classes] #**
            #now map the current_class label to +1 and every other to -1
                new_target = [1 if target_var_translated[i] == current_class else -1 for i in range(len(target_var_translated))]
                mySVM.train(data, new_target)
                class_to_compare.append(mySVM.get_plane())
                planes.append(class_to_compare)

        #Store these values globally for the predict method to use them
        self.planes = planes
        self.classes = classes
        self.classes_translated = classes_translated
        self.number_of_features = len(data[0])
        self.target_var = target_var

    def predict(self,point):
        classes = self.classes
        classes_translated = self.classes_translated
        votes = [0] * len(classes) # Votes to be awarded for each class

        for plane in self.planes:
```

```
            class_to_compare = [plane[0],plane[1]] #taking each binary␣
↪classifier one by one
            w = plane[2][0]
            b = plane[2][1]
            hypothesis = sum([point[i]*w[i] for i in range(self.
↪number_of_features)]) + b
            if hypothesis >= 0:
                #award one vote to the correct class
                votes[classes_translated.index(class_to_compare[0])] += 1
                for all_classes in class_to_compare[1]:
                    votes[classes_translated.index(all_classes)] -= 1 #remove a␣
↪vote from (all) the incorrect class(s)
            else:
                votes[classes_translated.index(class_to_compare[0])] -= 1
                for all_classes in class_to_compare[1]:
                    votes[classes_translated.index(all_classes)] += 1

        max_votes = max(votes) # find which class has the max vote
        classes_with_max_vote = [votes.index(mv) for mv in votes if mv ==␣
↪max_votes]

        count = Counter(self.target_var)

        #If there is a draw, return the most common class out of the equal␣
↪voted classes
        if len(classes_with_max_vote) > 1:
            oldcount=0
            for clas in classes_with_max_vote:
                newcount = count[classes[clas]]
                if newcount > oldcount:
                    oldcount = newcount
                    winner = clas
        else:
            winner = votes.index(max_votes)  # find the index of this max value


        return classes[winner] #return the class with most votes
```

[2]:
```
import random as rand
import pandas as pd
rand.seed(100) #setting the seed so our results are consistent for comparison␣
↪purposes

#In this chunk I test the performance of the Binary SVM

beer = pd.read_csv('beer.txt', sep="\t", header=None) #import the data
```

```
#label the data
beer.columns = ["calorific_value", "nitrogen", "turbidity", "style", "alcohol",␣
↪"sugars", "bitterness", "beer_id", "colour", "degree_of_fermentation"]

beer = beer[beer["style"] != "lager"] # removing lager class from target␣
↪variable
beer["style"] == "lager"
beer = beer.reset_index()
# now set ale = 1 and stout = -1
target = np.ones(len(beer))
for i in range(len(target)):
    if beer['style'][i] == 'stout':
        target[i] = -1

beer = beer.drop(columns=['index','style','beer_id']) #removing unnecessary␣
↪columns from our feature list

mySVM = SupportVectorMachine(2,1000,Kernel = 'linear') #initiate the Binary SVM

beerdata = np.array(mySVM.normalise(beer.values,"zero-to-one"))

#divide the data into 1/3 test and 2/3 train
number_of_test_points = int(len(target)/3)
rows_for_test = sorted(rand.sample(range(len(target)), number_of_test_points))

test_data = beerdata[rows_for_test].tolist()
test_target = target[rows_for_test].tolist()
train_data = np.delete(beerdata,rows_for_test,axis =0).tolist()
train_target = np.delete(target,rows_for_test,axis =0).tolist()



mySVM.train(train_data,train_target)

pred = [mySVM.predict(point) for point in test_data]
np.mean([pred[i] == test_target[i] for i in range(len(pred))]) #checking the␣
↪score of the predicticted output
```

[2]: 0.9393939393939394

[2]:
```
rand.seed(100)

#In this chunk I test the performance of the Multi-class SVM

beer = pd.read_csv('beer.txt', sep="\t", header=None)
beer.columns = ["calorific_value", "nitrogen", "turbidity", "style", "alcohol",␣
↪"sugars", "bitterness", "beer_id", "colour", "degree_of_fermentation"]
```

```
#seperate data in feature list and target
target =beer['style'].values
beer = beer.drop(columns=['style','beer_id'])


mySVM = MCSupportVectorMachine(2,1000, comparison_method = "one_v_one", Kernel␣
↪= "linear")
beerdata = np.array(mySVM.normalise(beer.values))

number_of_test_points = int(len(target)/3)
rows_for_test = sorted(rand.sample(range(len(target)), number_of_test_points))

test_data = beerdata[rows_for_test].tolist()
test_target = target[rows_for_test].tolist()
train_data = np.delete(beerdata,rows_for_test,axis =0).tolist()
train_target = np.delete(target,rows_for_test,axis =0).tolist()

mySVM.train(train_data,train_target)
pred = [mySVM.predict(point) for point in test_data]
print("z_normalised score =  " + str(np.mean([pred[i] == test_target[i] for i␣
↪in range(len(pred))])))

beerdata = np.array(mySVM.normalise(beer.values,"zero-to-one"))

number_of_test_points = int(len(target)/3)
rows_for_test = sorted(rand.sample(range(len(target)), number_of_test_points))

test_data = beerdata[rows_for_test].tolist()
test_target = target[rows_for_test].tolist()
train_data = np.delete(beerdata,rows_for_test,axis =0).tolist()
train_target = np.delete(target,rows_for_test,axis =0).tolist()

mySVM.train(train_data,train_target)
pred = [mySVM.predict(point) for point in test_data]
print("zero-to-one score = "  + str(np.mean([pred[i] == test_target[i] for i in␣
↪range(len(pred))])))

beerdata = beer.values

number_of_test_points = int(len(target)/3)
rows_for_test = sorted(rand.sample(range(len(target)), number_of_test_points))

test_data = beerdata[rows_for_test].tolist()
test_target = target[rows_for_test].tolist()
train_data = np.delete(beerdata,rows_for_test,axis =0).tolist()
train_target = np.delete(target,rows_for_test,axis =0).tolist()
```

```
SVM = MCSupportVectorMachine(3,1000, comparison_method = "one_v_one", gamma = 3␣
↪)
SVM.train(train_data,train_target)
pred = [mySVM.predict(point) for point in test_data]
print("Not Normalised score = "  + str(np.mean([pred[i] == test_target[i] for i␣
↪in range(len(pred))])))


#output predicted and actual values to a file

output = pd.DataFrame({'Predicted': pred,
                       'Actual': test_target})
output.to_csv(index=False)
```

```
z_normalised score =  0.3137254901960784
zero-to-one score = 0.49019607843137253
Not Normalised score = 0.29411764705882354
```

[ ]:
```
rand.seed(100)

#iterating through different hyper parameters to fine tune the SVM

beer = pd.read_csv('beer.txt', sep="\t", header=None)
beer.columns = ["calorific_value", "nitrogen", "turbidity", "style", "alcohol",␣
↪"sugars", "bitterness", "beer_id", "colour", "degree_of_fermentation"]

target =beer['style'].values
beer = beer.drop(columns=['style','beer_id'])

beerdata = np.array(mySVM.normalise(beer.values))

number_of_test_points = int(len(target)/3)
rows_for_test = sorted(rand.sample(range(len(target)), number_of_test_points))

test_data = mySVM.normalise(beerdata[rows_for_test].tolist())
test_target = target[rows_for_test].tolist()
train_data = mySVM.normalise(np.delete(beerdata,rows_for_test,axis =0).tolist())
train_target = np.delete(target,rows_for_test,axis =0).tolist()

regularization_parameter_ = [i for i in range(1,5)]
Kernel_ = ["linear","polynomial","RBF"]
c_ = [i for i in range(1,3)]
gamma_ = [i for i in range(1,6)]
d=2

for c__ in c_:
```

```
    mySVM = MCSupportVectorMachine(regularization_parameter =1␣
↪,number_iterations = 500,Kernel = "polynomial", c= c__,d=d,gamma =␣
↪1,comparison_method = None)
    mySVM.train(train_data,train_target)
    pred = [mySVM.predict(point) for point in test_data]
    m = np.mean([pred[i] == test_target[i] for i in range(len(pred))])
    print("polynomial score with c = " + str(c__) + " and d = " + str(d) + " =␣
↪" + str(m))

for C in regularization_parameter_:

    mySVM = MCSupportVectorMachine(regularization_parameter =C␣
↪,number_iterations = 500,Kernel = "linear",gamma = 1,comparison_method =␣
↪None)
    mySVM.train(train_data,train_target)
    pred = [mySVM.predict(point) for point in test_data]
    m = np.mean([pred[i] == test_target[i] for i in range(len(pred))])
    print("linear score with Regularization parameter = " + str(C) + " = " +␣
↪str(m))


for C in regularization_parameter_:
    for gam in gamma_:
            mySVM = MCSupportVectorMachine(regularization_parameter =C␣
↪,number_iterations = 500,Kernel = None,gamma = gam,comparison_method = None)
            mySVM.train(train_data,train_target)
            pred = [mySVM.predict(point) for point in test_data]
            m = np.mean([pred[i] == test_target[i] for i in range(len(pred))])
            print("RBF score with gamma = " + str(gam) + "and Regularization␣
↪parameter = " + str(C) + " = " + str(m))
```

```
polynomial score with c = 1 and d = 2 = 0.37254901960784315
polynomial score with c = 2 and d = 2 = 0.37254901960784315
linear score with Regularization parameter = 1 = 0.39215686274509803
linear score with Regularization parameter = 2 = 0.37254901960784315
linear score with Regularization parameter = 3 = 0.37254901960784315
linear score with Regularization parameter = 4 = 0.37254901960784315
RBF score with gamma = 1and Regularization parameter = 1 = 0.39215686274509803
RBF score with gamma = 2and Regularization parameter = 1 = 0.35294117647058826
RBF score with gamma = 3and Regularization parameter = 1 = 0.35294117647058826
RBF score with gamma = 4and Regularization parameter = 1 = 0.35294117647058826
RBF score with gamma = 5and Regularization parameter = 1 = 0.39215686274509803
RBF score with gamma = 1and Regularization parameter = 2 = 0.35294117647058826
RBF score with gamma = 2and Regularization parameter = 2 = 0.39215686274509803
RBF score with gamma = 3and Regularization parameter = 2 = 0.37254901960784315
RBF score with gamma = 4and Regularization parameter = 2 = 0.35294117647058826
```

```
RBF score with gamma = 5and Regularization parameter = 2 = 0.37254901960784315
```

[6]:
```python
from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

#Importing scikitlearn SVC as a base to compare
#Using RBF kernel for comparison
clf = make_pipeline(StandardScaler(), SVC(gamma='auto')) #This will scale the␣
↪data then use
mySVM = MCSupportVectorMachine(3,1000, comparison_method = "one_v_one", gamma =␣
↪3 )



my_preprocessed_data = np.array(mySVM.normalise(beerdata))

RBF_results = []
RBF_comparison = []
for cross_validation in range(10):
    rand.seed(7*cross_validation + 1) # a constant random seed each iteration␣
↪for comparison and tracing purposes

    number_of_test_points = int(len(target)/3)
    rows_for_test = sorted(rand.sample(range(len(target)),␣
↪number_of_test_points))


    test_target = target[rows_for_test].tolist()
    train_target = np.delete(target,rows_for_test,axis =0).tolist()

    clf_test_data = beerdata[rows_for_test].tolist()
    clf_train_data = np.delete(beerdata,rows_for_test,axis =0).tolist()

    my_test_data = my_preprocessed_data[rows_for_test].tolist()
    my_train_data = np.delete(my_preprocessed_data,rows_for_test,axis =0).
↪tolist()


    clf.fit(clf_train_data,train_target)
    clf_predict = [clf.predict([point]) for point in clf_test_data]
    clf_predict = [clf_predict[i][0] for i in range(len(clf_predict))]

    mySVM.train(my_train_data,train_target)
    my_predict = [mySVM.predict(point) for point in my_test_data]
```

```
    clf_score = np.mean([clf_predict[i] == test_target[i] for i in␣
 ↪range(len(pred))] )
    my_score = np.mean([my_predict[i] == test_target[i] for i in␣
 ↪range(len(pred))])

    RBF_results.append([my_predict,clf_predict,test_target])
    RBF_comparison.append([my_score,clf_score])

print("My 10 fold cross vaildation score = " + str(np.
 ↪mean([RBF_comparison[i][0] for i in range(len(RBF_comparison))])))
print("Base 10 fold cross vaildation score = " + str(np.
 ↪mean([RBF_comparison[i][1] for i in range(len(RBF_comparison))])))
```

```
My 10 fold cross vaildation score = 0.3411764705882353
Base 10 fold cross vaildation score = 0.972549019607843
```

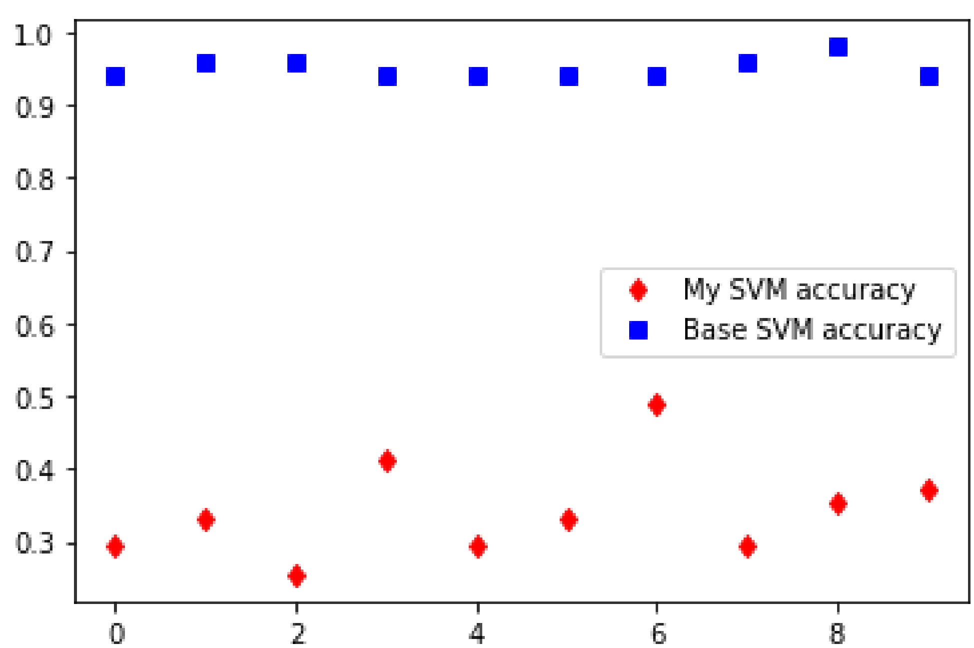
[7]:
```
clf = make_pipeline(StandardScaler(), SVC(kernel = 'linear'))
mySVM = MCSupportVectorMachine(2,1000, comparison_method = "one_v_one", Kernel␣
 ↪= 'linear' )
#Using linear kernel for comparison
my_preprocessed_data = np.array(mySVM.normalise(beerdata))

lin_results = []
lin_comparison = []
for cross_validation in range(10):
    rand.seed(7*cross_validation + 1)

    number_of_test_points = int(len(target)/3)
    rows_for_test = sorted(rand.sample(range(len(target)),␣
 ↪number_of_test_points))


    test_target = target[rows_for_test].tolist()
    train_target = np.delete(target,rows_for_test,axis =0).tolist()

    clf_test_data = beerdata[rows_for_test].tolist()
    clf_train_data = np.delete(beerdata,rows_for_test,axis =0).tolist()

    my_test_data = my_preprocessed_data[rows_for_test].tolist()
    my_train_data = np.delete(my_preprocessed_data,rows_for_test,axis =0).
 ↪tolist()


    clf.fit(clf_train_data,train_target)
    clf_predict = [clf.predict([point]) for point in clf_test_data]
    clf_predict = [clf_predict[i][0] for i in range(len(clf_predict))]
```

```
    mySVM.train(my_train_data,train_target)
    my_predict = [mySVM.predict(point) for point in my_test_data]

    clf_score = np.mean([clf_predict[i] == test_target[i] for i in␣
 ↪range(len(pred))] )
    my_score = np.mean([my_predict[i] == test_target[i] for i in␣
 ↪range(len(pred))])

    lin_results.append([my_predict,clf_predict,test_target])
    lin_comparison.append([my_score,clf_score])

print("My 10 fold cross vaildation score = " + str(np.
 ↪mean([lin_comparison[i][0] for i in range(len(lin_comparison))])))
print("Base 10 fold cross vaildation score = " + str(np.
 ↪mean([lin_comparison[i][1] for i in range(len(lin_comparison))])))
```

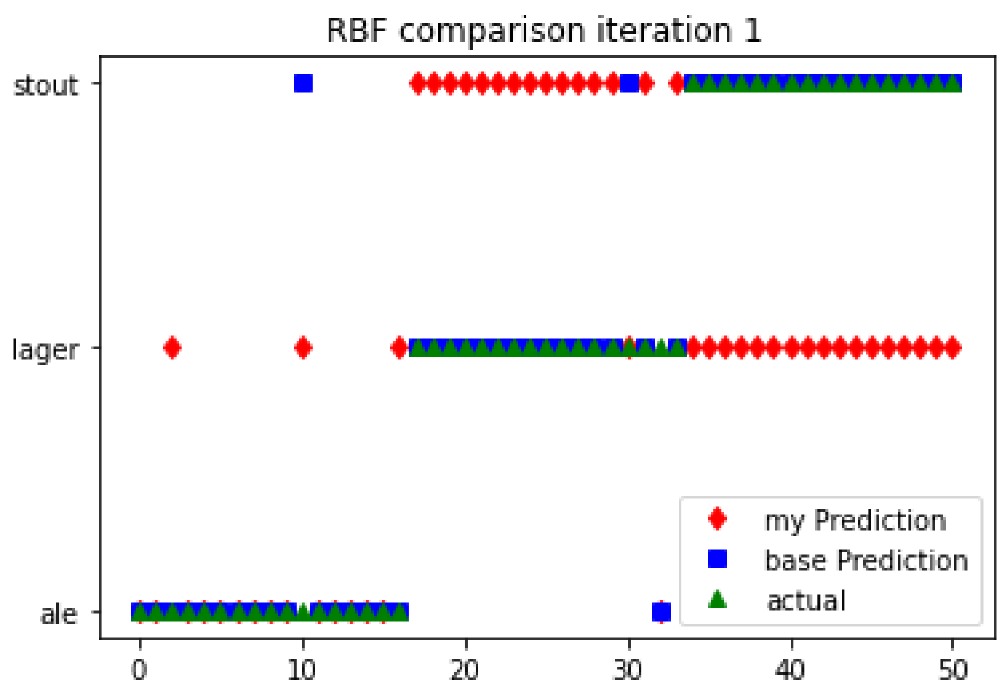
```
My 10 fold cross vaildation score = 0.3431372549019608
Base 10 fold cross vaildation score = 0.9509803921568627
```

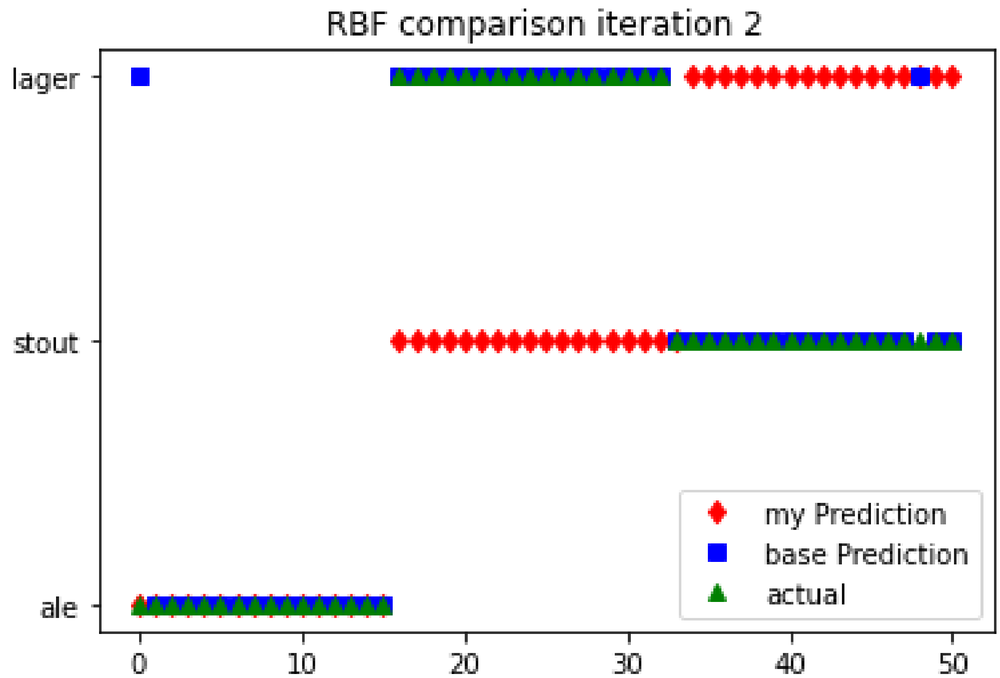
[10]:

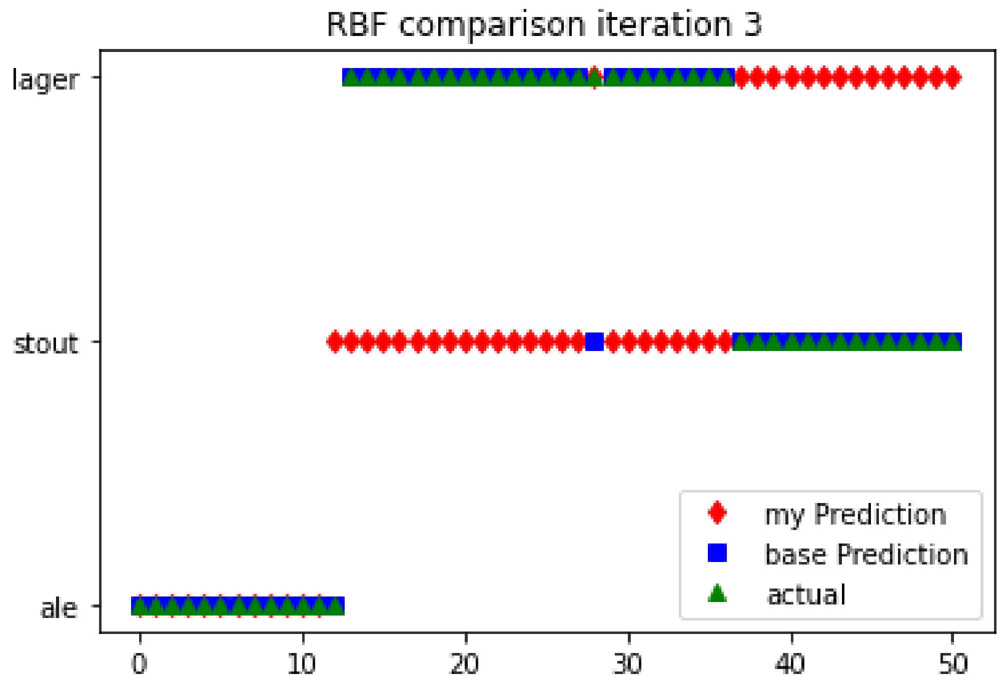
```
y1 = [lin_comparison[i][0] for i in range(10)]
y2 = [lin_comparison[i][1] for i in range(10)]

my_accuracy, = plt.plot(y1,'rd', label='My SVM accuracy')
base_accuracy, = plt.plot(y2,'bs', label='Base SVM accuracy')
plt.legend(handles=[my_accuracy, base_accuracy])
plt.show()
```

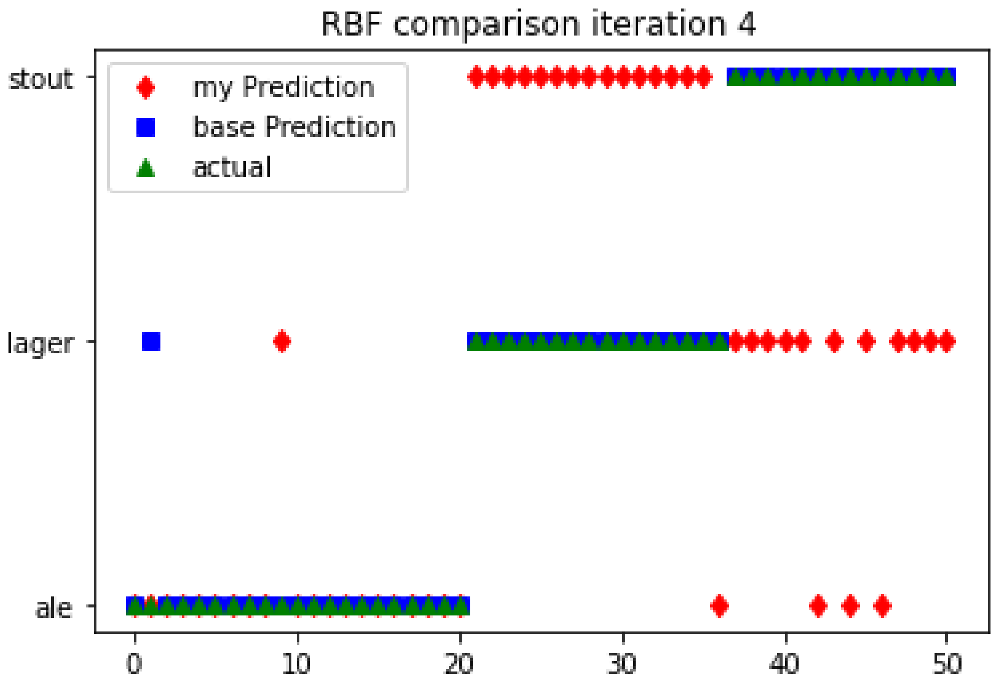


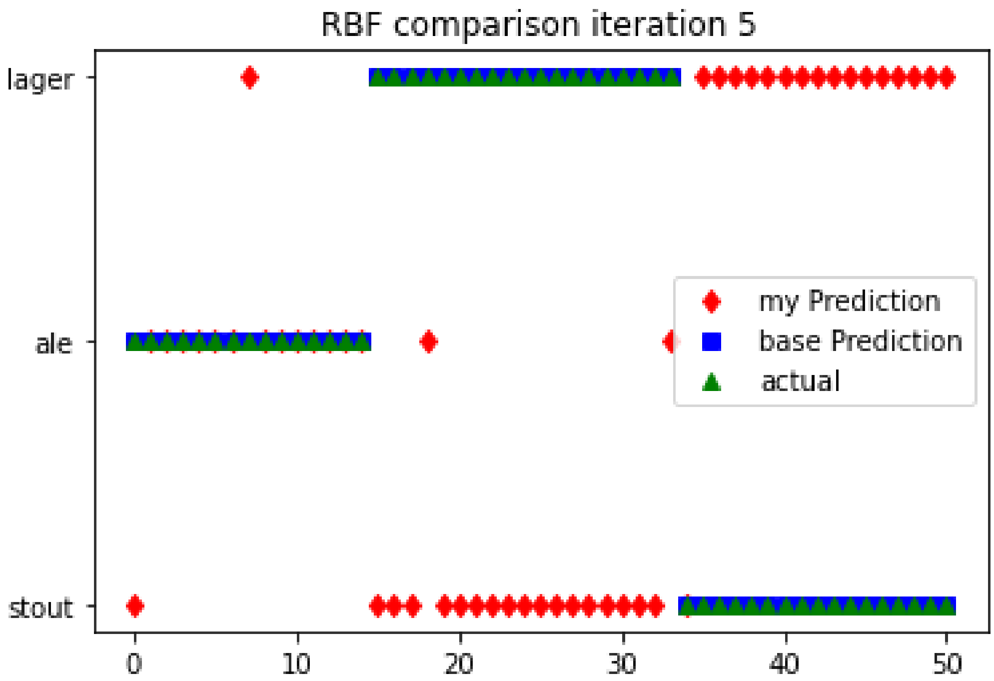
[13]:
```
Y1 = [RBF_results[i][0] for i in range(len(RBF_results))]
Y2 = [RBF_results[i][1] for i in range(len(RBF_results))]
Y3 = [RBF_results[i][2] for i in range(len(RBF_results))]

for i in range(10):
    plt.figure()
    plt.title("RBF comparison iteration " + str(i+1) )
    plt.plot(Y1[i],'rd', label = 'my Prediction')
    plt.plot(Y2[i],'bs',label = 'base Prediction')
    plt.plot(Y3[i],'g^',label = 'actual')
    plt.legend()
    plt.show()
```

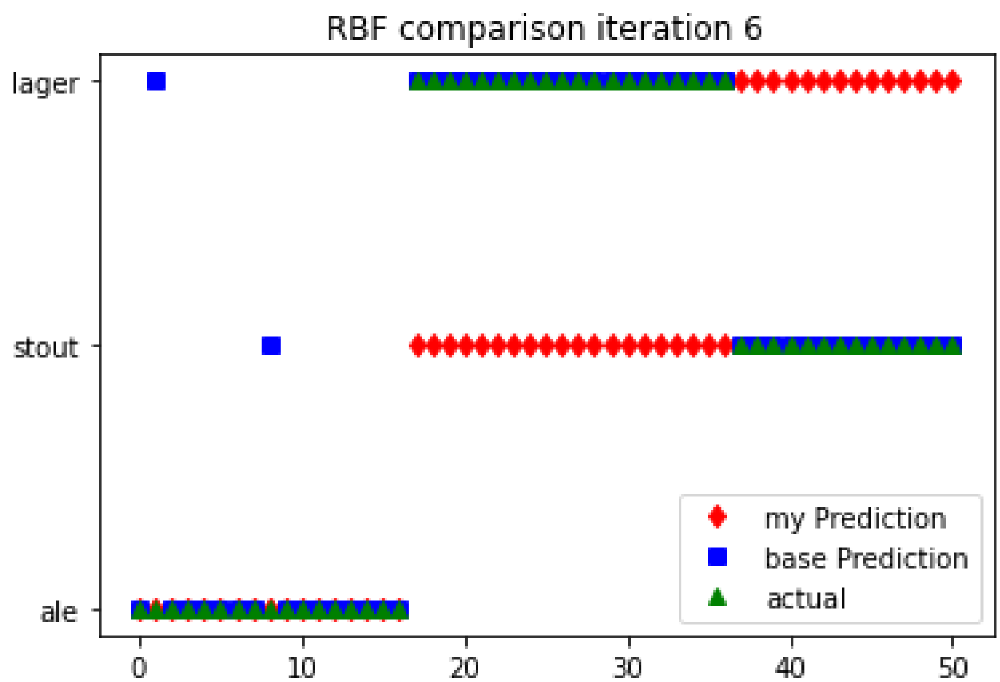


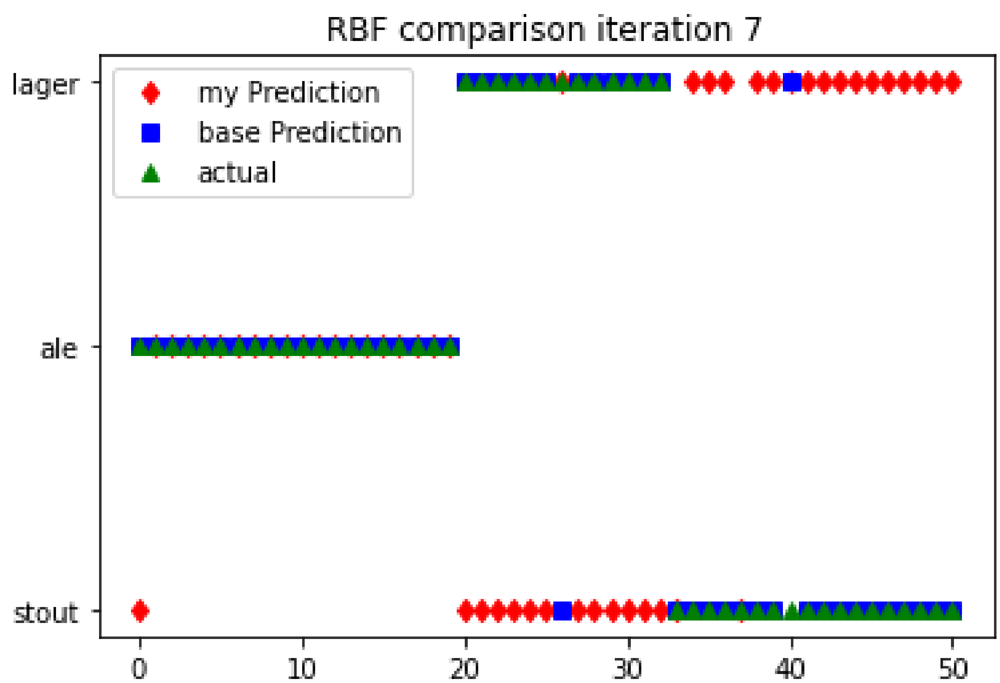

RBF comparison iteration 2
lager
stout
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual

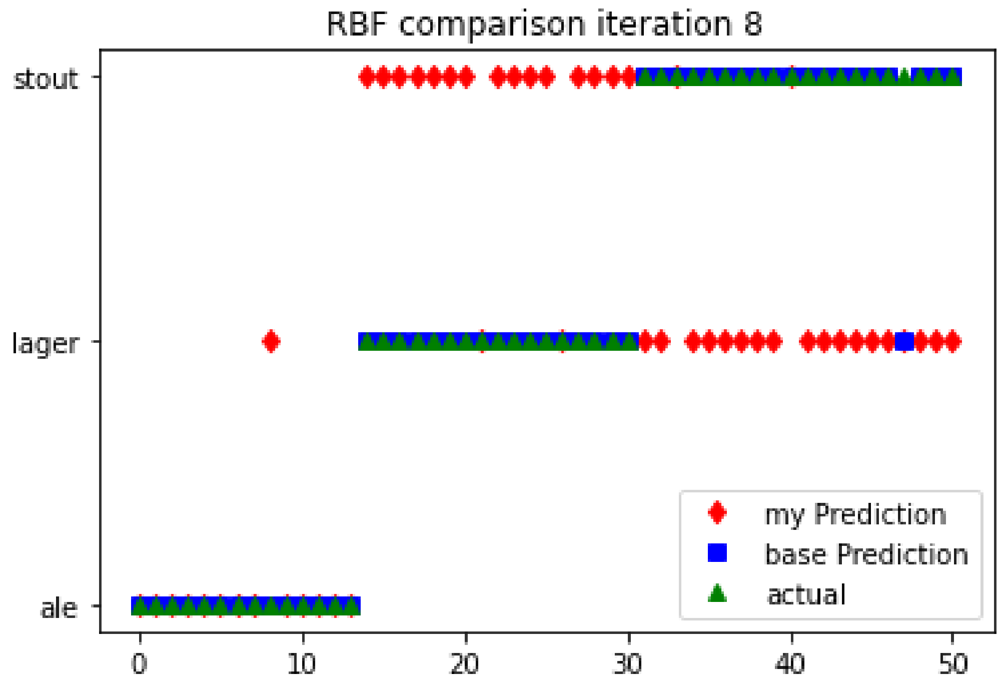

RBF comparison iteration 3
lager
stout
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual

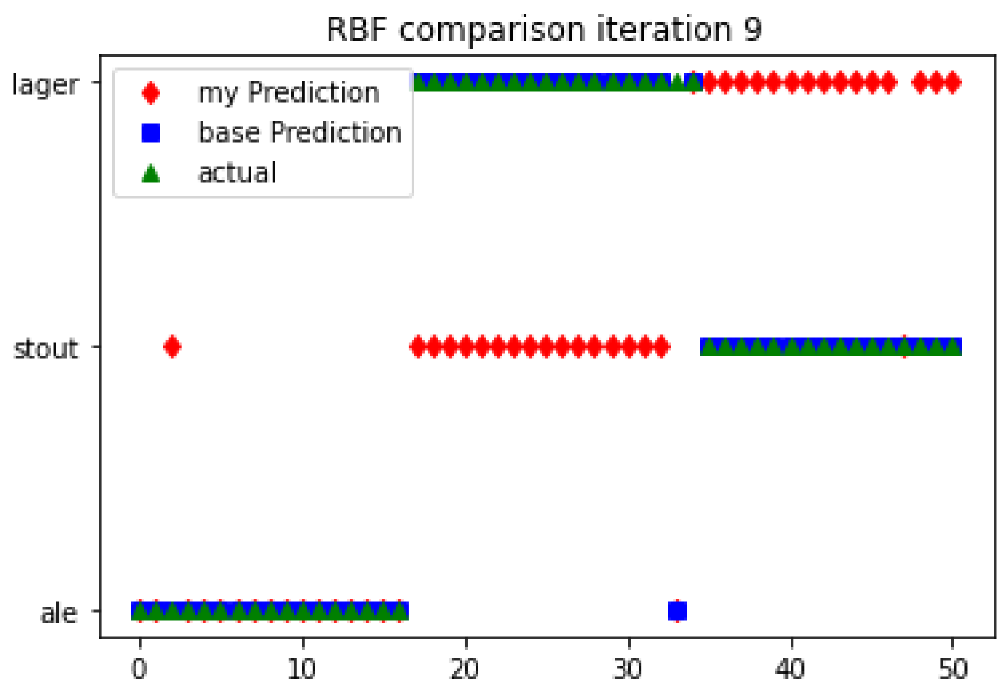

RBF comparison iteration 4
my Prediction
base Prediction
actual
stout
lager
ale
0
10
20
30
40
50

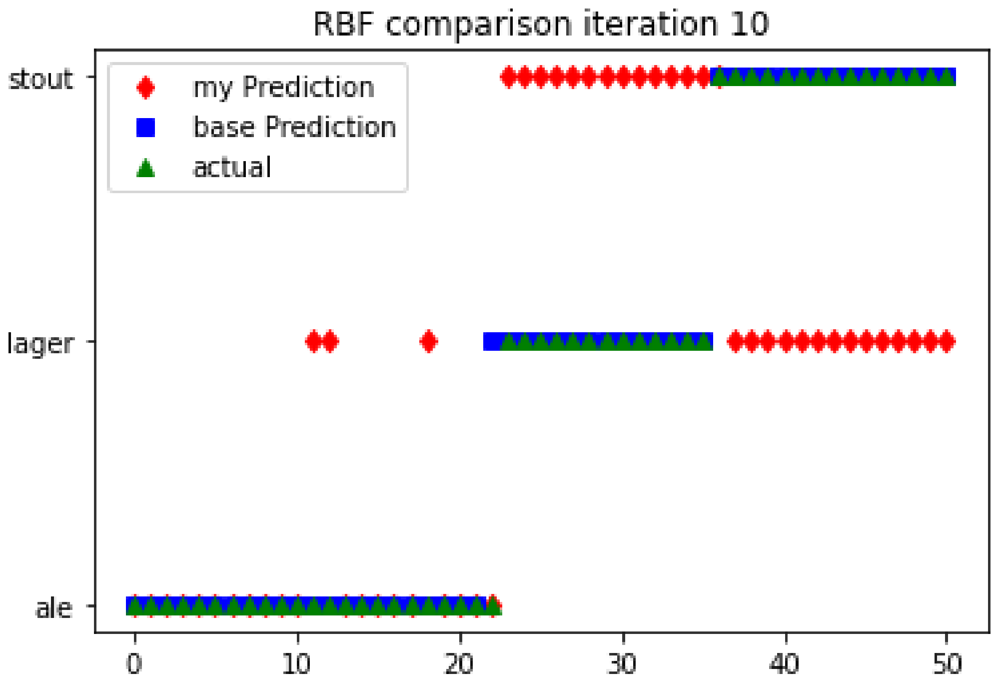

RBF comparison iteration 5
my Prediction
base Prediction
actual
lager
ale
stout
0
10
20
30
40
50


RBF comparison iteration 6
lager
stout
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual

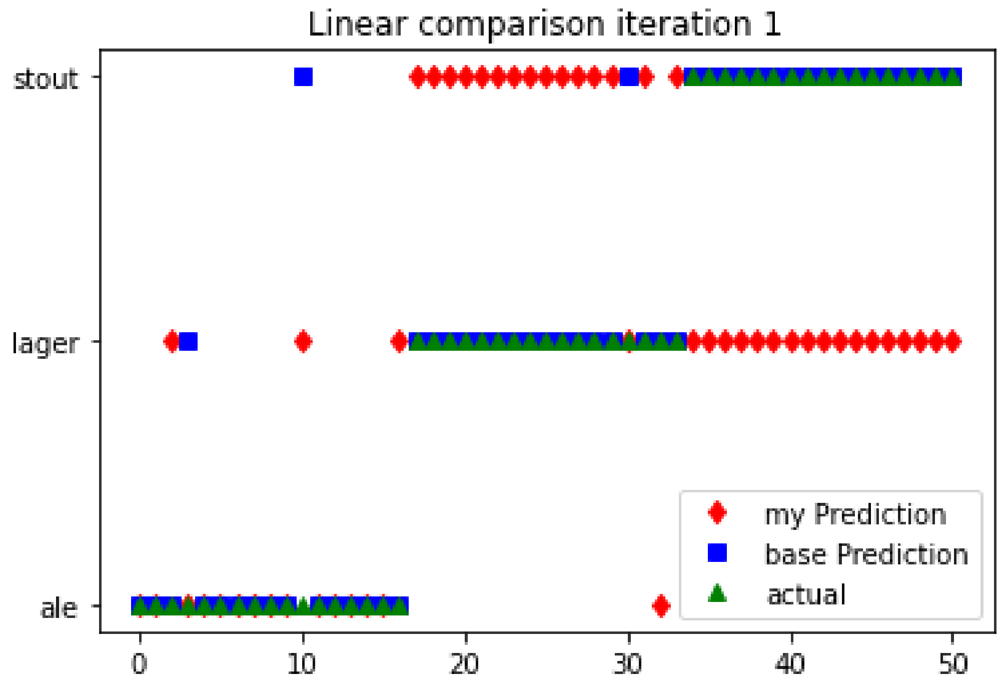

RBF comparison iteration 7
lager
ale
stout
0
10
20
30
40
50
my Prediction
base Prediction
actual

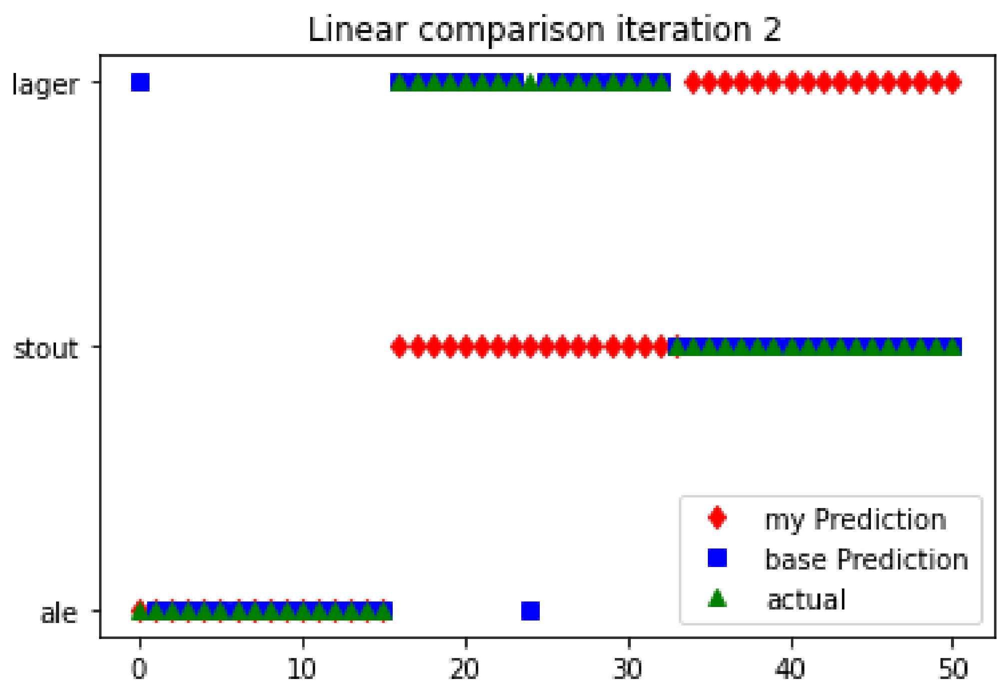

RBF comparison iteration 8
stout
lager
ale
my Prediction
base Prediction
actual
0
10
20
30
40
50

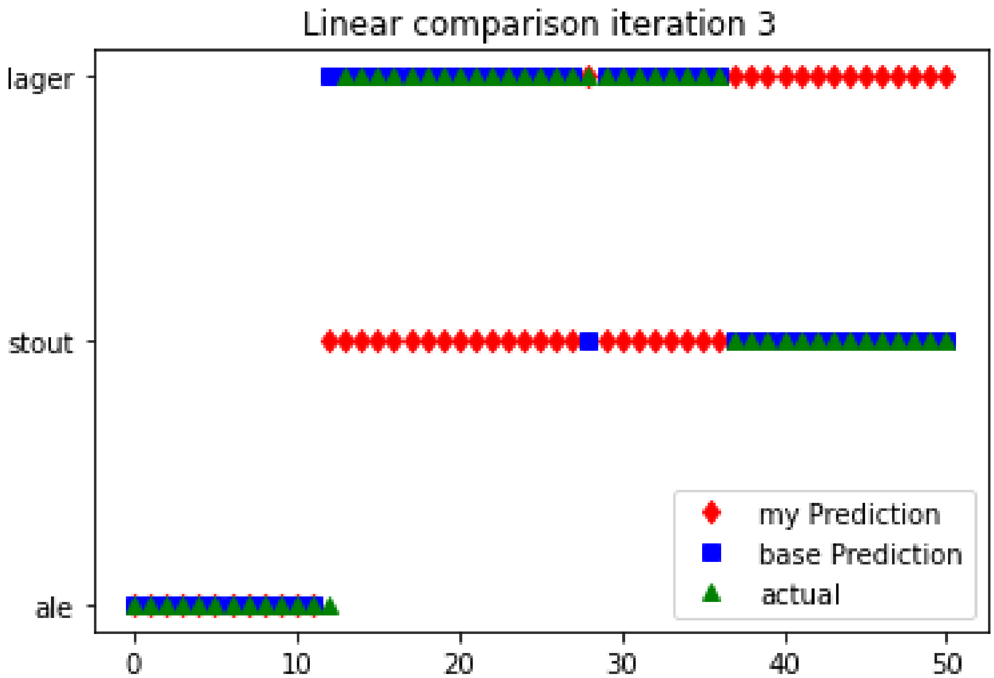

RBF comparison iteration 9
lager
stout
ale
my Prediction
base Prediction
actual
0
10
20
30
40
50

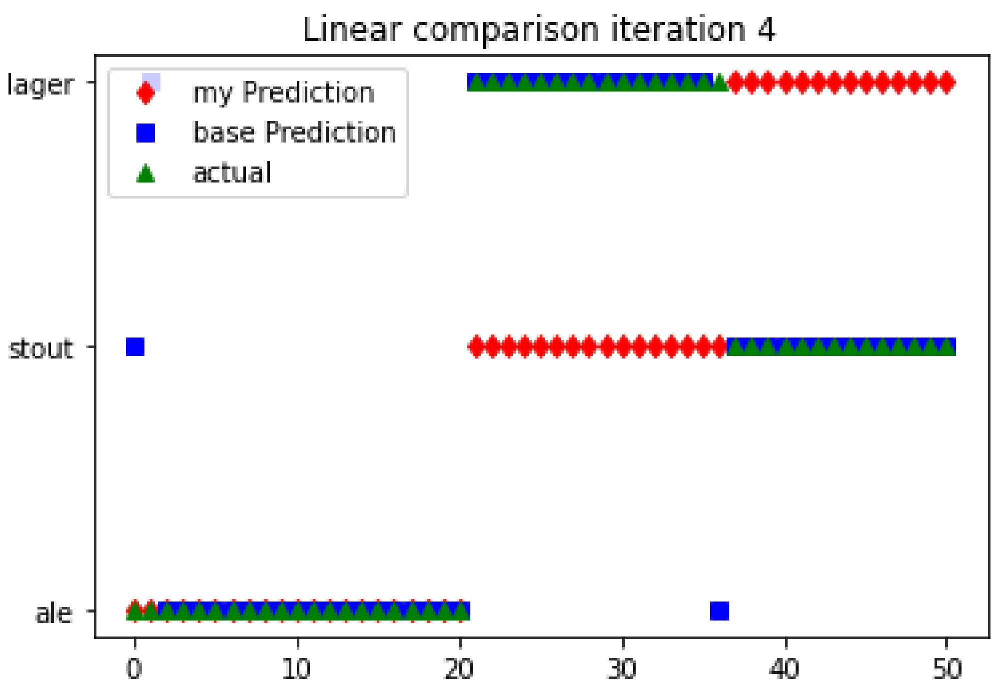


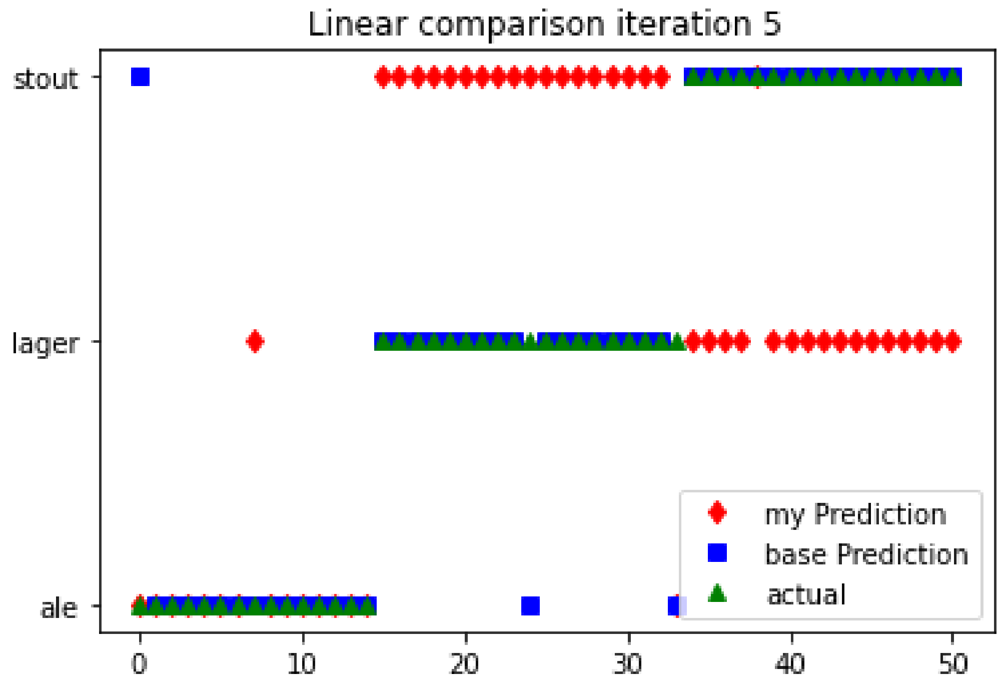

```
[15]: Y1 = [lin_results[i][0] for i in range(len(lin_results))]
      Y2 = [lin_results[i][1] for i in range(len(lin_results))]
      Y3 = [lin_results[i][2] for i in range(len(lin_results))]

      for i in range(10):
          plt.figure()
          plt.title("Linear comparison iteration "  + str(i+1))
          plt.plot(Y1[i],'rd', label = 'my Prediction')
          plt.plot(Y2[i],'bs',label = 'base Prediction')
          plt.plot(Y3[i],'g^',label = 'actual')
          plt.legend()
          plt.show()
```


Linear comparison iteration 1
stout
lager
ale
my Prediction
base Prediction
actual
0
10
20
30
40
50

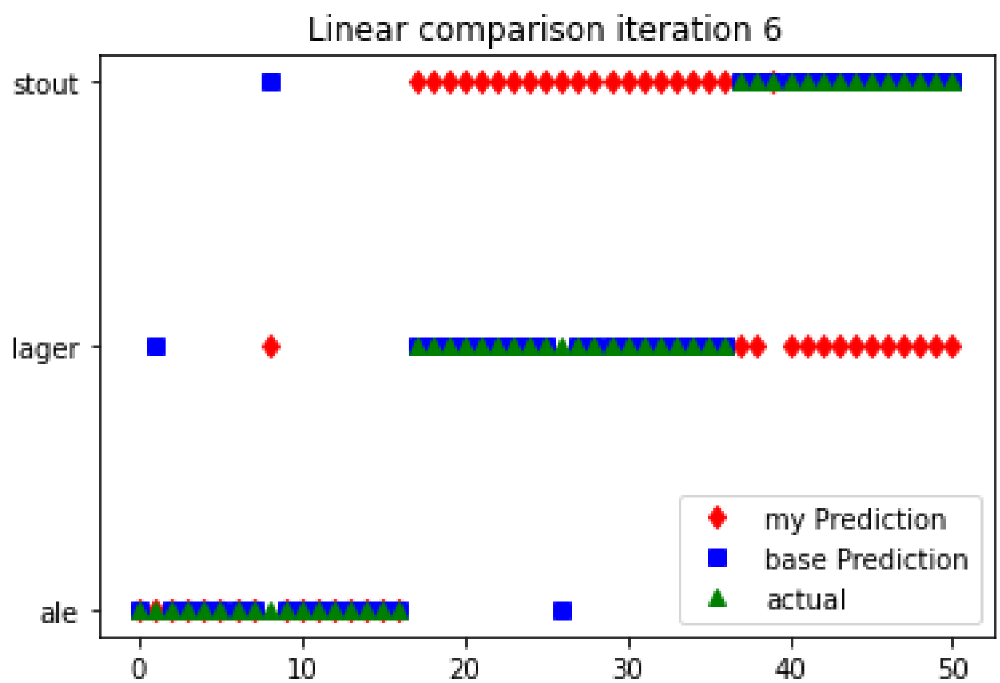

Linear comparison iteration 2
lager
stout
ale
my Prediction
base Prediction
actual
0
10
20
30
40
50


Linear comparison iteration 3
lager
stout
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual

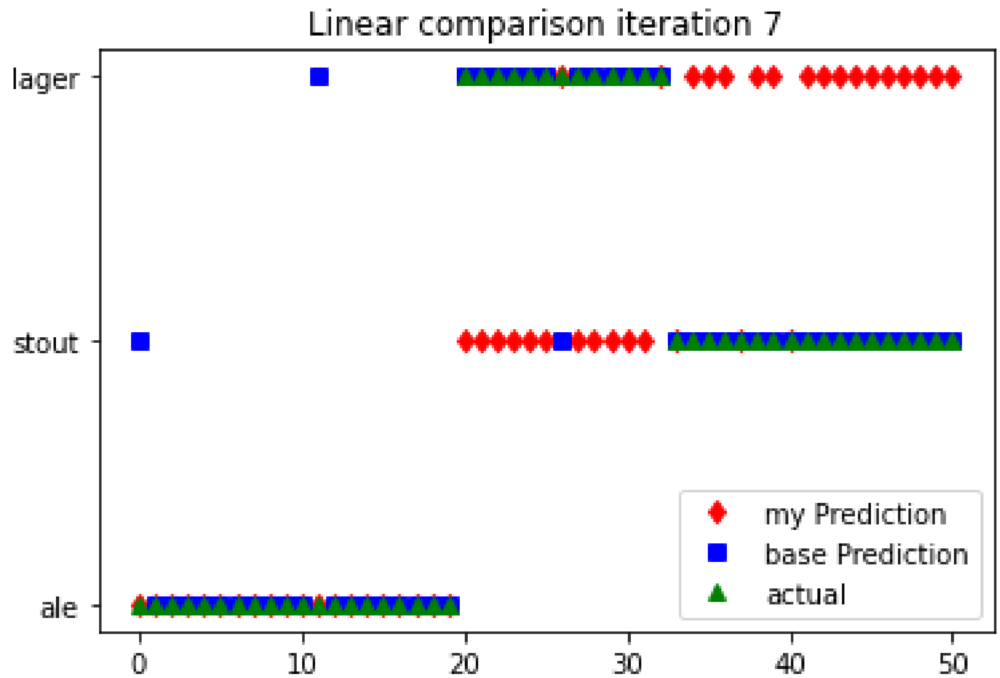

Linear comparison iteration 4
lager
stout
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual

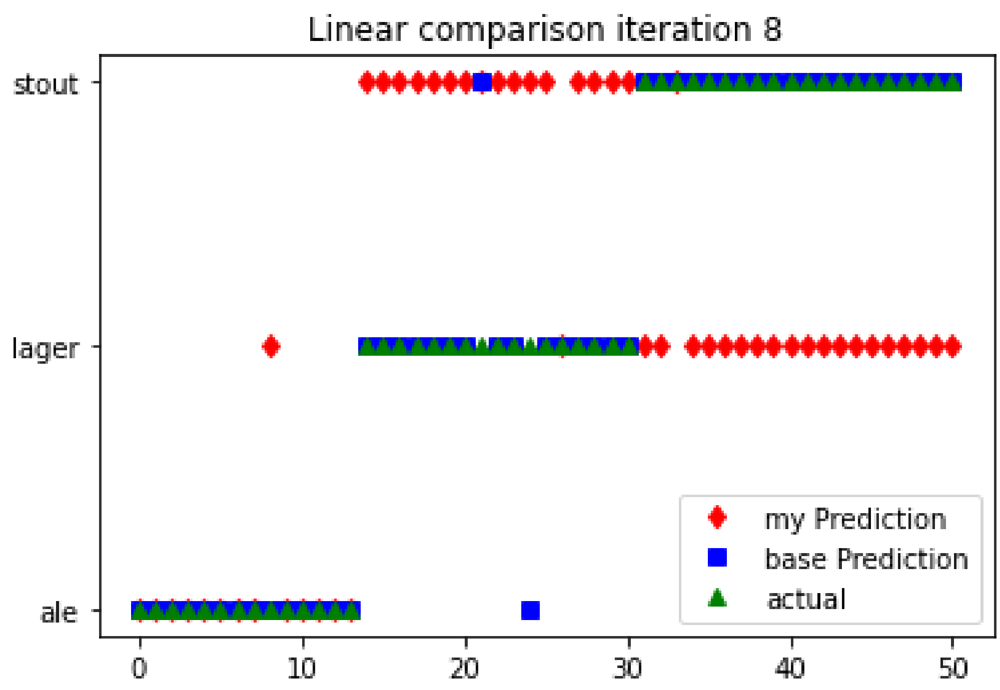


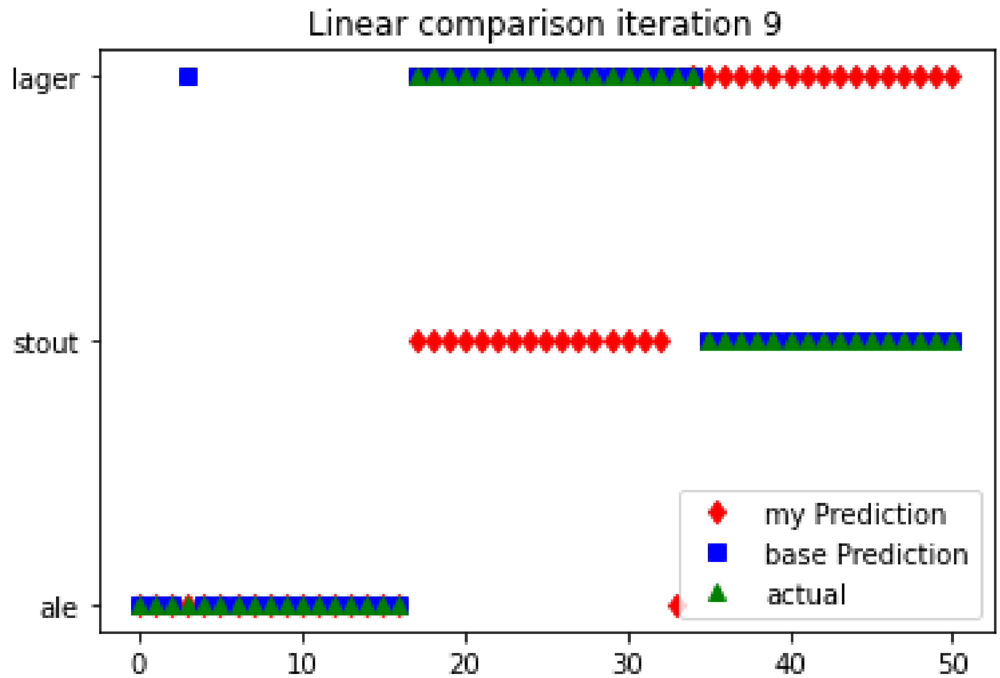
Linear comparison iteration 5
stout
lager
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual

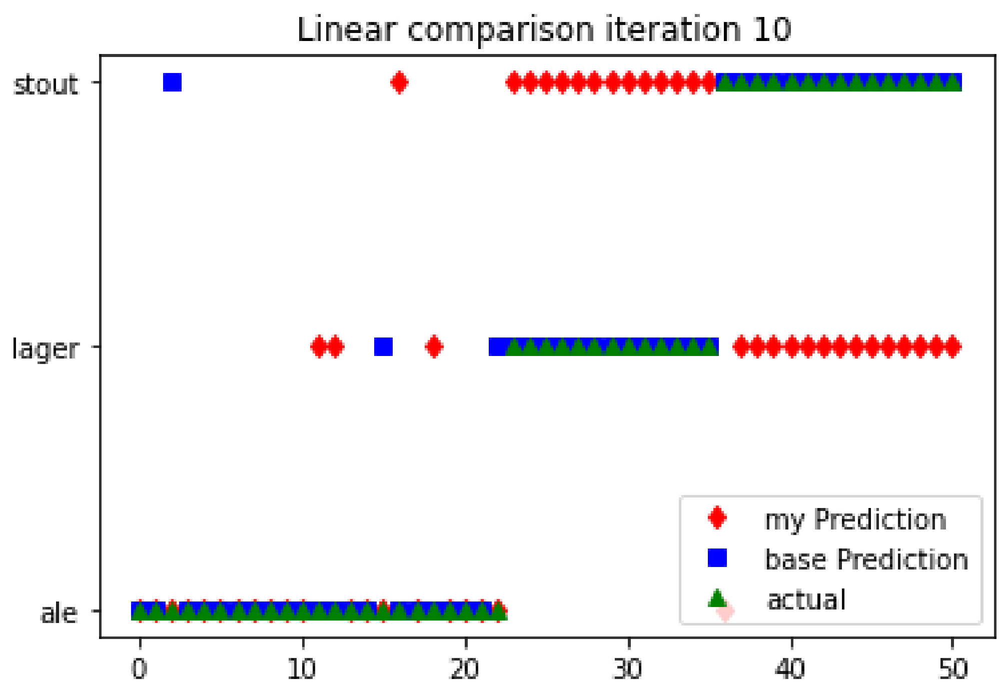


Linear comparison iteration 6
stout
lager
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual


Linear comparison iteration 7
lager
stout
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual


Linear comparison iteration 8
stout
lager
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual


Linear comparison iteration 9
lager
stout
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual


Linear comparison iteration 10
stout
lager
ale
0
10
20
30
40
50
my Prediction
base Prediction
actual